AN EMPIRICAL STUDY ON EARLY WARNING SYSTEMS FOR BANKING SECTOR

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
THE DEPARTMENT OF ECONOMICS

APRIL 2012

Approval of the Graduate School of Social Sciences.

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ABSTRACT

AN EMPIRICAL STUDY ON EARLY WARNING SYSTEMS FOR BANKING SECTOR

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April 2012, 225 pages

Early Warning Systems (EWSs) for banking sectors are used to measure occurrence risks of banking crises, generally observed with a rundown of bank deposits and widespread failures of financial institutions. In countries with a small number of banks, for example Turkey with 48 banks (BDDK, 2011), every bank may be considered to have a systematic importance since the failure of any individual bank may carry a potential threat to lead to a banking crisis. Taking into account this fact the present study focuses on EWSs in Turkey. Since there is no single correct EWS to apply to all cases, in this study, 300 models were constructed and tested to find models as accurate as possible by using a trial-and-error process and by searching optimal feature subset or classifier methods. Empirical results indicate that prediction accuracy did not increase significantly while we got closer to the actual occurrence of bankruptcy. An important finding of the study was that trends of financial ratios were very useful in the prediction of bank failures. Instead of failures as a result of instant shocks, the banks' failures followed through a path: first a downward movement affected the efficiency of the banks' officers and the quality of management structure measured with "Activity Ratios", then the profitability of the banks measured with "Profit Ratios" declined. At last, the performance and the stability of banks' earnings stream measured with "Income-Expenditure Structure Ratios" and the level and quality of the banks' capital base, the end line of defense, measured with "Capital Ratios". At the end of study, we proposed an ensemble model which produced probability ratios for the success rates of the banks. The proposed model achieved a very high success rate for the banks we considered.

Keywords: Early Warning Systems, Banking Crises, Bank Failures, Turkish Banking System

ÖZ

BANKACILIK SEKTÖRÜ İÇİN ERKEN UYARI SİSTEMLERİ ÜZERİNE DENEYSEL BİR ÇALIŞMA

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Tez Yöneticisi : Yrd.Doç.Dr. Esma GAYGISIZ

Nisan 2012, 225 pages

Bankacılık sektörü için erken uyarı sistemleri, mevduat stokunda ciddi azalış ve finansal kurum başarısızlıkları olarak tanımlayabileceğimiz bankacılık krizlerinin ortaya çıkış riskinin ölçümü için kullanılmaktadır. Sadece 48 bankası bulunan (BDDK, 2011) Türkiye gibi bir ülkede her bir banka sistematik önem taşıyor olabilir ve herhangi bir bankanın başarısızlığı bir bankacılık krizi ile sonuçlanabilir. Erken uyarı sistemleri tasarlanırken, her durumda uygulanabilecek, tek bir doğru model bulunmamaktadır. Bu çalışmada daha başarılı sonuç verecek değişken altkümesinin ve sınıflandırma metodunun tespiti için 300 model kurulup test edilmiştir. Ampirik sonuçlar göstermiştir ki, tahmin başarısı iflasın olduğu zamana yaklaştıkça kayda değer biçimde artmamaktadır. Ayrıca finansal oranların eğilimlerinin banka başarısızlık tahmininde faydalı olduğu görülmüştür. Bunların yanı sıra bankaların batma süreçlerinin ani bir şok olmadığı, daha ziyade bankaların bir rota takip ederek battığı tespit edilmiştir. Bankalarda aşağı doğru hareketin önce banka personelinin ve yönetiminin kalitesinde ve verimliliğinde (Faaliyet Oranları), daha sonra banka karlılığında (Karlılık Oranları) ve son olarak da banka kazanç sisteminin

performansında ve istikrarında (Gelir-Gider Yapısı Oranları) ve bankanın son savunma hattı olan sermaye tabanını seviyesinde ve kalitesinde (Sermaye Oranları) hissedilmekte olduğu gözlemlenmiştir. Son olarak da bankalar için başarı olasılığı üreten bir “birleşik model” önerilmiştir ve bu model ile %97,50 başarı oranı yakalanmıştır.

Anahtar sözcükler: Erken Uyarı Sistemleri, Bankacılık Krizleri, Banka Başarısızlığı, Türk Bankacılık Sistemi to my love

ACKNOWLEDGMENTS

The author wishes to express his deepest gratitude to his supervisor Asst. Prof. Dr. Esma GAYGISIZ for her guidance, advice, criticism, encouragements and insight throughout the research.

The author would also like to thank Prof. Dr. Erdal ÖZMEN and Asst. Prof. Dr. Bedri Kamil Onur TAŞ for their suggestions and comments.

The technical assistance of Mr. Fatih ALTINEL, Ms. Rukiye YAYLA, and Ms. Ekin ÖNŞAN are gratefully acknowledged.

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LIST OF ABBREVIATIONS

BFP	: Business Failure Prediction
BPNN	: Back Propagation Trained Neural Network
BRSA	: Banking Regulation and Supervision Agency
CART	: Classification And Regression Trees
DA	: Discriminant Analysis
DEA	: Data Envelopment Analysis
DMU	: Decision-Making Unit
EWSs	: Early Warning Systems for banking crises
FSI	: Financial Soundness Indicators
GA	: Genetic Algorithm
GP	: Genetic Programming
ID3	: Iterative Dichotomiser 3
IIA	: Independence of Irrelative Alternatives
IID	: Independent and Identically Distributed
k-NN	: k-Nearest Neighbor
LDA	: Linear Discriminant Analysis
LP	: Linear Programming
LVQ	: Learning Vector Quantization
Logit	: Logistic Regression
MARS	: Multivariate Adaptive Regression Splines
MDA	: Multivariate Discriminant Analysis
MSD	: Minimized Sum of Deviations
QDA	: Quadratic Discriminant Analysis
PCA	: Principal Component Analysis
RBF	: Radial Basis Function
SDIF	: Savings Deposit Insurance Fund
SOM	: Self-Organizing Feature Map
SVM	: Support Vector Machine

CHAPTER 1

INTRODUCTION

Banking sectors have a key position in the allocation of financial resources and hence in economic growth. However these sectors are also highly sensitive to macroeconomic and political instabilities and they are prone to crises. Because of their pervasive structure in financial systems and all over economies, these crises affect entire societies. For instance, in Turkish economy, total assets of banking sector exceeded 91,12% of Turkish Gross Domestic Product by the end of 2010 (BDDK (2011) and TÜİK (2011)). This comes from the fact that banks are integrated with almost all of the economic agents and with each other. Laeven and Valencia (2008) observed 124 systematic banking crises in different countries which cost on an average 13,3% of GDPs with a maximum of 55% of GDP. The sole cost of recent global crisis according to IMF (2010) is 3283,5 billion dollars and according to FDIC (2011), the number of unsuccessful US banks reached 367 in the recent global crisis.

The development of Early Warning Systems (EWSs) for banking sectors has been an extensive research area since 1970s. One of the main reasons behind this is the importance that banking sectors in financial systems. Another reason is that bank failures threaten economic systems as a whole. Not only stock holders, senior managements, creditors and auditors but also all agents of economies are interested in bankruptcy prediction for banks. According to Canbas et al. (2005), the study of EWSs is important because of two reasons. First, an understanding of the factors related to banking crises enable regulatory authorities to manage and supervise banks more efficiently. Second, the ability to differentiate between sound banks and troubled ones will reduce the expected costs of bank failures. In other words, if examiners can detect problems early enough, regulatory actions can be taken either to prevent a bank from failing or minimize the costs to the public and thus taxpayer of the failure.

In this study we examine EWSs and try to develop EWSs for Turkey. The main problem is that there is no single correct method to apply all cases although there may be a best way for each case. For this reason, researchers are basically trying to find more accurate models by using a kind of a trial-and-error process. In this study, we construct 300 different models by combining 7 datasets, 9 feature selection methods and 5 classifiers. We compare these 300 models by grouping them according to datasets, feature selection methods and classifiers used in the model. In order to find the optimal one we seek answers to the following questions: "Which classifier and feature selection method achieves best performance?", "Does the prediction accuracy increase while we get closer to the actual occurrence of bankruptcy?", "Does the usage of trend data increase the prediction performance?", "When different feature selection methods applied, which features are selected the most?" and many other questions. By doing so actually we test whether unsuccessful Turkish banks were failed following through a path or they failed instantly after a shock, which ratios reflected the bank failures the most, in which variables a downward movement can be seen first and which of the banks were the unsuccessfully predicted at the highest level. These shed light on the crises in 2000 and 2001 and there are some interesting results found with these comparisons. Finally, we formed a new model as a linear combination of the models used in this study and this new model achieved a 97,5% success rate. The analyses leading to this finding in the thesis are described below.

In chapter 2, a brief description of early warning systems, measuring the occurrence risk of a crisis, and their relation with neighboring areas were described. In this chapter, the role of early warning systems in the achievement of financial system stability is emphasized and the methods employed by financial sectors' authorities to detect the crises using these systems are shown. The methods used in this study are exhibited.

In chapter 3, we review the theoretical and empirical literature in an organized manner. Researches in Bank Failure Prediction (BFP) are basically trying to find more accurate models by using trial-and-error processes: either one predictive model has been determined to be used and optimal feature subsets searched or a gather of optimal feature subset has been determined to be employed and more accurate classifier will be found by comparisons among various models (Li & Sun, Predicting business failure using forward ranking-order case-based reasoning, 2011). Studies that are aimed at finding better results by trying different classifier methods are reviewed under the winning classifiers' title. In this context, first a classifier technique is reviewed briefly, then the advantages and disadvantages of the technique are listed and lastly studies that use the technique are surveyed. Studies that tried to find a better result by applying different feature selection methods are reviewed under "Feature selection and feature extraction" title and studies that used Turkish data are reviewed under "Studies related to Turkey" title.

In chapter 4, the experimental design used in this study is described. First, data collection and preparation step is reviewed. Then feature selection methods used in this study are discussed. After that classifiers used in this study are explained. Lastly training step is described as a conclusion of this section. In this study, an early warning system for Turkish banking sector with 300 models was designed.

In chapter 5, empirical results are presented and discussed. The predictions that models made are listed. The results are grouped according to dataset, feature selection method and classifier used in the models and significance of the differences between these groups are tested using paired samples t-test and nonparametric Wilcoxon two-related-samples test. So whether the predictive performances of datasets, feature selection methods and classifiers significantly different from each other are tested.

Finally, chapter 6 summarizes the findings of the study and reviews the results mentioned in chapter 5 with the conclusions.

CHAPTER 2

EARLY WARNING SYSTEMS

Early warning systems are used to measure the risk of a crisis. The literature on early warning systems covers three main types of crises: (i) currency crises which indicate sudden, sizable depreciation of the exchange rate and loss of reserves; (ii) debt crises which indicate default or restructuring on external debt; and (iii) banking crises which indicate a rundown of bank deposits and widespread failures of financial institutions (World Bank, International Monetary Fund, 2005). In general, banking crises are hard to identify, tend to be protracted, and, thus, have a larger macroeconomic effect (World Bank, International Monetary Fund, 2005). Although EWSs do not offer a perfect accuracy, they offer a systematic method to predict crises. For this purpose we are focusing on EWSs.

Generally the literature on forecasting banking crises focuses on three approaches: (i) the macroeconomic approach, which is based on the idea that macroeconomic structures cause crises, uses macroeconomic variables; (ii) the bank balance-sheet approach, which assumes that poor banking practices cause crises, uses bank balance-sheet data and (iii) the market indicators approach, which assumes that equity and debt prices contain information on bank conditions beyond that of balance-sheet data, uses equity and debt data (World Bank, International Monetary Fund, 2005).

In the literature some studies uses analyses of financial soundness indicators for individual banks, along with other supervisory information, serves as a form of EWS (Sahajwala & Van den Berg, 2000). In a country like Turkey, which has relatively low number of banks (as of 12.08.2011 there are 48 banks in Turkey), every bank may have systematic importance (BDDK, 2011). In this respect, the failure of any bank in Turkey can be considered as a potential threat to cause a banking crisis. Because of this the EWSs analyses which in predicting banking crises bear a big importance for Turkey.

In the next sub-section the macro usages and in section 2. 2 micro usages of EWSs are examined. Business failure prediction methodologies are reviewed in section 2. 3.

2. 1. Financial stability and early warning systems[1]

Financial system stability is an important subject that covers both the avoidance of financial institutions failing in large numbers and the avoidance of serious disruptions to the intermediation functions of the financial system: payments, savings facilities, credit allocation, efforts to monitor users of funds, and risk mitigation and liquidity services. To monitor financial stability, a framework with four elements can be used, namely; surveillance of financial markets, macroprudential surveillance, analysis of macrofinancial linkages, and surveillance of macroeconomic conditions.

• Surveillance of financial markets aims to assess the risk that a shock will hit the financial sector by using tools such as EWSs.

• Macroprudential surveillance helps to assess the health of the financial system and its vulnerability to potential shocks by using a combination of qualitative and quantitative methods. The key qualitative methods focus on the quality of the legal, judicial, and regulatory framework, as well as governance practices in the financial sector and its supervision whereas the key quantitative tools are the analysis of financial soundness indicators (FSIs) and stress testing. EWSs traditionally focus on vulnerabilities in the external position while using macroeconomic indicators. Macroprudential analysis generally focuses on vulnerabilities in domestic financial system arising from macroeconomic shocks, whose likelihood and severity can be judged from EWSs.

[1] This section is based on (World Bank, International Monetary Fund, 2005). To facilitate reading, only other sources used in this section are referenced after sentences.

The analysis of FSIs typically involves examination of trends, comparison between relevant peer groups of countries and institutions, and disaggregation into various groupings. The International Monetary Fund has developed two sets of FSIs; a core set covering only the banking sector and an encouraged set covering additional FSIs for the banking system as well as FSIs for key nonfinancial sectors, as weaknesses in these sectors are a source of risk for banks (Jones, Hilbers, & Slack, 2004). (see Appendix A) Although these sets provide an initial prioritization, the choice should not be limited to these sets. In countries with well-developed markets, market-based indicators can be used to monitor risks assuming they contain information on market beliefs, so contain information about the future. Market based indicators cover market prices of financial instruments, indicators of excess yields, spreads, market price volatility, credit ratings, and sovereign yield spreads. The advantage of these data is that most of them are frequent, which allows for more sophisticated analysis, such as the analysis of volatility and covariance. Also, confidentiality is generally not an issue. In addition to market-based indicators, structure based indicators can be used. They cover quantitative information on the structure, ownership and market shares, and degree of concentration of the financial system. For instance, within the group of domestically owned, private banks, internationally active banks are exposed to significant risk through their foreign branches and subsidiaries and so FSIs should include the activities of those foreign branches and subsidiaries, even though the latter are not part of the domestic activity.

Stress testing assesses the vulnerability of a financial system to exceptional but plausible events by applying a common set of shocks and scenarios to analyze both the aggregate effect and the distribution of that effect among the institutions. Stress tests are useful because they provide a quantitative measure of the vulnerability which can be used with other analyses to draw conclusions about the overall stability of a financial system. In individual financial institutions, a stress test is a rough estimate of how the value of a portfolio changes when a set of extreme but plausible shocks happened (Jones, Hilbers, & Slack, 2004). For financial systems, system-focused approaches are used. System-focused approaches aim to identify common vulnerabilities across institutions that could undermine the overall stability of the financial system (Jones, Hilbers, & Slack, 2004). System-focused stress tests can be classified into two types: simultaneous stress tests of multiple portfolios using a common scenario, or a single scenario applied to an aggregated portfolio or model of the entire system (Jones, Hilbers, & Slack, 2004). A stress test begins with the identification of specific vulnerabilities or areas of concern to narrow the focus of the exercise, since it is unrealistic to attempt to stress every possible risk factor for a portfolio or system (Jones, Hilbers, & Slack, 2004). For this purpose knowledge about broader macroeconomic environment would be useful to understand an overall context for the performance of the financial system, potential sources of shocks and mainly what is "normal" for an economy, with respect to its own history and in comparison with other countries (Jones, Hilbers, & Slack, 2004). After, a scenario is constructed in the context of a consistent macroeconomic framework (Jones, Hilbers, & Slack, 2004). The third step is to map the outputs of the scenario into a usable form for an analysis of financial institutions' balance sheets and income statements (Jones, Hilbers, & Slack, 2004). Then second round effects are considered and finally the results are summarized and interpreted (Jones, Hilbers, & Slack, 2004).

• <u>Analysis of macro-financial linkages</u> focuses on macroeconomic and sectoral implications of financial instability and aims to understand the exposures that can cause shocks to be transmitted through the financial system to the economy. Macro-financial linkages differ significantly across countries, but they are likely to include (i) the dependence of nonfinancial sectors (e.g., corporate, household, and government sector) on financing provided by banks; (ii) the deposits and wealth of those sectors placed with the financial sector; (iii) the role of the banking system on monetary policy transmission; and (iv) the financial sector's holdings of securities issued by, the government.

• <u>Surveillance of macroeconomic conditions</u> then monitors the effect of the financial system on macroeconomic conditions especially on debt sustainability. Even initially sovereign debt is at a sustainable level, a crisis can worsen the government's balance sheet and result unsustainable debt ratios. Debt sustainability problems in the nonfinancial sectors can further weaken the financial system by affecting the value of loans and securities held by the financial sector. The extent of the crisis can be magnified by the effect on financial prices as interest rates typically rise and as credit becomes less readily available. To prevent these, debt sustainability should be assessed and the two-way linkages between financial system soundness and financial soundness of nonfinancial sectors should be monitored. Although it is difficult to assess the debt sustainability by specifying a precise level at which a given stock of debt becomes “unsustainable,” it is possible to detect warning signs of excessive debt accumulation by examining a few key indicators and ratios such as growth rates of the stock of debt (e.g., debt-to-GDP or debt-to-equity ratios). There is an important point that needs to be addressed here. Country authorities may be faced with a tradeoff between economic growth and financial sector soundness since fast growth can make financial markets vulnerable to shocks. Because of this, country authorities need to distinguish to what extent a rapid financial sector growth reflects improvements in access to finance and to what extent the growth reflects a loosening in risk management practices and supervision.

2. 2. CAMELS, Off-site Monitoring and Early Warning Systems

Banking sector is governed with stronger regulations than other sectors and watched closely by authorities. Ağır et al. (2009) listed four reasons behind this. First of all banks are very sensitive to failure. If they have hard times because of mismanagement or macroeconomic shocks and if the deposit owners believe that banks would not fulfill their duties and they draw their deposits; banks will be faced with a liquidity inadequacy. Second bank failures have very serious negative effects. The banks’ obligations may be used as a payment tool since banks are trusted parties in economies. So the effects of bank failures will spread to all over the economy and a credit crunch in the economy may happen. This may also has social effects due to the loss of savings of households’. The third reason is the asymmetric knowledge between the bank owners and deposit owners. Finally the fourth reason is that there is no optimal regulation for financial markets.

Banking regulators oversee banks by off-site monitoring and on-site auditing. For on-site auditing, most of the regulators use CAMELS rating system to evaluate banks. CAMELS is an acronym for the six major components of a bank's financial and operational conditions: **C**apital adequacy, **A**sset quality, **M**anagement expertise, **E**arnings strength, **L**iquidity, and **S**ensitivity to market risk. FDIC (Federal Deposit Insurance Corporation) revised CAMEL and integrated "Sensitivity to market risk" to the system on December 20, (1996). To assist on-site bank examinations and indicate the safety and soundness of banks CAMELS provide a rating system with a scale from 1 to 5 with 1 being strongest and 5 being weakest. Every component is evaluated by utilizing some characteristics, and then weighted average of these evaluations is calculated to form a bank's final evaluation where the weights are defined by the auditor. These ratings are not released to the public but only to the top management. In addition to US, CAMELS or CAMELS-based-rating-systems have been used by many countries such as Hong Kong, England, South Korea, Chile, Argentina and Turkey (Kaya, 2001). While CAMELS ratings clearly provide regulators with important information, Cole and Gunther (1995) reported that if a bank has not been examined for more than two quarters, off-site monitoring systems usually provide a more accurate indication of survivability than its CAMEL rating. Although on-site auditing is an effective method, off-site monitoring is also important since on-site auditing is an expensive and a long process. So, off-site monitoring should not be seen as an alternative of on-site auditing but a complement of it (Cole & Gunther, 1995).

For off-site monitoring, there are mainly two approaches, i.e. data-oriented prediction and human preference-oriented prediction. The former approach, which is a quantitative method, is carried out on the foundation of data, mostly financial data, which indicate a company's state. The latter approach, which is a qualitative method, is implemented on the foundation of experiential knowledge of human beings (Li & Sun, 2008). Although the latter approach is used widely, the subjective conclusions and risk sourced from dependence to human nature made it not quite suitable to be used single-handedly. So, the two approaches are supplementary for each other. When there are enough distress symptoms in data, data-oriented models can effectively generate a signal of early warning. However, when there is little or almost no distress symptom in data, human preference-oriented models can produce an early warning signal (Li & Sun, 2008).

2. 3. Business failure prediction

The aim of a Business Failure Prediction (BFP) model is to classify a number of businesses into two predefined classes (successful and unsuccessful) using historical data. In this manner it looks like a pattern recognition problem but it is different from classical pattern recognition problems, since its objective is not only providing a classification of a company's financial state but also providing information on how the classification was reached (Li & Sun, 2010). The BFP has 5 steps: (i) data collection and preparation, (ii) feature selection and extraction, (iii) classifier choice, (iv) training and (v) evaluation.

Data collection and preparation is probably the most time-intensive step of the BFP. Source of data and target time interval for the study are decided in this step. Especially when the target time interval for the study is not selected the past several years from the study, data collection may become the biggest challenge for the researcher. In data preparation (i) possible missing values are handled by either deleting entire rows or using mean, previous or following values, (ii) data can be normalized which transforms data, for instance into the [0,1] interval, to avoid different characteristics and (iii) whether there exists a correlation between two or more predictor variables is checked. Sometimes models could not generalize the relations they discovered from historical data to the future data since they specialize to historical data and produces nearly perfect results for them but for other data their performance fails poorly. This is called over-fitting. To discover whether there is over-fitting in the model or not, in data collection and preparation step, most of the studies divided their dataset into two subsets: training sample and holdout sample. As their names state, training sample is used for training and holdout sample is used for testing. Some studies named them as estimation sample and validation sample.

Feature selection and extraction step is about selecting or extracting the distinctive aspects, qualities or characteristics of an object – in this study, a bank. It is easy to see that, a case that matches important features but not less important ones will almost certainly be a better match than one that matches less important features but does not match important ones. For this reason, feature selection and extraction which aim to integrate the domain knowledge is highly important in modeling (Park & Han, 2002). The quality of a feature set in a model is related to its ability to discriminate examples from different classes. In a model, the objects from the same class should have similar feature values while objects from different classes have different feature values (Gutierrez-Osuna).

Classifier choice may be the most crucial step for the success of a BFP model. The aim of classifiers in BFP is to classify a number of businesses into two predefined classes: successful and unsuccessful. Although a large number of methods like discriminant analysis, logit analysis, neural networks, etc., have been used in the past for the prediction of business failures and some of these leaded to a satisfactory discrimination rate between healthy and unsuccessful firms; the methods suffer from some limitations, often due to the unrealistic assumption of statistical hypotheses or due to a confusing language of communication with the decision makers (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

Training is the step where classifier explores relations from the data to explain the data by minimizing overall misclassification rate or error cost function. Although in many studies misclassification rate was used; it is not the best choice in the case of bank failure prediction since classification accuracy can be considered as a special case of misclassification cost when misclassification costs of classification of the unsuccessful firm into the successful group and costs of classification of the successful firm into the unsuccessful group are equal and this assumption does not hold at all (Zhao, Sinha, & Ge, 2009). Classification of an unsuccessful firm into a successful group error is considered by banking regulators to be far more costly than classification of a successful firm into an unsuccessful group. While the first one would allow a potential problem bank to pass by unnoticed, with severe consequences if the bank eventually fails, the second one would only result in a healthy bank being placed in the on-site examination queue. Training may be the easiest step when data is enough. But in real life researcher rarely enjoy such a situation. When data is limited, it is common practice n-fold cross-validation for training to assess how the results of a model will generalize to entire data set. For this purpose, the data is randomly split into n mutually exclusive subsets or folds of approximately equal size. Of these subsamples, one single subsample is selected as the validation data for testing the model, and the remaining $n-1$ subsamples are used as training data. This process is then repeated n times and each of the n subsamples is used as holdout sample while the other subsamples used as training data. The results from the folds then can be averaged to produce a single estimation (Maimon & Rokach, 2010).

Evaluation is the step where the trained model will be assessed or compared with other models. In literature, Type I and Type II errors are used to verify models prevalently. Type I error, also known as a false positive, refers to the error of rejecting a null hypothesis although it is the true, that is, in BFP, classification of a successful firm into an unsuccessful group. Type II error, also known as a false negative, refers to the error of not rejecting a null hypothesis although the alternative hypothesis is the true, that is, in BFP, classification of an unsuccessful firm into a successful group. Also in the literature, three terms are also important and commonly used to verify models: accuracy, specificity and sensitivity. Accuracy is the true classification rate, specificity is the true-negative rate and sensitivity is the true-positive rate of the model. In some studies receiver operating characteristic or simply ROC curve and the area under the ROC curve, or AUC (area under curve) were used for the evaluation of the model. ROC curve is a graphical plot with sensitivity on the X-axis and one-specificity on the Y-axis criterion. AUC is the area under the ROC curve.

2. 4. Why do banks fail?

The failure of banks or firms can be caused from internal reasons or/and external reasons. In business failure prediction literature some focused on internal reasons.

Ravi and Ravisankar (2010) grouped the factors that determine the health of a bank or firm in a highly competitive business environment as; (i) how financially solvent it is at the inception, (ii) its ability, relative flexibility and efficiency in creating cash from its continuous operations, (iii) its access to capital markets and (iv) its financial capacity and staying power when faced with unplanned cash short-falls. In addition, Tsai (2009) mentioned the effect of a highly distressing event, such as a major fraud. Lensberg et al. (2006) categorized various factors affecting bankruptcy potentially as audit, financial ratios, fraud indicators, start-up and stress. For the causes of failure of banks or firms some focused on external reasons. Canbas and Erol (1985) deliberated on the general the economy policies. According to Hutchison and McDill (1999), financial liberalization combined with explicit deposit insurance and weak law enforcements (moral hazard problem) increases probability of failure. Demirguc-Kunt and Detragiache (1998) listed the external reasons as low GDP growth, high inflation and real interest rates, explicit deposit insurance scheme and weak law enforcement. For Turkish banks, BRSA reported that the main partner abuses were found to be the main reason for bank failures (BDDK, 2009).

Although there are strategies that banks can choose to prevent failure such as re-organization, acquisitions and mergers; in this study we will define failed banks as banks that were transferred to the SDIF by the BRSA. Because it is nearly impossible to discriminate whether these strategies are chosen to prevent the failure or these strategies are chosen for other reasons.

CHAPTER 3

LITERATURE REVIEW ON BUSINESS FAILURE PREDICTION

Since Altman's work in 1968, the business failure prediction problem received a lot of interest (Daubie & Meskens, 2002). Forty more years have passed since this area was opened and no single-model outperforms other models under all circumstances. Researches in BFP are basically trying to find more accurate models by using trial-and-error processes: either one predictive model has been determined to be used and optimal feature subsets searched or a gather of optimal feature subset has been determined to be employed and more accurate classifier will be found by comparisons among various models (Li & Sun, Predicting business failure using forward ranking-order case-based reasoning, 2011).

Although all the steps of BFP are very important for a model's success, classifier choice may be the most crucial step for the success of a BFP model. For this reason, in literature, it is more common to classify previous studies according to classifier method it used (Ravi Kumar & Ravi, 2007). In this study, for the literature review, studies that used Turkish data are reviewed under section "3. 3. Studies related to Turkey", studies that compared feature reduction methods are reviewed under section "3. 2. Feature selection and feature extraction" all other studies are reviewed under section "3. 1. Classifiers".

3. 1. Classifiers

As mentioned before the aim of classifiers in BFP is to classify a number of businesses into two predefined classes: successful and unsuccessful. Since the classifier does not differ according to whether the data used in a study is firms' data or banks' data, not only studies that use banks' data but also studies that use firms' data are examined in this section.

In this section, classifiers used in BFP literature are examined under 11 titles, in a manner based on Ravi Kumar and Ravi used (2007): (1) statistical techniques, (2) neural networks, (3) case-based reasoning, (4) decision trees, (5) operational research, (6) evolutionary approaches, (7) rough set based techniques, (8) fuzzy logic based techniques (9) support vector machines (10) other techniques and (11) soft computing techniques. When multiple techniques are compared in a paper, the paper is categorized according to the technique it proposed. From the studies examined here, as seen in Figure 1, soft computing family is the most widely applied technique with 35 papers. Neural networks family with 28 papers and statistical techniques family with 23 papers follow soft computing. Next, operational research techniques were applied in 8 papers, case-based reasoning were applied in 7 papers, decision trees and rough set based techniques accounted for 6 papers. Also evolutionary approaches and other techniques had 4 papers, each. Finally, support vector machines had 3 papers and fuzzy logic based techniques had 2 papers.

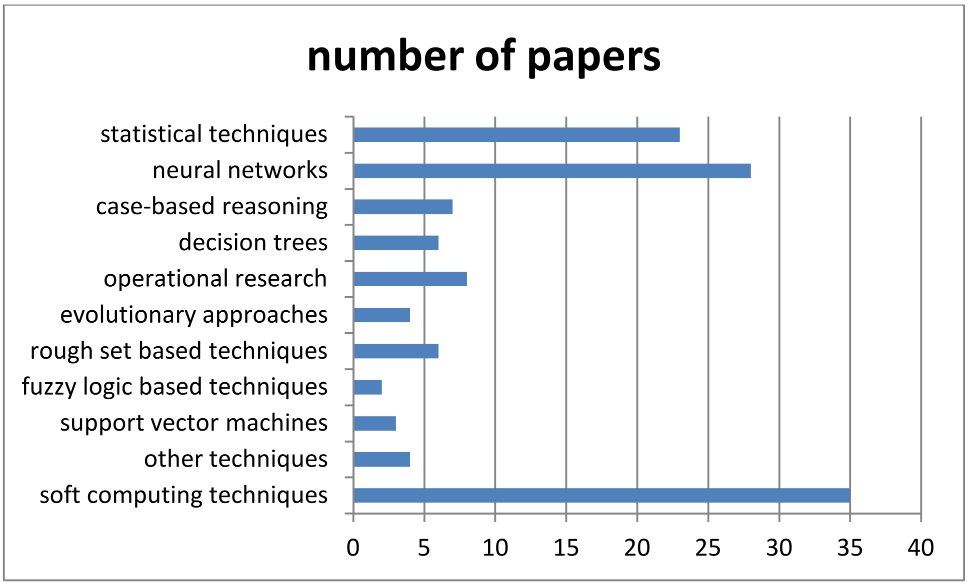

Figure 1: Literature classified in according to the classifier method used

Every classifier technique is examined under a sub-section. Each sub-section is organized as follows: first the classifier technique is reviewed briefly, then the advantages and disadvantages of the technique are listed and lastly studies that use the technique are surveyed.

3. 1. 1. Statistical techniques

First studies in BFP used statistical techniques. These studies can be grouped under three titles: (i) discriminant analysis, (ii) logit and probit models and (iii) other statistical techniques.

Discriminant analysis (DA) aims to find a combination of features which characterize or separate two or more classes of objects. In the DA, it is assumed that any object is characterized by a vector of features.

The objective of this method is to obtain a (linear/quadratic/…) combination of the independent variables that maximizes the variances between the populations relative to within-group variance (Canbas, Cabuk, & Kilic, 2005). In the equation below, this combination in a LDA model can be seen. The linear combination of the features provides a score Z_i for each object i where X_i denote a vector of features for ith object and β be a vector of unknown parameters. After this calculation, the Z_i value is compared with Z^* value which is calculated for achieving minimum error: if $Z_i > Z^*$ then the ith object is classified as “successful” else if $Z_i < Z^*$ then the ith object is classified as “failed”.

$$Z_i = \sum_j \beta_j X_{ij}$$

Classifiers derived from the DA are known to be optimal in minimizing the expected cost of misclassifications, provided the following conditions are satisfied: (i) each group follows a multivariate normal distribution, (ii) the covariance matrices of each group are identical, (iii) the mean vectors, covariance matrices, prior probabilities, and misclassification costs are known (Tam & Kiang, 1992).

Since violations of these assumptions occur regularly and the output of DA is a score which has little intuitive interpretation (since it is basically an ordinal ranking (discriminatory) device), Ohlson (1980) applied a logit model for BFP. After Ohlson, most studies preferred logit model over DA (Tam & Kiang, 1992). Also it was shown that even when all the assumptions of DA hold, a logit model is virtually as efficient as a linear classifier (Tam & Kiang, 1992).

In logit model, the probability of a business' failure can be shown as follows: let X_i denote a vector of features for ith object, β be a vector of unknown parameters and $0 \leq P_i \leq 1$ denote the probability of bankruptcy for any given X_i and β.

$$P_i = \frac{1}{1 + e^{-Z_i}}, \quad \text{where } Z_i \equiv \sum_j \beta_j X_{ij}$$

In probit model, the probability of a business' failure can be shown as cumulative standard normal distribution function:

$$P_i = \int_{-\infty}^{Z_i} \frac{1}{\sqrt{2\pi}} e^{-z/2} \mathrm{d}z, \quad \text{where } Z_i \equiv \sum_j \beta_j X_{ij}$$

Since probit model needs more complex calculations, in BFP literature, many researchers chose logit over probit (Kılıç, 2006).

<u>Advantages:</u>

- Statistical techniques require less calculation than most techniques. Since complicated procedures do not necessarily provide better results, sometimes it is better to use statistical techniques.

Disadvantages:

- Violations of the assumptions of statistical techniques occur regularly (Tam & Kiang, 1992).

Literature on Discriminant Analysis:

- In 1968, Altman applied a MDA model using a data set consist of the following financial ratios of 66 firms (33 unsuccessful - 33 healthy firms): (i) working capital/total assets; (ii) retained earnings/total assets; (iii) earnings before interest and taxes/total assets; (iv) market value of equity/book value of total debt; (v) sales/total assets. (Altman, 1968). Afterwards, this feature set was used in many other studies.

- In 1972, Deakin compared the BFP performance of Beaver's dichotomous classification test and Altman's DA to using 64 firms' data (32 healthy – 32 unsuccessful) from 1964-1970. He concluded that Beaver's dichotomous classification test was found to be successful to predict business failure five years in advance while Altman's DA could have been used to predict business failure from accounting data as far as three years in advance with a fairly high accuracy. (Deakin, 1972).

- In 1975, Sinkey applied MDA using 10 variables of 110 pairs of banks in health and distress observed in the period 1969-1972. He reported that asset composition, loan characteristics, capital adequacy, sources and uses of revenue, efficiency, and profitability were found to be good discriminators between the groups (i.e., group mean differences existed) and the model designed here achieved different success rates between 64,09%-75,24%. (Sinkey, 1975).

- In 1977, Altman et al. developed a new bankruptcy classification model called Zeta® Credit Risk Model using 111 firms with seven variables covering the period 1969–1975 and they reported that the classification accuracy of the model ranged from 96% for one period to 70% for five periods. (Altman, Haldeman, & Narayanan, 1977).

- In 1982, Dietrich and Kaplan developed a loan classification model from ordinary least squares (OLS) and MDA using variables suggested by experts (debt-equity ratio, funds-flow-to-fixed-commitments ratio, and sales trend), and compared it with Zeta model and Wilcox bankruptcy prediction and they found that the simple three variable linear model gave better predictions. (Dietrich & Kaplan, 1982).

- In 1987, Karels and Prakash, using a random sample of 50 companies, conducted a study in a threefold manner; (i) investigated the normality condition of financial ratios; (ii) when these ratios are non-normal, they constructed ratios which are either multivariate normal or almost normal; (iii) using these ratios to compare the prediction results of DA with other studies and they reported 96% classification rate for non-bankrupt firms and 54.5% for bankrupt firms. (Karels & Prakash, 1987).

- In 2001, Grice and Ingram evaluated the generalizability of Altman's (1968) Z-score model using a proportionate sample of distressed and non-distressed companies from time periods, industries, and financial conditions other than those used by Altman to develop his model. They examined three research questions: (i) whether Altman's original model was as useful for predicting bankruptcy in recent periods as it did for the periods in which it was developed and tested by Altman; (ii) whether the model was as useful for predicting bankruptcy of non-manufacturing firms as it is for predicting bankruptcy of manufacturing firms and (iii) whether the model was as useful for predicting financial stress conditions other than bankruptcy as it is for predicting bankruptcy. For the first research question, although Altman reported an 83.5% overall accuracy for the 1958 - 1961 sample, the overall accuracy for the 1988–1991 sample was 57.8%. For the second research question they reported that Altman's model was sensitive to industry classifications in the sample used in this study. They concluded that their results were consistent with negative answers to questions one and two and a positive answer to question three. (Grice & Ingram, Tests of the generalizability of Altman's bankruptcy prediction model, 2001).

- In 2011, Li and Sun proposed a new hybrid method for BFP by integrating PCA with MDA and logit. They compared the hybrid method with the two classifiers with features selected by stepwise method of MDA. For the hybrid method’s feature selection, PCA was employed in four different means, that is, the use of PCA on all available features, the use of PCA on the features selected by stepwise method of MDA, the use of PCA on the features selected by stepwise method of logit, and the use of PCA on the features selected by independent sample t test. The best way of employing PCA in the two methods of MDA and logit was to use PCA to extract features on the processed results of stepwise method of MDA. The best predictive performance of MDA and logit was not significantly different, though MDA achieved better mean predictive accuracy than logit. They concluded that the employment of PCA with MDA and logit can help them produce significantly better predictive performance in short-term BFP of Chinese listed companies. (Li & Sun, Empirical research of hybridizing principal component analysis with multivariate discriminant analysis and logistic regression for business failure prediction, 2011).

In addition to the studies above, Canbas et al.’s study (2005), which was surveyed under section “3. 3. Studies related to Turkey”, also used statistical techniques.

Literature on Logit and Probit Models:

- In 1977, Martin used logit model to predict the probability of failure of banks. (Martin, 1977).

- In 1980, Ohlson used logit model to predict firm failure and he reported that the classification accuracy was 96.12%, 95.55% and 92.84% for prediction within one year, two years and one or two years respectively. Ohlson also criticized studies that used MDA because of three reasons: (i) there are certain statistical requirements imposed on the distributional properties of the predictors (for example, the variance-covariance matrices of the predictors should be the same for both groups (failed and non-failed firms); moreover, a requirement of normally distributed predictors certainly mitigates against the use of dummy independent variables) (ii) the output of a MDA model is a score which has little intuitive interpretation, since it is basically an ordinal ranking (discriminatory) device (iii) there are also certain problems related to the "matching" procedures which have typically been used in MDA. He claimed that the use of logit avoids all these problems since in logit, without making any assumptions, the fundamental estimation problem can be reduced simply to the following statement: “given that a firm belongs to some pre-specified population, what is the probability that the firm fails within some pre-specified time period”. (Ohlson, 1980).

- In 1984, Zmijewski examined two potential biases caused by sample selection/ data collection procedures used in most financial distress studies using probit method with the data covering all firms listed on the American and New York Stock Exchanges during the period 1972 through 1978 which have industry (SIC) codes of less than 6000. The biases were; (i) when a researcher first observes the dependent variable and then selects a sample based on that knowledge (ii) when only observations with complete data are used to estimate the model and incomplete data observations occur non-randomly. He reported that for both biases the results were the same, which was, the bias was clearly shown to exist, but, in general, it did not appear to affect the statistical inferences or overall classification rates.(Zmijewski, 1984).

- In 1985, West used a combined method of factor analysis and logit to create composite variables to describe banks’ financial and operating characteristics, to measure the condition of individual institutions and to assign each of them a probability of being a problem bank and he reported that his method was promising in evaluating bank’s condition. (West, 1985).

- In 1985, Gentry et al., compared logit with DA and found that logit outperformed DA, and in 1987, they compared probit with DA and found that probit outperformed DA. In both studies they used a dataset consisted of 33 pairs of companies in health and distress observed in the period 1970-1981. (Gentry, Whitford, & Newbold, 1985).(Gentry, Newbold, & Whitford, 1987).

- In 2000, Laitinen and Laitinen tested whether Taylor's series expansion can be used to solve the problem associated with the functional form of bankruptcy prediction models. To avoid the problems associated with the normality of variables, logit was applied to describe the insolvency risk. Then Taylor's expansion was used to approximate the exponent of logit. They used data from the Compustat database and generated two datasets: the estimation sample included 400 firms (200 bankrupt and 200 non-bankrupt companies) and validation sample included 170 firms (85 bankrupt and 85 non-bankrupt companies). Four types of models were used to predict bankruptcy: a first-order model of the three basic ratios, the original Taylor expansion model with the second-order and interaction variables, a stepwise model derived from 32 financial ratios, and the stepwise Taylor expansion model derived from the three basic ratios and their second order and interaction terms. The cash to total assets, cash flow to total assets, and shareholder's equity to total assets ratios was found to be the factors affecting the insolvency risk. They concluded that for one year and two years prior to the bankruptcy, Taylor's expansion was able to increase the classification accuracy but not for three years prior to the bankruptcy.(Laitinen & Laitinen, 2000).

- In 2001, Grice and Dugan evaluated the generalizability of Zmijewski (1984) and Ohlson (1980) bankruptcy prediction models to proportionate samples of distressed and non-distressed companies from time periods, industries, and financial conditions other than those used to develop their models. They concluded that (i) both models were sensitive to time periods, the accuracy of the models declined when applied to time periods different from those used to develop the models (ii) the accuracy of each model continued to decline moving from the 1988–1991 to the 1992–1999 sample period (iii) Ohlson's (Zmijewski's) model was (was not) sensitive to industry classifications.(Grice & Dugan, The Limitations of Bankruptcy Prediction Models: Some Cautions for the Researcher, 2001).

- In 2004, Jones and Hensher presented mixed logit model for firm distress prediction and compared it with multinomial logit models by classifying firms into three groups: state 0: non-failed firms; state 1: insolvent firms, state 2: firms which filed for bankruptcy and concluded that mixed logit obtained substantially better predictive accuracy than multinomial logit models. (Jones & Hensher, 2004).

- In 2007, Jones and Hensher employed the multinomial nested logit (NL) model to BFP problem using a four-state failure model based on Australian company samples. They concluded that the unordered NL model outperformed the standard logit and unordered multinomial logit models and so, NL's prediction accuracy was satisfactory for BFP problems. (Jones & Hensher, 2007).

- In 2009, Lin examined the bankruptcy prediction ability of MDA, logit, probit and BPNN using a dataset of matched sample of failed and non-failed Taiwan public industrial firms during 1998–2005. They reported that the probit model possessed the best and stable performance; however, if the data did not satisfy the assumptions of the statistical approach, then the BPNN achieved higher prediction accuracy. In addition, the models used in this study achieved higher prediction accuracy and generalization ability than those of Altman's (1968), Ohlson's (1980), and Zmijewski's(1984).(Lin T. H., 2009).

Literature on Other Statistical Techniques

- In 1966, Beaver published the first significant study about BFP. He applied dichotomous classification test using a balanced sample of 158 firms which covers 79 unsuccessful firms which went bankrupt between 1954 and 1964 and 79 healthy firms approximately the same size and industry group for each of the failed firms. He calculated fourteen financial ratios for each firm and used them individually to predict business failure five years in advance. He reported that dichotomous classification test achieved 78% accuracy rate and from the ratios the cash-flow to total-debt ratio had excellent discriminatory power. (Beaver, 1966).

- In 2002, Kolari et al. compared two EWSs for large US banks. One of the models was based on logit analysis and it correctly classified over 96% of the banks 1 year prior to failure and 95% of the banks 2 year prior to failure. The other model, which was based on trait recognition, achieved 100% data classification accuracy for both 1 year and 2 year prior to failure. In the model, only half of the original sample could have been used and because of this reduction in the sample size, the model has disadvantages over logit model. They concluded that trait recognition outperformed logit model in terms of type-I and type-II errors. (Kolari, Glennon, Shin, & Caputo, 2002).

- In 2005, Pompe and Bilderbeek applied dichotomous classification and tested two hypotheses using small- and medium-sized Belgian industrial firms' data from period 1986-1994: (i) whether a downward movement could have first seen in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and finally the liquidity ratios, when a firm is heading towards bankruptcy (ii) whether the bankruptcy of young firms was more difficult to predict than the bankruptcy of established firms. For the first hypothesis they reported that it was not supported by the results and ratios that evaluate different dimensions of a firm's financial position showed similar predictive efficacies 5 years before failure. For the second hypothesis they reported that it was supported by the results. They also found that virtually every ratio investigated had some predictive power; some ratios, such as [cash flow/total debt], achieved results that were close to the results of the models (MDA and BPNN); ratios that performed well with old firms also showed a good performance with young firms; and the univariate and multivariate importance of ratio stability were not very high.(Pompe & Bilderbeek, 2005).

- In 2006, Lanine and Vennet applied a parametric logit model and a nonparametric trait recognition approach to predict failures among Russian commercial banks. The data obtained from 1997-2004 period and 3, 6, 9 and 12 months prior to failure models were constructed. In every model, the holdout sample consists of 100 healthy and 20 unsuccessful banks. The trait recognition approach was modified such that instead of assigning binary probabilities of default $p = 0$ or $p = 1$, the modified approach allowed calculation of default probabilities in the closed interval from zero to one. Return on assets [net income/total assets], general liquidity ratio [liquid assets/total assets], government debt securities [government debt securities/ total assets], capital adequacy ratio [capital/total assets], overdue loans [(overdue loans + overdue promissory notes)/total loans], loans to total assets [total loans/total assets] and size [total assets] were used as features in the model. They reported that the modified trait recognition approach significantly outperformed logit and the traditional trait recognition approach employed by Kolari et al. (2002) in both the original and the holdout samples. They concluded that liquidity, asset quality and capital adequacy were found to be important in bank failure prediction. (Lanine & Vennet, 2006).

3. 1. 2. Neural networks

Artificial neural networks technology was first developed to mimic the acquisition of knowledge and organization skills of the human brain. A neural network consists of a number of interconnected simple processing units which are called nodes. Figure 2 shows a simple neural network node. A node has many inputs, but has only one single output, which can spread out to many other nodes in the network. In a neural network each connection has a connection strength called weight. w_{ij} implies the weight of the connection between node i and j.

$$S_i = \sum_j w_{ij} O_j + \phi_i \qquad \text{and} \qquad O_i = \frac{1}{1 + e^{S_i}}$$

As seen in the equations above, in its simplest form, a node i receives input signals from other units, aggregates these signals by calculating weighted sum, S_i, where ϕ_i represents the bias of unit i and generates an output signal based on its transfer function, O_i, which is most likely a sigmoid function. The output signal is then routed to other units as directed by the topology of the network (Tam & Kiang, 1992). The output of jth node became an input for ith node.

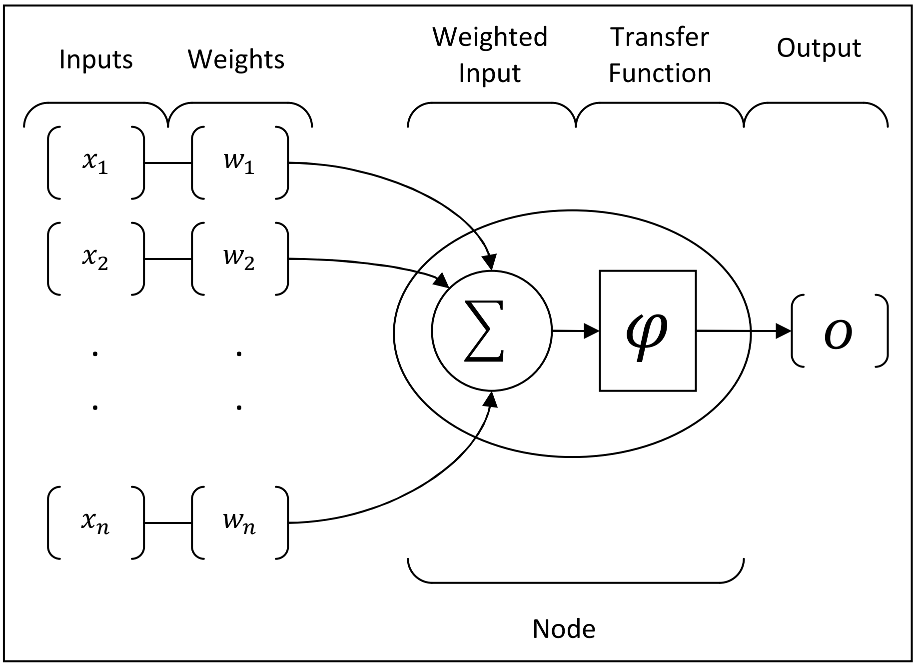

Figure 2: A simple neural network node

In Figure 3, a simple 3-layered neural network can be seen. These types of neural networks usually called feed-forward neural networks. In these kinds of topologies each link is assigned a numerical value representing the weight of the connection (Tam & Kiang, 1992). Weights are adaptive coefficients within the network that determine the intensity of the input signal. The set of nodes which run simultaneously, or in parallel, is called a layer and in a topology there are input layer, output layer, and hidden layer(s) (Ahn, Cho, & Kim, 2000). The nodes in input layer, accept signals from the environment. The nodes in output layer send signals to the environment. Other layer(s) is (are) called “hidden” layer(s), because the nodes in hidden layer(s) do not interact directly with the environment, i.e. hidden from the environment. Connections within a layer or from a higher layer to a lower are prohibited.

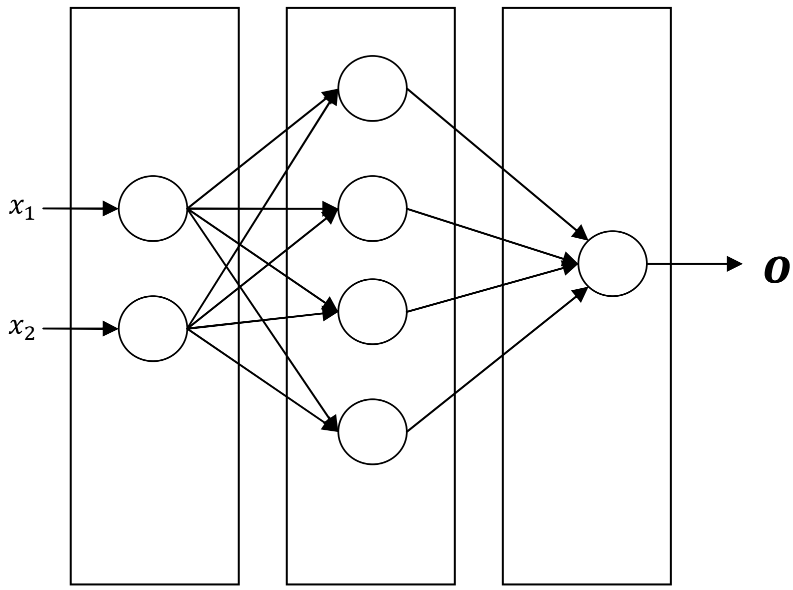

Figure 3: Three-layered feed-forward neural network topology

The pattern of connectivity of a feed-forward neural network, what it knows and how it will respond to any arbitrary input from the environment are described by the weights associated with the connections (Tam & Kiang, 1992) For assigning appropriate weights, which is a very difficult task, the network is trained. There are two types of training approaches in the literature: supervised training and unsupervised training.

In supervised training, inputs and target outputs are given to the network. The network learns the case by training with examples and search through the space for a set of weights offering the best fit with the given examples. In other words, the network learns by making mistakes. The learning algorithm calculates the difference between actual outputs and target outputs, the error terms, and then reassigns the weight values. This process is repeated until a maximum error rate is achieved or maximum number of iterations executed. Back-propagation, which is a generalization of delta rule, is an example for supervised training. Back-propagation neural network (BPNN) and learning vector quantization (LVQ) are commonly used supervised learning algorithms. As stated in its name, BPNN is a neural network model that uses back-propagation training algorithm. LVQ is an improved version of SOM where supervised learning is used.

In unsupervised learning, also known as the competitive learning, only inputs are given to the network. There is no need for target outputs. Competitive algorithm and the Kohonen algorithm are two examples for unsupervised learning. In competitive algorithm the network learns to classify input vectors. It returns neuron outputs of 0 for all neurons except for the “winner”, and returns the maximum output 1 for the “winner”. Over time only the winner’s weight gets updated (Alam, Booth, Lee, & Thordarson, 2000). However, in the Kohonen algorithm, the weights of the winner and its neighbors get updated through learning iteration (Alam, Booth, Lee, & Thordarson, 2000). The self-organizing map (SOM – sometimes called Kohonen map) and adaptive resonance theory (ART) are commonly used unsupervised learning algorithms. The SOM was introduced by Kohonen (1982). In SOM nearby locations in the map represent inputs with similar properties. The ART model was introduced by Carpenter and Grossberg (1988). In ART, the number of clusters can be changed with problem size and the degree of similarity between members of the same clusters can be controlled by the user.

Between the two approaches, supervised learning is retrospective, researchers often have to describe and explain experiments with past events (Lee, Booth, & Alam, 2005).

In other words, the findings of the networks trained in a supervised approach cannot be readily generalized to real-time or future mode, especially when the underlying business environment is radically changing (Lee, Booth, & Alam, 2005). In this perspective, unsupervised learning is much more successful. However, unsupervised learning has some disadvantages: low accuracy, the decision about number of clusters to be included, and the identification of cluster characteristics when exposed to classification tasks (Lee, Booth, & Alam, 2005).

As seen above, in literature, the neural networks differ in many aspects. As Ravi Kumar and Ravi, we will examine the literature of neural networks in three sub-sections covering the applications of (i) back propagation trained neural networks (BPNN), (ii) self-organizing feature map (SOM) and (iii) other neural network topologies such as probabilistic neural networks, auto associative neural networks and cascade correlation neural networks (Ravi Kumar & Ravi, 2007).

Advantages:

- It shows better prediction accuracy (Min & Lee, 2005).
- It offers significant support in terms of organizing, classifying, and summarizing data (Ahn, Cho, & Kim, 2000). Data is stored in connections as weights.
- It requires few assumptions.
- It can produce generalized rules from the data. Because of this, a trained network can operate with incomplete and defective data and adapt to new situations (Öztemel, 2003).
- Since nodes work parallel, neural networks have fast solving capability (Aktaş, Doğanay, & Yıldız, 2003).

Disadvantages:

- It has a difficulty in explaining the prediction results due to the lack of explanatory power (Min & Lee, 2005).
- Construction of a "best" architecture needs too much time and effort (Min & Lee, 2005).
- Over fitting may be a problem (Ahn & Kim, 2009).

Literature on Back Propagation Trained Neural Network:

- In 1990, Odom and Sharda compared the BFP performance of BPNN with that of MDA using firms' data that went bankrupt between 1975 and 1982 obtained from Moody's Industrial Manuals and consisted of a total of 129 firms, 65 of which went bankrupt during the period and 64 non-bankrupts. They found that BPNN obtained better results.(Odom & Sharda, 1990).
- In 1991, Tam applied BPNN for bankruptcy prediction using the data obtained from Texas banks, one year and two years prior to failure where the variables were selected based on CAMEL criteria of FDIC and as a result, he showed that BPNN offered better predictive accuracy than other methods viz., DA, factor-logistic, k-NN and ID3. (Tam, 1991).
- In 1992, Tam and Kiang compared the performance of (i) LDA, (ii) logit, (iii) k-NN, ($k = 1$ and $k = 3$ networks were constructed) (iv) ID3, (v) feed-forward neural network (net0) and (vi) BPNN (net10) on bankruptcy prediction problems in banks and found that BPNN outperformed other techniques when jackknife method was used. They concluded that while rule-based expert systems were satisfactory for off-line processing, a neural net-based system offered on-line capabilities. (Tam & Kiang, 1992).
- In 1992, Salchenberger et al. presented a BPNN to predict the probability of failure for savings and loan associations, compared its performance with a

logistic model. They concluded that BPNN which uses the same financial data, requires fewer assumptions, achieves a higher degree of prediction accuracy, and is more robust than logit. They performed stepwise regression considering 29 variables from the CAMEL categories and chose five variables. (Salchenberger, Cinar, & Lash, 1992).

- In 1993, Sharda and Wilson compared the BPNN having five input nodes, ten hidden nodes and two output nodes with MDA by using Altman's five variables based on re-sampling technique. They used several performance measures and concluded that BPNN outperformed DA in all cases. (Sharda & Wilson, 1993).

- In 1994, Altman et al. analyzed over 1,000 healthy, vulnerable or unsound industrial Italian firms' ten financial ratios using LDA and BPNN and they concluded that both techniques displayed acceptable, over 90%, accuracy and suggested a combined approach for predictive reinforcement. (Altman, Marco, & Varetto, 1994).

- In 1994 Tsukuda and Baba, in 1994 Wilson and Sharda, in 1996 Leshno and Spector, in 1996 Rahimian et al. compared the predictive accuracy of BPNN with DA using firms' data and all concluded that BPNN outperformed DA. (Tsukuda & Baba, 1994). (Wilson & Sharda, 1994).(Leshno & Spector, 1996)(Rahimian, Singh, Thammachote, & Virmani, 1996).

- In 1997, Barniv et al. compared BPNN, multi-state ordered logit and non-parametric multiple DA for classification of bankrupt firms into three states viz. acquired by other firms, emerging as independent operating entities, or liquidated, using two models viz., (i) twelve variable model and (ii) five variable model and reported that both models outperformed Ohlson's nine variable logit model and that BPNN outperformed both models. (Barniv, Agarwal, & Leach, 1997).

- In 1997, Bell compared logit and BPNN with 12 input nodes, six hidden nodes and one output node, in prediction of bank failures using 28 candidate predictor variables and reported that neither logit nor BPNN dominated the other in terms of predictive ability, but, for complex decision processes BPNN was found to be better. He claimed that the results showed that bank regulators use simple linear decision processes when making judgments about whether to close commercial banks. (Bell, 1997).

- In 1999, Zhang et al. used generalized reducing gradient (GRG2) trained three-layered BPNN for bankruptcy prediction of firms. They claimed that while traditional statistical methods worked well for some situations, they might have failed miserably when the statistical assumptions were not met. They reported that overall classification rates of GRG2 trained BPNN ranged from 77.27% to 84.09% whereas that for logit ranged from 75% to 81.82%. They used fivefold cross-validation technique for testing and reported that BPNN were robust to sampling variations in overall classification performance. (Zhang, Hu, Patuwo, & Indro, 1999).

- In 2001, Atiya developed novel indicators namely: (i)book value/total assets BV/TA, (ii) cash-flow/total assets CF/TA, (iii) gross operating income/total assets GOI/TA, (iv) rate of change of cash-flow per share ROC(CF), (v) return on assets ROA, (vi)price/cash-flow ratio P/CF, (vii) rate of change of stock price ROC(P), $(viii)$stock price volatility VOL; for a neural network model and using data from defaulted and solvent US firms, he reported that these indicators provided significant improvement. (Atiya, 2001).

- In 2001, Swicegood and Clark compared DA, BPNN and human judgment in predicting bank failures and concluded that BPNN shows slightly better predictive ability than that of the regulators and both models significantly outperformed DA. (Swicegood & Clark, 2001).

- In 2004, Lam compared technical analysis with BPNN for rate of return on common shareholders' equity prediction of firms by using two BPNN models viz. (i) first model uses 16 financial and 11 macroeconomic variables and (ii) second model uses only financial variables. She concluded that although second model significantly outperformed the minimum benchmark (the overall market average return) but not maximum benchmark (the average return from the top one-third returns in the market), first model could not outperform neither minimum nor maximum benchmark. (Lam M. , 2004).

- In 2005, Lee et al. compared BPNN with Kohonen self-organizing feature map (SOM), DA and logit and concluded that the BPNN outperformed the all other techniques. The four-fold cross-validation testing was used for all the models. (Lee, Booth, & Alam, 2005).

In addition to the studies above, Boyacioglu et al.'s study (2009), which was surveyed under section "3. 3. Studies related to Turkey", also proposed BPNN.

Literature on Self-Organizing Maps (SOM):

- In 1996, Lee et al. proposed three hybrid BPNN viz., (i) MDA-assisted BPNN (ii) ID3-assisted BPNN and (iii) SOM-assisted BPNN for predicting bankruptcy in firms using 57 financial variables from Korean bankruptcy data and concluded that SOM-assisted neural network models performed better than MDA and ID3. (Lee, Han, & Kwon, 1996).

- In 1996, Serrano-Cinca complemented and compared SOM based decision support system with LDA and BPNN in financial diagnosis using Altman's variables as data set. He proposed two hybrid systems viz., (i) a combination of LDA with SOM, (ii) a combination of BPNN with SOM. The DSS model provides a more detailed analysis than the traditional models based on the construction of a solvency indicator also known as Z score, without renouncing simplicity for the final decision maker. (Serrano-Cinca, 1996).

- In 1998, Kiviluoto used RBF-SOM hybrid with LDA, LVQ and k-NN for firm bankruptcy prediction and concluded that RBF-SOM performed slightly better than other classifiers. The parameters for each classifier were determined using v-fold cross-validation technique. (Kiviluoto, 1998).

- In 2001 Kaski et al. introduced Fisher information matrix based metric and implemented SOM with it. They compared Euclidean metric based SOM (SOM-E) with Fisher metric based SOM (SOM-F) in prediction of bankruptcies of firms and concluded that the SOM-F performed better than the SOM-E. (Kaski, Sinkkonen, & Peltonen, 2001).

Literature on Other Neural Network Topologies:

- In 1995 Lacher et al. proposed a cascade-correlation neural network (Cascor) for classifying financial health of a firm using Altman's five financial ratios. Although MDA had been used commonly for BFP, it has limitations based on its assumptions. They reported that cascor model yielded a higher overall classification rates than Altman Z-score model. (Lacher, Coats, Sharma, & Fant, 1995).

- In 1999 Yang et al. compared original probability neural network (PNN), probability neural network without pattern normalization (PNN*), Fisher DA (FDA), DA and BPNN to solve bankruptcy prediction problem using data from the U.S. oil and gas industry. They used two data sets: non-deflated data used by Plat et al. (1994) and deflated data where first four ratios were deflated. They concluded that the PNN* and BPNN with non-deflated data achieved better classification rates while FDA produced better classification results with deflated data. (Yang, Platt, & Platt, 1999).

- In 2003 Baek and Cho proposed the auto-associative neural network (AANN) for Korean firm bankruptcy prediction. One of the major problems in bankruptcy prediction is the imbalance of data, i.e. much more solvent data than default data. They trained the AANN with only solvent firms' data and then they applied the test data containing both solvent and insolvent firms. So, any solvent firm data that shared common characteristics with the training data resulted in small error at the output layer while the bankrupt firms' data resulted in a large error at the output layer. They reported that AANN yielded classification rates of 80.45% for solvent and 50.6% for defaulted firms while the 2-class BPNN produced classification rates of 79.26% for solvent and 24.1% for defaulted firms. Therefore, they concluded that AANN outperformed 2-class BPNN. (Baek & Cho, 2003).

In addition to the studies above, from the studies surveyed under section "3. 3. Studies related to Turkey", Ravi and Ravisankar's study (2010), which used group method of data handling, counter propagation neural network and fuzzy adaptive resonance theory map; Chauhan et al.'s study (2009), which used differential evolution trained wavelet neural network, and Ravi and Pramodh's study (2008), which applied variants of principal component neural network, can be classified under this section.

3. 1. 3. Case-based reasoning

When people face a new problem, they often seek for an answer using past similar experiences and reuse or modify solutions of these experiences to generate a possible answer. Similarly, CBR is a reasoning methodology that exploits similar experienced solutions, in the form of past cases, to solve new problems (Park & Han, 2002). Key issues in the CBR process are indexing and retrieving similar cases in the case base and measuring case similarity to match the best case. The k Nearest Neighbor method (k-NN) is usually used as heart of CBR models for case retrieval and the indexing process. k-NN classifies unlabeled examples based on their similarity to examples in the training set using a similarity algorithm.

In the basic k-NN method, to identify which class x belongs; first the closest (nearest) k neighbors of x is identified. Here, neighbors are from the past experiences of the model. To find the closest examples, Euclidean distance is used as a measure of how similar a previous case is to a given problem. Then by majority voting the class of x can be identified. In other words, x is compared with past experiences of the model. For instance, suppose we set $k = 5$ neighbors and of the 5 closest neighbors, 4 of them belong to group A and 1 of them belongs to group B, then x is assigned to group A. Basically, a k-NN model stores all of the available training data and when a new case appeared, all of the training cases will be searched to find the closest neighbors, then by majority voting the new case will be classified.

A primary weakness of the traditional k-NN algorithm is that it is sensitive to the presence of irrelevant features (Park & Han, 2002). Although in a prediction model, some attributes are inherently more relevant than others; a pure k-NN algorithm assumes that all attributes are equally important; which will distort the performance of the algorithm if there are irrelevant attributes present (Yip, 2004). To surpass this handicap, a weight that expresses the significance of an attribute is needed so that more important attributes are assigned with higher weights (Yip, 2004). By doing so, the sensitivity of the k-NN method to noisy features would decrease.

The distance between two examples or the similarity determined by a weighed k-NN is:

$$Similarity = \sqrt{\sum_{i=1}^{n} w_i (T_i - S_i)^2}$$

where w_i is the weight of feature i, T is the target case, S is the source case, and n is the number of attributes in each case.

Advantages:

- Simple implementation.
- Analytically tractable, information on how the classification was reached can be provided by the CBR methodology, since the prediction was generated by integrating similar historical cases (Li & Sun, 2010).
- CBR is considered as non-parametric method which does not require any data distribution assumption for input case (Li & Ho, 2009). Although some of the statistical methods for example, MDA, logit, and two-step clustering, that

assume normal distribution of the data, can produce acceptable, even excellent, predictive performance in various applications, the theoretical foundation of the results would be weak (Li & Sun, 2010).

Disadvantages:

- Its accuracy degrades with the introduction of noise or irrelevant attributes.
- Its performance is highly sensitive to the definition of its similarity function (Park & Han, 2002).
- Compared to its alternatives, it has large storage requirements, because it stores all of the available training data in the model.
- It is computationally intensive and slow during execution, since all of the training cases must be searched in order to classify each new case.
- As a result of the last two disadvantages mentioned above, it cannot be applied to large data sets.

Literature:

- In 1997, Bryant compared a case-based reasoning (CBR) system with Ohlson's logit model for bankruptcy prediction and concluded that the accuracy rates of Ohlson's (1980) logit model outperformed CBR in the means of accuracy and Type I error rate, but CBR succeeded better Type II error rate. (Bryant, 1997).
- In 1997, Jo et al. used MDA, BPNN and CBR to predict bankruptcy of Korean firms and reported that the average hit ratio was 82.22%, 83.79% and 81.52%, respectively, so they concluded that BPNN outperformed DA and CBR however DA and CBR are not significantly different in their performances. 20 variables were selected using stepwise selection and t-test. Further, they stated that, maybe the reasons behind the CBR's being the least successful were the dependent variable being a binary variable and the low correlation between

dependent and independent variables. They tried to find reasons behind CBR's unsuccessful results since, based on previous studies, that CBR had been comparatively useful when the training data is not sufficient. (Jo, Han, & Lee, 1997).

- In 2002, Park and Han proposed an analogical reasoning structure for feature weighting using a new framework called the analytic hierarchy process (AHP)-weighted k-NN algorithm. They compared this AHP – k-NN model with pure k-NN and logit – k-NN and reported that the classification accuracies were 83.0%, 68.3% and 79.2%, respectively. For this comparison they examined several criteria, both quantitative (financial ratios) and qualitative (non-financial variables). (Park & Han, 2002).

- In 2004, Yip compared weighted k-NN, pure k-NN and DA to predict Australian firm business failure and she reported that the overall accuracies were 90.9%, 79.5% and 86.4%, respectively. She concluded that weighted k-NN outperformed DA and was an effective and competitive alternative to predict business failure in a comprehensible manner. (Yip, 2004).

- In 2008, Li and Sun introduced ranking-order case-based reasoning (ROCBR) in financial distress prediction and compared it with three well-known CBR models with Euclidean distance (ECBR), Manhuttan distance (MCBR), and inductive approach (ICBR) as its heart of retrieval and two statistical models of logit and MDA using 306 firms' data (153 unsuccessful - 153 healthy) from Shanghai Stock Exchange and Shenzhen Stock Exchange. ROCBR is a method that uses ranking order metric as similarity measure in place of Euclidean metric, to find the distance between target case and each historical case on each feature to generate similarities between pair-wise cases. Using stepwise method of MDA, logit and ANOVA for feature selection, they formed 3 combinations of each models. They concluded that ROCBR outperformed ECBR, MCBR, ICBR, MDA, and logit significantly in financial distress prediction of Chinese listed companies 1 year prior to distress, if irrelevant information among features handled effectively. (Li & Sun, 2008).

- In 2009, Li et al. proposed a new similarity measure mechanism for k-NN algorithm based on outranking relations, including strict difference, weak difference, and indifference, between cases on each feature. Accuracy of the CBR prediction method based on outranking relations, which was called as OR-CBR, was determined directly by such four types of parameters as difference parameter, indifference parameter, veto parameter, and neighbor parameter. For the experiment designed with three year's real-world data from 135 pairs of Chinese listed companies, the cross-validation of leave-one-out was utilized to assess models, the method of stepwise DA was used to select features, grid-search technique was used to get optimized model parameters. They concluded that OR-CBR outperformed MDA, logit, BPNN, SVM, decision tree, Basic CBR, and Grey CBR in financial distress prediction. (Li, Sun, & Sun, 2009).

- In 2011, Li and Sun compared a forward ranking-order case-based reasoning (FRCBR) method, with the standalone RCBR, the classical CBR with Euclidean metric as its heart, the inductive CBR, logit, MDA, and support vector machines. FRCBR is a combination of forward feature selection method and ranking-order case-based reasoning (RCBR) which uses ranking-order information among cases to calculate similarity in the framework of k-NN. For FRCBR wrapper approach was used and for comparative methods, stepwise MDA was employed to select optimal feature subset. Hold out method was used to assess the performance of the classifiers. They concluded that FRCBR can produce dominating performance in short-term business failure prediction of Chinese listed companies. (Li & Sun, Predicting business failure using forward ranking-order case-based reasoning, 2011).

3. 1. 4. Decision trees

Decision trees classify objects by sorting them down the tree from the root to some leaf node. Each node in the tree specifies a test of some feature of the object, and each branch descending from that node corresponds to one of the possible values for this feature. An object is classified by starting at the root node of the tree, testing the attribute specified by this node, then moving down the tree branch corresponding to the value of the feature. This process is then repeated at the new node (Mitchell, 1997).

For instance, in Table 1, Figure 4 and Figure 5, Quinlan's decision tree example of classification of Saturday mornings according to whether they are suitable for playing tennis can be seen (Quinlan, 1986). Here, the set of Saturday mornings is the universe of objects that are described in terms of a collection of features, *A* = {*Outlook*; *Temperature*; *Humidity*; *Wind*} is the set of attributes, *Outlook* = {sunny; overcast; rainy}, *Temperature* = {cool; mild; hot}, *Humidity* = {high; normal} and *Wind* = {true; false} are the sets of discrete, mutually exclusive values of each feature.

As seen in Figure 4 and Figure 5 there are more than one correct way of decision tree. Given a choice between two decision trees, each of which is correct over the training set, it seems sensible to prefer the simpler one on the grounds that it is more likely to capture structure inherent in the problem and therefore would be expected to classify correctly more objects outside the training set (Quinlan, 1986).

For building decision tree from information table, a number of algorithms are used including ID3, CHAID (Chi squared automatic interaction detection), CART, Quest C4.5 and C5.0 which use recursive partitioning technique and measures like Gini and entropy to induce decision trees on a data set (Ravi Kumar & Ravi, 2007).

Table 1: Information table for Quinlan's decision tree examples (Quinlan, 1986)

No	Attributes				Class
	Outlook	**Temp.**	**Humid.**	**Windy**	
1	sunny	hot	high	false	**N**
2	sunny	hot	high	true	**N**
3	overcast	hot	high	false	**P**
4	rain	mild	high	false	**P**
5	rain	cool	normal	false	**P**
6	rain	cool	normal	true	**N**
7	overcast	cool	normal	true	**P**
8	sunny	mild	high	false	**N**
9	sunny	cool	normal	false	**P**
10	rain	mild	normal	false	**P**
11	sunny	mild	normal	true	**P**
12	overcast	mild	high	true	**P**
13	overcast	hot	normal	false	**P**
14	rain	mild	high	true	**N**

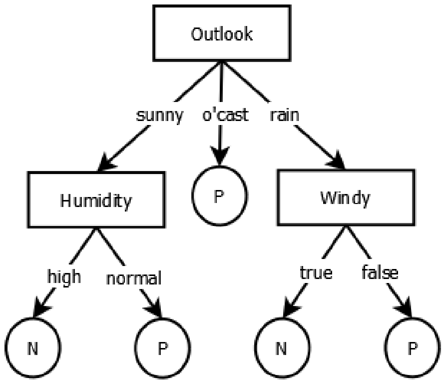

Figure 4: Quinlan's decision tree example - 1 (Quinlan, 1986)

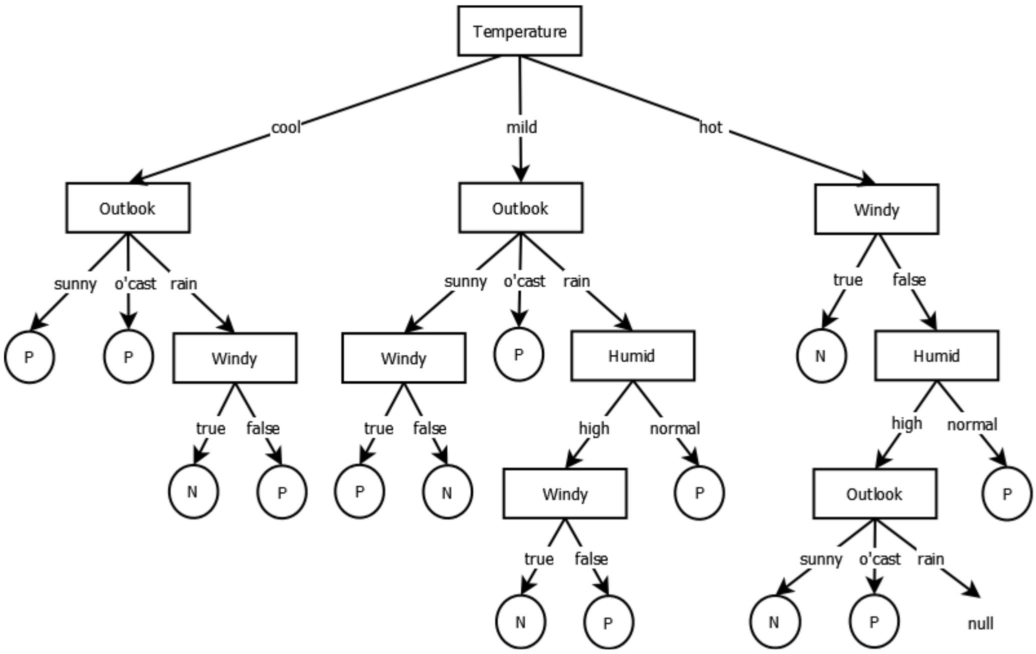

Figure 5: Quinlan's decision tree example - 2 (Quinlan, 1986)

Advantages:

- They are user-friendly since they give straight ‘yes’ or ‘no’ output with binary ‘if– then’ rules.
- They can show how result was obtained (via branches and nodes) and the accuracy of this result (Cielen, Peeters, & Vanhoof, 2004).
- They do not need prior assumptions about the data (Berry & Linoff, 2004).
- They are able to process both numerical and categorical data (Berry & Linoff, 2004).
- They can work with incomplete data.

Disadvantages:

- Over fitting may be a problem (Ravi Kumar & Ravi, 2007).
- They require a lot of data samples in order to get reliable predictions (Ravi Kumar & Ravi, 2007).
- There is no way to determine an ‘optimal tree’ (Cielen, Peeters, & Vanhoof, 2004).

Literature:

- In 1984, Marais et al. compared recursive partitioning algorithm (RPA) with polytomous (i.e., two or more categories) probit and used the commercial bank loan environment to illustrate their empirical significance. Although when all the variables were used, polytomous probit outperformed recursive partitioning in terms of expected misclassification rates in both resubstitution and bootstrap methods, the small sample properties of the recursive partitioning technique may make it a viable competitor to parametric methods such as polytomous probit even when the assumptions underlying the parametric model are satisfied. They also concluded that publicly available indicators (i.e., bond or commercial paper ratings, stock price characteristics) may provide as much explanatory power as relatively complex combinations of financial statement data.(Marais, Patell, & Wolfson, 1984).

- In 1985, Frydman et al. compared DA with two decision tree models viz., (i) RPA1 (recursive partitioning algorithm) with relatively complex tree and (ii) RPA2 with smallest v-fold cross-validation risk using data of 200 companies (58 unsuccessful) observed in the period 1971-1981and concluded that (i) RPA1 model outperformed DA models for all costs, (ii) RPA2 tree turned out to be sub tree of RPA1 tree for every cost, (iii) RPA2 had larger resubstitution risk. (Frydman, Altman, & Kao, 1985).

- In 2005, Razi and Athappilly performed a three-way comparison of prediction accuracy involving nonlinear regression, BPNN and CART models. They found that although BPNN and CART models produced better prediction accuracy than non-linear regression model, neither BPNN nor CART model showed clear advantage of one over the other in terms of prediction accuracy. However, the advantage of decision tree based models, was that the decision tree based models are scalable to large problems and can handle smaller data set than BPNN models.(Razi & Athappilly, 2005).

- In 2008, Sun and Li proposed a decision tree model to BFP problem by combining attribute-oriented induction and attribute relativity analysis based on information gain. They used 35 financial ratios and 135 pairs of listed companies for the experiment and concluded that the empirical results indicated the feasibility and validity of the proposed method for listed companies' financial distress prediction. (Sun & Li, 2008).

- In 2010, Li et al. compared the bankruptcy prediction performance of CART with SVM, k-NN, MDA and logit using Li and Sun's data (2008). Thirty times' hold-out method was employed as the assessment. Stepwise method of MDA was employed to select optimal feature subset for SVM, k-NN, MDA and logit.

They reported that the CART outperformed all the other methods in terms of predictive performance and significance test in short-term BFP of Chinese listed companies. They also reported that the employment of stepwise method of MDA did not help CART to produce more accurate predictions, so it might be more suitable for CART to work with all available features. (Li & Sun, 2010).

- In 2011, Chen applied decision tree classification methods (C5.0, CART, and CHAID) and logit models to the BFP problem using 37 financial and non-financial ratios of 100 listed companies (50 unsuccessful – 50 healthy) of the Taiwan Stock Exchange Corporation (TSEC) sampled 2, 4, 6, 8 seasons prior to the financial crisis occurrence. To extract suitable variables principle component analysis was used. They concluded that (i) with the decision tree classification approach, the more PCA used, the less accuracy obtained; (ii) with the decision tree classification approach, the closer they got to the actual occurrence of financial distress, the higher the accuracy they obtained; (iii) the decision tree classification approach obtained better prediction accuracy than the logit approach in short run (less one year); however, on the contrary, the logit approach got better prediction accuracy in long run (above one and half year); and (iv) the satisfying results of the experiments indicated the possibility and validity of the proposed methods for the BFP problem.(Chen Y. M., 2011).

3. 1. 5. Operational research

Operational research is an interdisciplinary science covering a handful of methods and techniques that seeks optimal solutions to complex decision-making problems (Taha, 2010). Since the origin of operational research – World War II – researchers developed many operational research techniques. A typical operational research problem consists of (an) objective function(s) to optimize (minimize or maximize) subject to (a) constraint(s) on the variables. These objective and constraint functions can be linear or nonlinear. In linear programming (LP) all of the objective and constraint functions are linear and all of the constraints are continuous. If some of the constraint or the objective functions are nonlinear in an operational research problem, then it is called non-linear programming. Quadratic programming is a special form of non-linear programming in which objective function is quadratic and constraints are linear. As seen below, from these techniques, mostly minimized sum of deviations (MSD) and data envelopment analysis (DEA) were used in bankruptcy prediction literature.

MSD is a combination of linear programming and discriminant analysis whose objective focuses on the minimization of total group overlap, i.e. the sum of external deviations of erroneously classified observations (Cielen, Peeters, & Vanhoof, 2004). Let k be the number of independent variables and there are $n + m$ observations on k independent variables where n of the observations belong to group 1 and m belong to group 2. The model will be,

$$\begin{aligned} &\text{Min } z = C_1 d_1 + C_2 d_2 \\ &\text{s.t:} \qquad Ax - d_1 \leq b \\ &\qquad\qquad Bx - d_2 \geq b \end{aligned}$$

where A represents the $(n \; x \; k)$ matrix made up of the observations from group 1 and the $(m \; x \; k)$ matrix B similarly for group 2, X is a vector of decision variables, b is a real valued variable, C_1 and C_2 are cost coefficients and $d_1, d_2 \geq 0$ are external deviation (unwanted) vectors that measure the distance of the observations. The solution of this model gives a hyper-plane that separates groups if the objective has value zero. MSD has the advantage that the variables involved are real valued, so LP solver can be used (Cielen, Peeters, & Vanhoof, 2004). However, it minimizes a sum of distances and there is not always consistency between different segments hence for different cost factors the coefficients obtained vary heavy and there are sign inversions. For these reasons the models may become unemployable (Cielen, Peeters, & Vanhoof, 2004).

DEA was first proposed by Charnes, Cooper and Rhodes (1978) to find the efficient frontier of the production possibility surface. It is a nonparametric method to assess efficiency of each decision-making unit (DMU) relative to all the DMUs in the sample, including itself by applying linear programming method. This relative efficiency is calculated as shown in the equation below by obtaining the ratio of the weighted sum of all outputs and the weighted sum of all inputs where the weights are selected so as to achieve Pareto optimality for each DMU (Ravi Kumar & Ravi, 2007).

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs}$$

Let n be the number of DMUs, each with m inputs and s outputs. The relative efficiency of DMU p will be (Talluri, 2000):

$$\text{Max}\ Efficiency = \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}}$$

$$s.t: \qquad \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \leq 1, \quad \forall\ i$$

$$v_k, u_j \geq 0, \qquad \forall\ k, j$$

where y_{ki} represents amount of output k produced by DMU i, x_{ji} represents amount of input j utilized by DMU i, v_k represents weight given to output k and u_j represents the weight given to input j. In BFP applications, financial ratios with a positive correlation are defined as inputs represented with x and ratios with a negative correlation are defined as outputs represented with y (Cielen, Peeters, & Vanhoof, 2004). By doing so, sign inversion problem in MSD is not an issue for DEA. But now fractional form of the model is the main issue. Instead of fractional form, by limiting the denominator of the objective function and only allowing the maximization of the nominator, the model can be converted to a LP model as (Talluri, 2000):

$$\text{Max}\ z = \sum_{k=1}^{s} v_k y_{kp}$$

$$s.t: \qquad \sum_{j=1}^{m} u_j x_{jp} = 1$$

$$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0, \quad \forall\ i$$

$$v_k, u_j \geq 0, \qquad \forall\ k, j$$

In this topic we mentioned more than one method; the advantages and disadvantages of these methods are in the text except DEA model. The "Advantages" and "Disadvantages" parts below belong to DEA model. But the "Literature" part covers all of the operational research models.

Advantages:

- It can work with small amount of data.
- It does not require price or cost data (Charnes, Cooper, & Rhodes, 1978).
- It takes into consideration returns to scale in calculating efficiency (DFID, 2005).
- It has the benefit of not assuming a particular functional form/shape for the frontier, since it is a non-parametric approach (Cielen, Peeters, & Vanhoof, 2004).
- It helps to identify inefficient DMUs and amounts of inefficiency of inputs and/or outputs (Ravi Kumar & Ravi, 2007).

Disadvantages:

- It does not provide a general relationship (equation) relating output and input, since it is a non-parametric approach (Cielen, Peeters, & Vanhoof, 2004).
- The results are usually sensitive to the selection of features, so their relative importance needs to be analyzed prior to the calculation. However, there is no way to test their appropriateness (DFID, 2005).
- When there is no relationship between explanatory features DEA views each company as unique and fully efficient and efficiency scores are very close to "1" (DFID, 2005).

Literature:

- In 1994, Banks and Prakash applied a linear programming heuristics to a quadratic transformation of data to predict firm bankruptcy prediction and they reported that for the four 'real world' research data sets in the literature, the proposed quadratic transformation method outperformed quadratic DA. (Banks & Abad, 1994).

- In 2002, Lam and Moy used a weighted combination method, which was a way to combine results of different classification techniques with respect to their classification score. As classification methods Fisher linear DA (FLDF), cluster-based LP (CBLP) and MSD and as test method simulation experiments were used for this study. The combined model of these three classification methods outperformed each of them individually.(Lam & Moy, 2002).

- In 2003, Luo applied a DEA model to a sample of 245 large banks for three purposes: (i) to compare profitability efficiency (activities generating more profits for a bank) with the marketability efficiency (activities generating more market value) of large banks; (ii) whether there was a relation between the geographical location of banks with the profitability or marketability efficiency; and finally (iii) which of the four efficiency scores and the geographical location variable had a relation with the bankruptcy of banks. The four efficiency scores were overall technical profitability efficiency; pure technical profitability efficiency in stage; overall technical efficiency in marketability stage; pure technical efficiency in marketability stage. He reported for (i) that large banks had relatively lower level of marketability efficiency; for (ii) that the geographical locations of banks were not related to either the profitability or marketability efficiency; and for (iii) that only overall technical efficiency of the profitability performance can predict the likelihood of bank failures. He concluded that, although the banks achieved lower efficiency in the marketability dimension than in the profitability dimension, their failures could not be attributed to either low marketability efficiency or different geographic locations. (Luo, 2003).

- In 2004, Cielen et al. compared the classification performance of a MSD model, a DEA model and a decision tree (C5.0) model on the problem of bankruptcy of banks and reported that the models obtained classification rates of 78.9%, 86.4% and 85.5%, respectively. They concluded that although DEA outperformed MSD and decision tree (C5.0) model, decision tree (C5.0) model had a more user friendly interface. (Cielen, Peeters, & Vanhoof, 2004).

- In 2004, Kao and Liu used a DEA model that makes advanced predictions of the performances of 24 commercial banks in Taiwan based on their financial forecasts. Although DEA has been used as a tool for evaluating past accomplishments in the banking industry, due to a time lag, the results usually arrive too late for the evaluated banking institutions to react timely. The model in this paper proposed that instead of using past data, using forecasted data in DEA model, banks might have time to react appropriately. Both forecasts of financial data and predictions of the efficiency scores were presented in ranges, instead of as single values. They used a DEA model for interval data to predict the efficiency scores and concluded that input and output factors to measure the efficiencies of the banks and the solution method proposed in this paper was able to predict the bank performance based on their financial forecasts. (Kao & Liu, 2004).

- In 2009, Xu and Wang proposed a financial failure prediction model using efficiency as a predictor variable since they claimed that a main cause of financial failure is poor management, and that business operation efficiency is a good reflection of a firm's management. In the model DEA was employed as a tool to evaluate the input/output efficiency of each corporation. They used data of corporations listed in Shanghai stock exchange (SSE) compared the accuracy of the proposed method with MDA, logit and SVM. They concluded that efficiency is an effective predictor variable.(Xu & Wang, 2009).

- In 2009, Premachandra et al. compared DEA with logit using data obtained from obtained from Altman's bankruptcy database maintained at New York University and Standard and Poor's Compustat and the Centre for Research in

Security Prices (CRSP) databases. The data covered 200 large US firms of which 100 firms went bankrupt in the period 1991-2004. They concluded that DEA outperformed logit and DEA was a quick-and-easy tool for assessing corporate bankruptcy. (Premachandra, Bhabra, & Sueyoshi, 2009).

- In 2009, Sueyoshi and Goto compared the BFP performance of DEA with DEA–DA using a dataset used by Premachandra et al. (2009). The proposed comparative analysis had the three main criteria: (i) how to handle negative data in financial variables, (ii) how to handle data imbalance between default and non-default firms, and (iii) how to identify a failure process over time. They concluded that DEA was a more quick-and-easy tool than DEA–DA. They also concluded that the failure process was influenced by several factors over time and the bankruptcy was the final stage of an evolutionary process that occurs over time. (Sueyoshi & Goto, 2009).

3. 1. 6. Evolutionary approaches

Evolutionary approaches are meta-heuristic optimization algorithms that mimic Darwinian principles of evolution to solve highly nonlinear, non-convex global optimization problems (Ravi Kumar & Ravi, 2007). Evolutionary approaches, usually, randomly generates an initial population of solutions. This can be called the first generation. Then, the first generation is manipulated using various genetic operators, such as reproduction, crossover, mutation, dropping condition, to generate new populations. This generation is an iterative process consists of (i) selection, (ii) reproduction and (iii) modification. First the fitness function is applied to each candidate and every individual in the population is evaluated. Solutions that achieve higher fitness are selected as parents for the next generation. After selection, by using a reproduction operator, existing programs (in genetic programming) or string of numbers (in genetic algorithm) are copied into the new generation. And lastly, the new population is generated with mutation (randomly alters the genes of a candidate), crossover (recombines the parental genes), or other operators from a randomly chosen set of parents. The new population is used in the next iteration and it competes with old candidates in the next generation (survival of the fittest). This process is repeated until a predefined termination criterion has been satisfied, or a previously defined computational limit has been reached.

There are some different evolutionary approaches in the literature. The most popular one is genetic algorithm. Genetic algorithm seeks the solution of a problem in the form of strings of numbers (Varetto, 1998). Another popular algorithm is genetic programming which is a specialized genetic algorithm. Instead of strings of numbers, in genetic programming each individual is a computer program. Also the ability to solve a computational problem is the main parameter for candidates' fitness determination (Faraoun & Boukelif, 2006). In addition to genetic algorithm and genetic programming, there are some other evolutionary approaches such as, evolutionary programming, evolution strategy and neuro-evolution.

Advantages:

- They are data distribution-free, so no a priori knowledge is needed about statistical distribution of the data (Faraoun & Boukelif, 2006).
- They are good at finding global optimum of a highly nonlinear, non-convex function (Ravi Kumar & Ravi, 2007).
- They can detect the underlying but unknown relationship that exists among data and express it as a mathematical expression (Faraoun & Boukelif, 2006).
- Considered to neural networks, evolutionary approaches have a smaller chance of converging to local optima since they consider not a single point but many points in the search space simultaneously (Shin & Lee, 2002).

Disadvantages:

- Since the solution is only as good as evaluation function, determination of evaluation function is very critical in evolutionary approaches.

- Also calculation time is another problem. In complex problems fitness evaluation may require several hours to several days.
- The stop criterion is not clear in every problem.
- They may converge to a local optima rather than global optimum. They may not yield global optimal solution always unless it is augmented by a suitable direct search method (Ravi Kumar & Ravi, 2007).

<u>Literature:</u>

- In 1998, Varetto compared the bankruptcy prediction performance of GA with LDA using 1920 unsound and 1920 sound industrial Italian companies from 1982-1995. Two models were developed: (i) one year prior to bankruptcy data and (ii) three years prior to bankruptcy data. GA is used to find the parameters in a LDA model and called genetic linear function. He reported that for the first model, the genetic linear function yielded 92% classification rate for bankrupt companies while LDA yielded 90.1%; and for the second model, LDA outperformed the genetic linear function in the case of sound companies. He concluded that the LDA was slightly better than GA and LDA has a higher stability and generalization power. (Varetto, 1998).
- In 2001, Nanda and Pendharkar incorporated misclassification cost matrix into an evolutionary classification system using real-life and simulated bankruptcy data instead of minimizing misclassifications. They emphasized that, although there is evidence that Type I and Type II error costs for misclassifications are not equal, minimizing misclassification approach assumes that these costs are equal. They reported that for real-life set the classification accuracy of integrated cost preference based minimized sum of deviations (ICPBMSD) and integrated cost preference based GA (ICPB-GA) resulted in lower misclassification costs when compared to LDA, MSD and GA and for simulated holdout set the ICPB-GA outperformed others. They concluded that the

ICPBMSD or ICPB-GA might be promising when compared to traditional MSD or GA. (Nanda & Pendharkar, 2001).

- In 2002, Shin and Lee proposed a GA-based approach for bankruptcy prediction of firms, which was capable of extracting rules that are easy to understand for users like expert systems. They used 528 firms' data, 264 of which filed for bankruptcy and the other 264 for non-bankruptcy during the period 1995–1997. They reported that rules generated by GA got 80,8% accuracy and concluded that GA could successfully learn linear relationship among input variables. (Shin & Lee, 2002).

- In 2006, Lensberg et al. developed a genetic programming model. For feature selection, genetic programming was used to analyze 28 potential bankruptcy variables found to be significant in multiple prior research studies using data from a sample of 422 bankrupt and non-bankrupt Norwegian companies for the period 1993–1998 and six variables were determined to be significant. For training an expanded sample of 1136 bankrupt and non-bankrupt Norwegian companies was used. They reported that the model was 81% accurate on a validation sample, slightly better than prior genetic programming research on US public companies, and statistically significantly better than the 77% accuracy of a traditional logit model developed using the same variables and data. The most significant variable in the final model was the prior auditor opinion, thus validating the information value of the auditor's report. They concluded that, (i) the liquidity improved non-bankruptcy status regardless of the value of other variables like profitability and size; (ii) the bankruptcy risk decreased with increased size except when profits are negative; (iii) interest paying ability and accounting information, including the auditor's evaluation of it, had a more positive bankruptcy status impact for large firms than small ones; and (iv) for small firms the most important information was found to be liquidity and non-accounting information. (Lensberg, Eilifsen, & McKee, 2006).

3. 1. 7. Rough set based techniques

Rough set theory was first proposed by Pawlak (1982). The rough set philosophy is founded on the assumption that with every object of the universe of discourse we associate some information and objects characterized with the same information are indiscernible in view of the available information about them (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

In rough sets, for algorithmic reasons, knowledge about objects is represented in the form of an information table where the rows are labeled by objects, columns are labeled by attributes and entries of the table are attribute values (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999). An information table basically consists of $S = \{U, Q, V, f\}$, where U is a finite set of objects called universe, Q is a finite set of attributes, V is the set of domains of the attributes, and $f : U \times Q \rightarrow V$ is a total function such that $f(x, q) \epsilon V_q$ for every $q \epsilon Q$, $x \epsilon U$, called an information function (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

To define indiscerniblity mathematically, let $S = \{U, Q, V, f\}$ be an information table and let $P \subseteq Q$ and $x, y \epsilon U$. We say that x and y are indiscernible by the set of attributes P in S iff $f(x, q) = f(y, q)$ for every $q \epsilon P$ (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

Lower and the upper approximations are two basic operations in the rough set theory. But first elementary-crisp-rough sets should be defined. Any set of all indiscernible objects is called an elementary set. Each elementary set forms a basic granule of knowledge about the universe. Any set of objects being a union of some elementary sets is referred to as crisp - otherwise the set is rough (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999). Lower approximation is the union of all elementary sets of a rough set. Upper approximation is the union of all elementary sets that a rough set's any element is a member of. The lower approximation consists of all objects which certainly belong to the set and the upper approximation contains objects which possibly belong to the set (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999). Note that rough sets mainly interested in a certain universe U, such that intersection of two classes is an empty set: $X_i \subseteq U, X_i \neq \emptyset, X_i \cap X_j = \emptyset$ for $i \neq j, i, j = 1, 2, \ldots, n$ and $\bigcup X_i = U$ (Pawlak, 1991).

Advantages:

- It discovers important facts hidden in data and expresses them in the natural language of 'if–conditions-then-decisions' decision rules which do not normally need interpretation (Mckee, 2000) (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).
- It offers transparency of classification decisions; each decision rule is supported by a set of real examples, allowing for their argumentation (Mckee, 2000) (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).
- It takes into account background knowledge of the decision maker (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).
- Additional information like probabilities in statistics or grade of membership in fuzzy set theory is not required (Mckee, 2000) (Eibe, Del Saz, Fernández, Marbán, Menasalvas, & Pérez, 2005).

Disadvantages:

- It can be sometimes impractical as it may lead to an empty set (Ravi Kumar & Ravi, 2007).
- It can be sensitive to changes in data (Ravi Kumar & Ravi, 2007).
- It can be inaccurate (Eibe, Del Saz, Fernández, Marbán, Menasalvas, & Pérez, 2005).

Literature:

- In 1998 Greco et al. presented a new rough set method based on approximation of a given partition of a set of firms into pre-defined and ordered categories of risk by means of dominance relations instead of indiscernibility relations. They compared classical rough set with their proposed method for evaluation of bankruptcy in firms using the data set obtained from Greek industrial development bank (ETEVA) and showed that rules based on dominance relation are better to sort new actions than the rules based on indescernibility relation. (Greco, Matarazzo, & Slowinski, A new rough set approach to evaluation of bankruptcy risk, 1998).

- In 1998, Greco et al. proposed a new rough set approach which used the approximation of partitioning the objects in some pre-defined category as original rough set analysis but, employed not only indiscernibility relation but also dominance relation too. They concluded that the proposed approach showed improvements over the original rough set analysis. (Greco, Matarazzo, & Slowinski, A New Rough Set Approach to Multicriteria and Multiattribute Classification, 1998).

- In 1999, Dimitras et al. compared the accuracy of rough set based approach with DA and logit using financial characteristics of a large sample of 80 Greek firms from the perspective of credit manager of a large Greek commercial bank as decision maker and concluded that the rough set approach outperformed the other two in revealing the relevant attributes in evaluating the firm failure risk. The model developed in the study used VCR (valued closeness relation), which involves indifference, strict difference and veto thresholds on particular attributes and prevents major differences on one attribute from being compensated by number of minor differences on other attributes. VCR correctly classified 60% of objects not classified by exactly matching rules. (Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

- In 2000, McKee developed a rough set based bankruptcy prediction model using data from U.S. public companies and variables identified in prior recursive partitioning research. He reported that the model yielded 88% accuracy which was superior to the original recursive partitioning model with only 65% accuracy on the same data set. He also reported that the prediction accuracy of this model was superior to three previous rough set based models although this model employed fewer variables because of this model's larger sample size. (Mckee, 2000).

- In 2003, McKee compared rough set prediction capability with actual auditor bankruptcy signaling rates for US companies using four variables from the 11 possible variables mostly used in literature. His two models achieved classification accuracy of 61% and 68% on the validation set while auditors achieved classification accuracy of 66%. He concluded that the rough set models he developed offered no significant comparative predictive advantage over auditors' current methodologies. He also claimed that the reason of significantly lower accuracy rate of his model, compared with previous studies employing both rough sets theory and other methods, was because the samples employed in the study were more realistic than prior studies. (McKee, 2003).

- In 2007, Cheng et al. developed six rough set based BFP models using 124 firms' data (62 unsuccessful – 62 healthy). The dataset, which covered Taiwanese firms' data between 1998 and 2005, was obtained from Taiwan Economic Journal. For unsuccessful firms, the models included data three years before failure. In the model, 14 financial ratios commonly used in BFP literature, and a non-financial variable, auditor switching, which was used to indicate whether or not a firm had changed its auditor in the past one, two or three years before failure, were used. Six rough set models were constructed individually with and without the auditor switching variable. For training 66 firms' data and for testing 58 firms' data were used. They reported that that the models with "auditor switching" variable outperformed the models without “auditor switching” variable. They concluded that, “auditor switching” variable was the most significant attribute and played an essential role in enhancing the performance of rough set models. (Cheng, Yeh, & Chiu, 2007).

3. 1. 8. Fuzzy logic based techniques

In classification analysis, when dealing with inexact and imprecise data, often groups of objects that do not have clear boundaries appear in the problem domain. The imprecision of such classes is expressed in the possibility that an element may belong to an indeterminate grade, rather than to a certain group (Alam, Booth, Lee, & Thordarson, 2000). The fuzzy logic models this uncertainty and ambiguity in the data using fuzzy sets, which was first proposed by Zadeh (1965), and in some models, incorporates the human experiential knowledge into the model (Ravi Kumar & Ravi, 2007).

Normally, the dependence between an input situation and a conclusion is represented as “$IF\ \{\text{input situation}\}\ THEN\ \{\text{conclusion}\}$”. A fuzzy rule has an additional probabilistic part, for instance “$IF\ \{a_2 = 1, a_7 = 3\ and\ a_8 = 2\}\quad THEN\ \{\text{Firm} - \text{Status} = \text{Bankrupt}\}\ with\ 0{,}985$” where $a_2 = 1$ means that a_2 lies in the interval named as 1 (Michael, Georgios, Nikolaos, & Constantin, 1999).

In this part two methods that use fuzzy logic are examined: fuzzy rule generation and fuzzy clustering method. In fuzzy rule generation method, first of all, hypotheses in the form of if/then rules are generated and after that every single hypothesis is checked for relevance and evaluated with a rating index [0…1]. Afterwards, the rating index is used as certainty factor for approximate reasoning and an input for decision maker’s preferences. According to the decision maker’s preferences, a fuzzy rule set is exported to the fuzzy rule-based classification model and the classification of the objects is carried out. The classifier then assigns every object to the classes with a membership degree varying from 0 to 1 (Michael, Georgios, Nikolaos, & Constantin, 1999).

As fuzzy rule generation, fuzzy clustering also uses fuzzy logic to describe ambiguity in the data, such as the existence of points that lie between two classes. As stated in its name, fuzzy clustering is a cluster analysis. Cluster analysis is the methodology of finding patterns in data and it establishes groups whereas classification analysis assigns observations to predefined groups. The degree of membership of an object in a cluster is measured using a membership function whose domain is the interval [0, 1]. The sum of the membership coefficients of the object over all clusters is 1.0 (Alam, Booth, Lee, & Thordarson, 2000).

Advantages:

- It is good at deriving human comprehensible 'if–then' rules with modeling uncertainty and ambiguity in the data (Ravi Kumar & Ravi, 2007).
- It has low computational requirements (Ravi Kumar & Ravi, 2007).

Disadvantages:

- The plethora of choices for membership function shapes, connectives for fuzzy sets and defuzzification operators may affect the performance (Ravi Kumar & Ravi, 2007).

Literature:

- In 1999, Michael et al. proposed a combined use of a fuzzy rule generation method and a data mining technique for bankruptcy prediction and compared it with LDA, QDA, logit and probit using two samples of data from Greek firms consists of basic sample and holdout sample. The basic sample consisted of 80 firms' (40 bankrupt and 40 non-bankrupt) financial data up to five years before bankruptcy. The first year prior to bankruptcy (year –1) was used to develop the bankruptcy prediction model through the fuzzy rule generation method and the previous four years prior to bankruptcy were used to evaluate the discriminating ability of the developed model. The holdout sample consisted of

38 firms' (19 bankrupt and 19 non-bankrupt) financial data of three-year period before bankruptcy and the predictive ability of the developed bankruptcy prediction methodology was evaluated using the holdout sample. The combined method got 7.48% of type-I error, 44.83% of type-II error and overall error was 26.16% whereas the overall classification error of LDA, logit and probit analysis was 29.35%, 27.15% and 30.63%, respectively. They concluded that fuzzy knowledge-based decision aiding method outperformed other classification methods used in this paper. (Michael, Georgios, Nikolaos, & Constantin, 1999).

- In 2000, Alam et al. proposed fuzzy clustering algorithm for identifying potentially failed banks and compared it with two SOM networks viz., (i) competitive neural network and (ii) self organizing neural network and concluded that both fuzzy clustering and SOM are good tools in identifying potentially failing banks. They also mentioned that fuzzy clustering provides an ordinal rating of the data set in terms of failing likelihood possibility. For the experiment they used an unbalanced dataset that consisted of 3% unsuccessful banks.(Alam, Booth, Lee, & Thordarson, 2000).

3. 1. 9. Support vector machines

Support vector machine algorithm was invented by Vladimir Vapnik (Cortes & Vapnik, 1995)(Vapnik, 1995). SVM could be viewed as a special form of neural networks (Li, Huang, Sun, & Lin, 2010).

SVM produces optimal separating hyper-planes, through non-linear mapping the input vectors into the high-dimensional feature space. SVM constructs linear model to estimate the decision function using non-linear class boundaries based on support vectors (Shin, Lee, & Kim, 2005). The optimal separating hyper-plane, also known as the maximum margin hyper-plane, gives the maximum separation between decision classes. The training examples that are closest to the maximum margin hyper-plane are called support vectors. All other training examples are irrelevant for defining the binary class boundaries (Min & Lee, 2005).

Given training set $D = \{x_i, y_i\}_{i=1}^{N}$ with input vectors $x_i = (x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(n)})^T \in \mathbb{R}^n$ and target labels $y_i \in \{-1, 1\}$, the decision rules defined by an optimal hyper-plane separating the binary decision classes is given as the following equation in terms of the support vectors

$$Y = \operatorname{sign}\left(\sum_{i=1}^{N} y_i\, \alpha_i K(x, x_i) + b\right)$$

where Y is the outcome, b the bias and α_i are parameters that determine the hyper-plane and $K(x, x_i)$ is the kernel function. Data instances corresponding to non-zero α_i's are called support vectors. The most common kernel functions in the literature are linear kernel of $K(x_i, x_j) = x_i^T x_j$, the polynomial kernel of degree d of $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d$, the radial basis function of $K(x_i, x_j) = \exp\{-\gamma \|x_i - x_j\|^2\}$, and sigmoid kernel function of $K(x_i, x_j) = \tanh\{\gamma x_i^T x_j + r\}$ where d, $r \in \mathbb{N}$ and $\gamma \in \mathbb{R}^+$ are constants (Min & Lee, 2005).

The SVM classification training is solving a linearly constrained quadratic programming for finding the support vectors and determining the parameters b and α_i. For the separable case, there is a lower bound 0 on the coefficient α_i. But for the non-separable case a lower bound is not enough, an upper bound C on the coefficients α_i in addition to the lower bound can be used for generalization (Shin, Lee, & Kim, 2005).

Advantages:

- It can conduct classification learning with relatively small amount of data and despite this, it achieves similar to or better performance than BPNN in practical applications (Min & Lee, 2005).

- It has only two free parameters, namely the upper bound and kernel parameter, which are selected empirically, so it is a relatively easy task to obtain an optimal combination of parameters that produces the best prediction performance (Shin, Lee, & Kim, 2005).
- It guarantees the existence of unique, optimal and global solution since the training of SVM is equivalent to solving a linearly constrained quadratic programming (Shin, Lee, & Kim, 2005).
- It implements the structural risk minimization principle which trades off empirical error with an approach that seeks to minimize an upper bound of the generalization error rather than minimize the training error (Shin, Lee, & Kim, 2005).

Disadvantages:

- Selection of optimal kernel function and its parameters is a slow process and it has a high algorithmic complexity (Min & Lee, 2005).
- Its training process in searching corresponding optimal parameters is relatively long (Li & Sun, 2010).
- It cannot identify the relative importance of variables (Li & Sun, 2010).

Literature:

- In 2005, Min and Lee compared the bankruptcy prediction performance of SVM with MDA, Logit and three-layer fully connected BPNN using data obtained from the Korea's largest credit guarantee organization. They first used a PCA and t-test for feature selection, from 38 financial ratios, 23 financial ratios were initially selected and after that using the stepwise logit, they reduced the number of financial variables to 11. The data consisted of 1888 firms includes 944 bankruptcy and 944 non-bankruptcy cases placed in random order. They used radial basis function as basic kernel function of SVM. Since the parameters associated with radial basis function kernels (C and γ) play a crucial role in the performance of SVMs they used a grid-search technique using 5-fold cross-validation to find out the optimal parameter values of the upper bound C and the kernel parameter γ. As a result they set the upper bound C and kernel parameter γ to 2^{15} and 2^{-1}, respectively. They concluded that SVM outperforms the other methods. (Min & Lee, 2005).

- In 2005, Shin et al. compared the BFP performance of SVM and BPNN. The data was provided by Korea Credit Guarantee Fund and consisted of externally non-audited 2320 medium-size manufacturing firms, which filed for bankruptcy (1160 cases) and non-bankruptcy (1160 cases) from 1996 to 1999. For feature selection they applied a two-staged input variable selection process. At the first stage, they selected 52 variables among more than 250 financial ratios by independent-samples t-test and in the second stage, they selected 10 variables using a MDA stepwise method. About 80% of the data was used for a training set and 20% for a validation set. They concluded that the accuracy and generalization performance of SVM was better than that of BPN as the training set size gets smaller. (Shin, Lee, & Kim, 2005).

- In 2006, Hui and Sun compared the companies' financial distress prediction performance of SVM with MDA, logit and BPNN taking 135 pairs of Chinese listed companies' three-year data before special treatment as sample data. For feature selection stepwise MDA method was used. They adopted cross-validation and grid-search technique to find SVM model's good parameters. They concluded that financial distress early-warning model based on SVM obtained a better balance among fitting ability, generalization ability and model stability than the other models. (Hui & Sun, 2006).

3.1.10. Other techniques

In this section, we will discuss the papers applying techniques such as isotonic separation, UTilite´s additives DIScriminantes (UTADIS), since these techniques found fewer applications in bankruptcy prediction literature. In this category classifiers are not reviewed separately from the papers since there are more than one technique in this category and applications of each technique are quite few. Because of this, works under this category examined in a relatively more detailed manner.

Literature:

- In 2005, Ryu and Yue introduced isotonic separation for prediction of firm bankruptcy and compared it with DA, linear programming discrimination, BPNN, LVQ, rough set analysis and oblique decision tree method (OC1) using 23 ratios of firms obtained from Standard & Poor's COMPUSTAT North American database. Isotonic separation is a linear programming technique. For isotonic separation, the weakest form of order relation (quasi order), which is a reflexive and transitive relation, is sufficient. In isotonic separation a set A_0 of data belonging to a group 0, a set A_1 of data belonging to a group 1, and the order restriction S assumed to be given. It is also assumed that for a pair of data points i and j whose attribute vectors are $(a_{i1}, a_{i2}, \dots, a_{id})$ and $(a_{j1}, a_{j2}, \dots, a_{jd})$, respectively, $(i, j) \in S$ if and only if $a_{ik} \geq a_{jk}$ for $k = 1, 2, \dots,$ and d. A separation variable π_i is defined for each data point $i \in A_0 \cup A_1$, such that if $\pi_i = 1$ then i is labeled as 1, and if $\pi_i = 0$ then i is labeled as 0. So $A_0 = \{i \in A_0 \cup A_1 | \pi_i = 0\}$ and $A_1 = \{i \in A_0 \cup A_1 | \pi_i = 1\}$. Then, the separation of data in $A_0 \cup A_1$ is achieved by solving the following linear program

$$\begin{aligned} &minimize && \alpha \sum_{i \in A_1} (1 - \pi_i) + \beta \sum_{i \in A_0} \pi_i \\ &subject\ to && \pi_i - \pi_j \geq 0\ for\ (i, j) \in S \\ & && 0 \leq \pi_i \leq 1\ \ for\ i \in A_0 \cup A_1 \end{aligned}$$

  where $\sum_{i \in A_1} (1 - \pi_i)$ indicates the number of data points that are mislabeled as 0; $\sum_{i \in A_0} \pi_i$ indicates the number of data points that are mislabeled as 1; and $\alpha > 0$ and $\beta > 0$ are costs or penalties of misclassification. As for feature selection methods Ryu and Yue used the backward sequential elimination method for isotonic separation and LP because of its simplicity and empirical validation of its usefulness, the stepwise discriminant analysis method for DA since it was specifically developed for DA and the mutual information based feature selection method for BPNN since it had often been used for neural network learning in the literature. They employed ten-fold cross-validation for testing their method and concluded that the isotonic separation method outperformed other methods for short-term bankruptcy prediction and it is a viable technique for firm bankruptcy prediction. (Ryu & Yue, 2005).

- In 2009, Sun and Li put forward a group decision-making approach based on experts' knowledge and all kinds of financial or non-financial information to diagnose business financial distress. They adopted a method integrating linguistic label and interval value for decision makers to express their preference on attributes, and designed a multi-expert negotiation mechanism for weighting attributes. Diagnosis on business financial distress was made through the grey evaluation method, which also tried to find out the potential risks that may cause financial distress. A case study of Shanghai Kaikai Industry Company Limited, which was a Chinese public company, was carried out to validate the proposed financial distress early warning method based on group decision making. (Sun & Li, 2009).

- In 2010, Ioannidis et al. used UTilite´s additives DIScriminantes (UTADIS), BPNN, CART, k-NN, logit, MDA to classify banks into three categories: (i) very strong banks and strong banks, (ii) adequate banks and (iii) banks with weaknesses or serious problems. They used a sample of 944 banks from 78 countries. They compared models with financial variables only, with models that incorporate additional information in relation to the regulatory environment, institutional development, and macroeconomic conditions and reported a substantial improvement in accuracy when we consider the country-level variables. From classifiers, UTADIS and BPNN achieved the highest accuracies. They also developed stacked models that combine the predictions of the individual models at a higher level and found that while the stacked models outperformed the corresponding individual models in most cases, they could not found any evidence that the best stacked model outperformed the best individual model. (Ioannidis, Pasiouras, & Zopounidis, 2010).

In addition to the studies above, Kilic's study (2006), which was surveyed under section "3. 3. Studies related to Turkey", used ELECTRE TRI, which can be classified under this section.

3. 1. 11. Soft computing techniques

The term was first brought into attention by Zadeh (Zadeh, Soft computing and fuzzy logic, 1994) (Zadeh, Fuzzy logic, neural networks, and soft computing, 1994). It refers to the seamless integration of different, seemingly unrelated, intelligent technologies to derive the advantages and to minimize the disadvantages of the individual techniques that are complementary rather than competitive in several aspects such as efficiency, fault and imprecision tolerance and learning from example (Ravi Kumar & Ravi, 2007). The papers reviewed in this section employed one of the three varieties of soft computing architectures: (i) ensemble classifier, where individual techniques were employed to solve the problem in a stand-alone mode and then their results are combined through an arbitrator which performs simple majority voting or weighted majority voting schemes or a linear combination of predictions; (ii) an intelligent technique is used for feature selection task and another intelligent technique performs classification by taking the selected features and (iii) tightly integrated hybrid systems such as GA trained NN, neuro-fuzzy, GA-neuro-fuzzy, etc (Ravi Kumar & Ravi, 2007).

<u>Advantages:</u>

- It derives the advantages and to minimizes the disadvantages of the individual techniques used (Ravi Kumar & Ravi, 2007).

<u>Disadvantages:</u>

- It requires quite amount of data (Ravi Kumar & Ravi, 2007).

Literature:

- In 1996, Back et al. developed five hybrid models using LDA, logit, GA and BPNN methods and compared bankruptcy prediction performances of them using annual financial statements data of Finnish companies. The models were (i) DA used for feature selection + DA used for prediction, (ii) logit used for feature selection logit used for prediction, (iii) DA used for feature selection + BPNN used for prediction, (iv) logit used for feature selection + BPNN used for prediction and (v) GA used for feature selection+ BPNN used for prediction. They concluded that the best prediction results were achieved when using genetic algorithms. (Back, Laitinen, & Sere, 1996).

- In 1996, Ignizio and Soltys presented a hybrid approach for firm failure prediction called ontogenic NN where GA were used for design and training of neural networks simultaneously and they concluded that the ontogenic NN obtained less number of misclassified cases compared to other methods. (Ignizio & Soltys, 1996).

- In 1996, Wallrafen et al. studied the Genetic algorithm-neural network hybrid (GANN), where different parameters of BPNN such as topology, connection weights and input variables selection were encoded. They reported that the combination of GA and NN appeared promising as genetic algorithm reduced the Type-II error from 42.6% to 36.1%. As for the validation set, however, the genetically optimized neural networks did not outperform earlier solutions due to a problem which they named as “over-selection effect”. (Wallrafen, Protzel, & Popp, 1996).

- In 1996, Jo and Han designed a hybrid model using case-based forecasting (CBFS), BPNN and DA. Using data collected from Korean companies they concluded that the hybrid model achieved higher prediction accuracy than these individual models operated in standalone mode. They divided data into three groups: training, testing and generalization. The hybrid model was consisted of a linear combination of DA, BPNN1 (which is BPNN with one hidden layer), BPNN2 (which is BPNN with two hidden layers), CBFS1 (which uses a similarity measure to determine the number of base cases) and CBFS2 (which uses all the base cases). They performed numerical experiments with different weights and reported that the best combination of weights was (2, 3, 5, 1 and 4) with prediction accuracy of 90.78% for data set-I and (1, 5, 4, 2 and 3) with prediction accuracy of 89.72% for data set-II. Hit ratio of integrated model using equal weights was 89.36%. (Jo & Han, 1996).

- In 1997, Jeng et al. presented a fuzzy inductive learning method (FILM) that integrated fuzzy set theory with regular inductive learning process which is a method that creates decision trees from a set of existing cases. Basically the method is a fuzzy decision tree in which hurdle values for splitting branches and classes associated with leaves are fuzzy. They compared the FILM with DA and ID3 and reported that the prediction accuracy of FILM, DA and ID3 was 83.3%, 76.7% and 70%, respectively. Thus they concluded that FILM outperformed both DA and ID3 in the case of bankruptcy prediction. (Jeng, Jeng, & Liang, 1997).

- In 1997, Olmeda and Fernandez compared the accuracy of individual classifiers and their combined hybrids on bankruptcy prediction problem using Spanish banking data. Among the single classifiers, BPNN performed the best followed by logit, MARS, C4.5 and DA in that order. As for hybrids, they proposed compensating aggregation method to formulate the choice of the optimal mixture of the technologies as an optimization problem that minimize the expected costs of misclassification and solved it using an evolutionary programming. Overall prediction rates yielded by combined models viz., NN + logit + C4.5 + DA, NN + logit + C4.5, NN + logit + MARS + DA, NN + logit, NN + logit + C4.5 + MARS, NN + logit + DA, NN, all methods and NN + logit + MARS by simple voting scheme were 96.21%, 94.94%, 94.69%, 93.93%, 93.18%, 92.42%, 92.42%, 91.66% and 90.91%, respectively and the compensating aggregation method achieved 95.10%. They found that hybrid methods by simple voting gave more accurate predictions than the stand-alone methods and suggested that an optimal system for risk rating should combine two or more different techniques.(Olmeda & Fernández, 1997).

- In 1999, Gorzalczany and Piasta presented two different hybrid intelligent decision support systems for firm bankruptcy prediction viz., (i) neuro-fuzzy classifier that can be trained with both purely numerical data as well as qualitative, linguistic, fuzzy data that describe the decision-making process and (ii) rough classifier that combines all positive aspects of rule induction systems with the flexibility of statistical techniques for classification. Using Altman's data(1968) and leave-one-out method to test the models, they reported that classification accuracies of neuro-fuzzy classifier (with 10 hidden nodes), rough classifier (generated by ProbRough), C4.5 and CN2 on corporate bankruptcy data were 97%, 90.4%, 84.8% and 86.4%, respectively. They concluded that N-FC outperformed other techniques. (Gorzalczany & Piasta, 1999).

- In 2000, Ahn et al. proposed two hybrid models by combining rough sets and BPNN for Korean firm failure prediction. They employed 2D reduction data preprocessing algorithm, which reduces the information system both horizontally and vertically, where horizontal reduction implies attribute reduction and vertical reduction implies the deletion of conflicting objects, since for NN, reduction of attributes prevents over-fitting problem and saves training time and removing conflicting objects and train neural network with consistent cases can bring performance improvement as well as reduction of training time. They constructed two hybrid models; (i) hybrid model I by combining rough sets with BPNN trained with horizontally reduced information system and (ii) hybrid model II by combining rough sets with BPNN trained with horizontally and vertically reduced information system. Since the rules developed by rough set analysis achieved the best prediction accuracy if a case matched any of the rules, in the hybrid models, they used rules developed by rough sets for an object that matched any of the rules and neural network for one that did not match any of them. They employed 12-fold cross-validation technique in testing phase. The average prediction accuracy of DA, BPNN, RNN1, RNN2, Hybrid I and Hybrid II were 78.75%, 84.62%, 89.5%, 89.79%, 94.3% and 94.34%, respectively. They inferred that hybrid models I and II outperformed both BPNN and DA but not each other. They claimed that the reason behind neither of the hybrid models outperformed other one was because of the fact that both models used same rule set generated by rough set analysis, and this rule component covered rather large part compared to NN component. (Ahn, Cho, & Kim, 2000).

- In 2001, Lin and McClean compared BPNN, decision tree (C5.0), DA, logit and their hybrid combinations. Of the two feature selection methods – financial theory and human judgment and ANOVA – they reported that ANOVA performed better in all classifiers except DA. Among the individual classifiers BPNN and decision tree outperformed others. They also proposed hybrid models (Hybrid 1 – DA + logit + NN + C5.0, Hybrid 2 – DA + NN + C5.0, Hybrid 3 – logit + C5.0) and concluded that hybrid models produced better results. (Lin & McClean, 2001).

- In 2002, McKee and Lensberg integrated a rough set model with GP and proposed a two-staged hybrid model: (i) stage 1 used a rough set model to identify subsets of important explanatory variables and (ii) stage 2 used a GP algorithm to develop a structural model of bankruptcy based on those variables. The model achieved 80% accurate on a validation sample where the original rough sets model was 67% accurate. They concluded that genetic programming coupled with rough sets theory can be an efficient and effective hybrid modeling approach both for developing a robust bankruptcy prediction model and for offering additional theoretical insights. (McKee & Lensberg, 2002).

- In 2003, Bian and Mazlac proposed a fuzzy-rough-nearest Neighbor hybrid and compared the bankruptcy prediction performance of it with crisp k-NN and fuzzy k-NN. When using decision tree feature selection method, they concluded that the hybrid method provided more accurate prediction result by minimizing type I error, while having satisfactory type II error. (Bian & Mazlack, 2003).

- In 2004, Pendharkar and Rodger studied GA-based ANN on bankruptcy prediction problem using GA for different crossover operators to learn the connection weights in an ANN. They mentioned that GA-based ANN showed resistance towards over-fitting by keeping the ANN architecture constant. They concluded that GA-based ANN with 1-point crossover, arithmetic crossover and uniform crossover performed comparably with BPNN. (Pendharkar & Rodger, 2004).

- In 2004, Tung et al. proposed a new neural fuzzy system, the generic self-organizing fuzzy neural network based on the compositional rule of inference, GenSoFNN-CRI(S), which has the ability to capture the interactions between the features and present them in the form of IF-THEN fuzzy rules. The GenSoFNN-CRI(S) was compared with the Cox's proportional hazards model, BPNN and the modified cerebellar model articulation controller (MCMAC) in predicting bank failures based on a population of 3635 US banks observed over a 21 years period. They performed v-fold cross-validation. They concluded that although BPNN had a superior performance and the MCMAC had a slightly better performance over the GenSoFNN-CRI(S) network, the strengths of the GenSoFNN-CRI(S) network lies in its ability to formulate a set of intuitive IF–THEN fuzzy rules while the other two architectures function as black boxes. (Tung, Quek, & Cheng, 2004).

- In 2005, Tseng and Lin proposed a hybrid quadratic interval logit model based on Tanaka's (1998) quadratic programming approach to deal with binary response variables and apply it to forecast the bankruptcy in UK companies. The model obtained a classification rate of 78%. They concluded that the model can support the logit model to discriminate between groups, and it provides more information to researchers. (Tseng & Lin, 2005).

- In 2006, Min et al. designed a hybrid by integrating SVM and GA which used SVM for classification task as its heart and used GA for optimization of both the feature subset and parameters of SVM simultaneously for bankruptcy prediction. To test the proposed GA-SVM model, they used 32 financial ratios of 307 pairs of Korean companies in health and distress observed in the period 1999-2002. GA-SVM was compared with logit, BPNN and SVM. They concluded that GA-SVM improved the prediction of bankruptcy, and that the choice of the feature subset had an influence on the appropriate kernel parameters and vice versa. (Min, Lee, & Han, 2006).

- In 2007, Wu et al. developed a genetic-based SVM (GA-SVM) model that can automatically determine the optimal parameters of SVM and tested the performance of GA-SVM on the prediction of financial crisis in Taiwan by comparing the accuracy of the proposed GA-SVM with DA, logit, probit, BPNN and SVM. They used data of the failed and non-failed firms obtained from the database of the Taiwan Economic Journal and reported that GA-SVM performed the best predictive accuracy. (Wu, Tzeng, Goo, & Fang, 2007).

- In 2007, Hua et al. proposed integrated binary discriminant rule (IBDR) for corporate financial distress prediction and compared it with conventional SVM. The conventional SVM employs the structural risk minimization principle, thus empirical risk of misclassification may be high, especially when a point to be classified is close to the hyper-plane. To prevent the weaknesses of SVM, the proposed method interpreted and modified the outputs of the SVM according to the result of logit. In other words, depending on the vector's relative distance from the hyper-plane, if result of logit supported the output of the SVM classifier with a high probability, then IBDR accepted the output of the SVM classifier; otherwise, IBDR modified the output of the SVM classifier. They concluded that IBDR outperformed the conventional SVM. (Hua, Wang, Xu, Zhang, & Liang, 2007).

- In 2008, Ravi et al. presented an ensemble bank performance prediction system whose constituent models were a BPNN, a probabilistic neural network

(PNN) and a radial basis function neural network (RBFN), SVM, CART and a fuzzy rule based classifier and PCA based hybrid neural networks, viz. PCA-BPNN, PCA-PNN and PCA-RBFN. Both PNN and PCA-PNN were trained with a GA to optimize the smoothing factors. Two ensembles (i) pure majority voting and (ii) weighted majority voting were implemented. Ten-fold cross-validation was performed in the training sessions and results were validated with an independent production set. They concluded that both ensembles were able to yield lower Type I and Type II errors compared to its constituent models. (Ravi, Kurniawan, Thai, & RaviKumar, 2008).

- In 2008, Ng et al. proposed fuzzy CMAC (cerebellar model articulation controller) model based on compositional rule of inference, named FCMAC-CRI(S), as a new approach to identify the inherent traits and patterns of financial distress based on financial covariates derived from publicly available financial statements using localized learning. In FCMAC-CRI(S), its interactive relations among the selected pattern features were captured in the form of highly intuitive fuzzy IF–THEN rules, which formed the knowledge base of the early warning system and provided insights into the characteristics of financial distress. The performance of the FCMAC-CRI(S) was benchmarked against that of the Cox's proportional hazard model and Gen-SoFNN-CRI(S) network, in predicting bank failures based on a population of 3635 US banks (702 failed) observed over 21 years. They used 80% of dataset as training sample and 20% as holdout sample and also they applied five-fold cross-validation. Three sets of experiments were performed – bank failure classification based on the last available financial record and prediction using financial records one and two years prior to the last available financial statements. They concluded that the performance of the new approach as a bank failure classification and early warning system was found to be highly encouraging. (Ng, Quek, & Jiang, 2008).

- In 2008, Nguyen et al. constructed a novel fuzzy neural cerebellar model articulation controller (CMAC) with truth value restriction (TVR) inference scheme method, which they called Ying-Yang Fuzzy CMAC, to analyze bank solvency and tested this model using a dataset of a population of 3635 US banks (702 failed) observed between 1980-2000 years. Nine financial covariates (features) derived from publicly available financial statements were used and three sets of experiments were performed – bank failure classification based on the last available financial record and prediction using financial records one and two years prior to the last available financial statements. They concluded that the performance of the proposed Ying–Yang FCMAC network as a bank failure classification and early warning system was encouraging. (Nguyen, Shi, & Quek, 2008).

- In 2008, Nachev compared fuzzy ARTMAP neural networks with BPNN and statistical techniques as predictor of corporate bankruptcy and concluded that the fuzzy ARTMAP outperformed statistical techniques and BPNN. (Nachev, 2008).

- In 2009, Nachev et al. applied Fuzzy ARTMAP neural networks and BPNN to predict insolvency of Irish firms using financial information for a period of six years, preprocessed properly in order to be used with neural networks. For validation of accuracy of predictions ROC analysis, AUC metrics, and leave-one-out cross-validation was used. They concluded that with certain network parameters, the Fuzzy ARTMAP model outperformed BPNN and it also outperformed SOM as reported by other studies that use the same dataset. (Nachev, Hill, & Stoyanov, 2009).

- In 2009, Li and Sun presented a hybrid Gaussian CBR (GCBR) system which used Gaussian indicators to measure similarity, a combiner to generate case similarity on the basis of the Gaussian indicators and the consensus of nearest neighbors to generate forecasting on the basis of case similarity. They designed an experiment to compare the BFP performance of GCBR with DA, logit, decision tree and classical CBR systems using data of 135 pairs of companies in health and distress collected from the Shanghai Stock Exchange and Shenzhen Stock Exchange in China. They concluded that GCBR produced superior performance in short-term BFP of Chinese listed companies in terms of both predictive accuracy and coefficient of variation. (Li & Sun, Gaussian case-based reasoning for business failure prediction with empirical data in China, 2009).

- In 2009, Li and Sun designed a multiple case-based reasoning system by majority voting (Multi-CBR–MV) for financial distress prediction where four independent CBR models, deriving from Euclidean metric, Manhattan metric, grey coefficient metric, and outranking relation metric, were employed as classifiers. Two ensembles (i) pure majority voting and (ii) weighted majority voting were implemented. For the experiment, they used min–max normalization to scale all data into the specific range of [0, 1], 30 hold-out data sets to assess predictive performance of models and grid-search technique to get optimal parameters under the assessment of leave-one out cross-validation. They compared performance of the two Multi-CBR–MV systems with their composing CBRs and statistical models using data of 83 pairs of sample companies in health and distress collected from Shanghai and Shenzhen Stock Exchanges. They concluded that the proposed ensembles were found to be feasible and valid for listed companies' financial distress prediction in China. (Li & Sun, Majority voting combination of multiple case-based reasoning for financial distress prediction, 2009).

- In 2009, Li and Sun developed a novel combining-classifiers system for financial distress prediction, where four independent CBR systems with k-NN algorithms with Euclidean distance metric, Manhattan distance metric, Grey coefficient metric, and Outranking relation metric were employed as classifiers to be combined and SVM was utilized as the algorithm fulfilling combining-classifiers. They named this new combining-classifiers system as Multiple CBR systems by SVM (Multi-CBR-SVM). Outputs of independent CBRs were transferred as inputs of SVM to carry out combination. The experiment was designed using 83 pairs of sample companies in health and distress from Shanghai and Shenzhen Stock Exchange, grid-search technique was utilized to get optimal parameters, leave-one-out cross-validation was used as assessment in parameter optimization, and predictive performances on 30-times hold-out data were used to make comparisons among Multi-CBR–SVM, its components and statistical models. They reported that Multi-CBR–SVM was found to be feasible and validated for listed companies' business failure prediction in China.(Li & Sun, Predicting business failure using multiple case-based reasoning combined with support vector machine, 2009).

- In 2009, Ahn and Kim proposed a new CBR based hybrid approach that used GA for optimization of feature weighting and the instance selection simultaneously for CBR and compared the BFP performance of this new model with conventional CBR, FSCBR (Feature Selection using GA for CBR), FWCBR (Feature Weighting using GA for CBR), ISCBR (Instance Selection using GA for CBR) and BPNN using Korean heavy industry firms' data. 164 financial ratios of 1335 bankrupt and 1335 healthy firms' data observed in the period 1996-2000 was used. First, 111 ratios were selected by using two independent samples t-test and then 15 financial ratios were selected as independent variables through the forward selection procedure based on logistic regression and the opinions of the experts who are responsible for approving and managing loans in a bank. They concluded that the prediction accuracy of conventional CBR might be improved significantly by using the proposed model and the proposed model produced at least as good results as BPNN. (Ahn & Kim, 2009).

- In 2009, Chen et al. compared the BFP performance of neuro-fuzzy, a hybrid approach combining the functionality of fuzzy logic and the learning ability of neural networks, with logit and BPNN using data obtained Securities and Exchange Commission (SEC) from the period 1998–2002. The training sample included 140 cases: 70 bankrupt and 70 healthy whereas the test sample included 60 cases: 30 bankrupt and 30 healthy. The banking industry was excluded, as its unique features of capital structure. For future reduction, factor analysis was applied. They subjectively assumed that the cost of a Type II error is at least 100 times that of a Type I error and also performed a sensitivity analysis by changing a multiple of 50, 200, 500 and 1000 each in turn to investigate if the cost gap between a Type I error and a Type II error affects model performance. They concluded that neuro-fuzzy demonstrated a better accuracy rate and lower misclassification cost than did logit and BPNN and also neuro-fuzzy demonstrated a higher detecting power than did logit. (Chen, Huang, & Lin, 2009).

- In 2010, Li and Sun constructed a hybrid[2] CBR (H2CBR) forecasting method by integrating six hybrid CBR modules. The first hybridization was that each CBR was a combination of a modified outranking preference function from ELECTRE, PROMETHEE, and ORESTE (the true preference function, quasi preference function, pseudo preference function, multilevel preference function, Gaussian preference function, and ranking-order preference function), with the k-NN algorithm. The six hybrid CBR modules were named TCBR, QCBR, PCBR, MCBR, GCBR, and RCBR based on their preference function. The second hybridization was a trial-and-error iterative process which was employed to identify the optimal hybrid CBR module of the H2CBR forecasting system. Stepwise MDA was used for feature selection. The 30-times hold-out method and leave-one-out cross-validation were combined and used to assess the performance of models and both predictive accuracy and the coefficient of variation were used for this assessment. Ranking-order case-based reasoning (RCBR) outperformed other CBR models, MDA, logit and pure CBR at the level of 1% for short-term BFP of Chinese listed companies. Also the time consumed by RCBR is very short, since there are no parameters to be optimized in RCBR. (Li, Sun, & Wu, 2010).

- In 2009, Cho et al. proposed a hybrid method for effective bankruptcy prediction, based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance with variable weight. They reported that the proposed approach outperformed BPNN, logit, CBR model using the Euclidean distance with variable weight and CBR model using the Euclidean distance without variable weight. (Cho, Hong, & Ha, 2010).

- In 2010, Kim and Kang applied two popular ensemble methods, Bagging and Boosting, with BPNN for improving the performance of BPNN on bankruptcy prediction tasks. They defined Bagging as: "Bagging is a bootstrap aggregation method that creates and combines multiple classifiers, each of which is trained on a bootstrap replicate of the original training set… The final classifier is generated by combining ensemble of classifier with un-weighted majority voting… Bagging improves generalization performance due to a reduction in variance while maintaining or only slightly increasing bias." and Boosting as: "Boosting constructs a composite classifier by sequentially training classifiers while increasing weight on the misclassified observations through iterations. The observations that are incorrectly predicted by previous classifiers are chosen more often than examples that were correctly predicted. Thus Boosting attempts to produce new classifiers that are better able to predict examples for which the current ensemble's performance is poor. Boosting combines predictions of ensemble of classifiers with weighted majority voting by giving more weights on more accurate predictions." They designed an experiment using 32 financial ratios of 1458 externally audited Korean manufacturing firms, half of which went bankrupt during 2002–2005 while healthy firms were selected from active companies at the end of 2005. They reported that boosted and bagged BPNN consistently showed an improved predictive accuracy in all of 10 different topologies. Also, boosted BPNN generated a relatively small improved performance compared with bagged classifier. They concluded that the two proposed ensemble methods could be effective tools to improve the performance of BPNN for bankruptcy domain. (Kim & Kang, 2010).

- In 2010, Ravisankar et al. presented novel neural network–genetic programming hybrids to predict the failure of dotcom companies using a dataset collected from Wharton Research Data Services (WRDS) consisted of 240 companies of which 120 were failed and 120 were healthy. The hybrids designed were (i) BPNN–GP, (ii) BPNN – BPNN, (iii) PNN–GP, (iv) PNN–PNN, (v) t-statistic– GP, (vi) f-statistic–GP, (vii) RS– BPNN, $(viii)$ RS–PNN, (ix) RS–

GP and (x) GP–GP, wherein the first technique performed feature subset selection and the second one took care of classification. In each of these cases, top 10 features of 24 features were selected. Also, the neural networks–GP hybrids were compared with BPNN, PNN and GP in their stand-alone mode without feature selection. Ten-fold cross-validation was performed throughout the study. They reported that in terms of average accuracy, average sensitivity, average specificity and area under the receiver operating characteristic curve (AUC) the GP outperformed all the techniques with or without feature selection and the superiority of GP–GP is demonstrated by t-test at 10% level of significance. (Ravisankar, Ravi, & Bose, 2010).

- In 2010, Wu et al. proposed a comprehensive model and compared it with (i) Altman (1968) – MDA model based on accounting variables; (ii) Ohlson (1980) – logit model with accounting ratios; (iii) Zmijewski (1984) – probit model using accounting data; (iv) Shumway (2001) – hazard model which included accounting, market and firm-characteristics variables; and (v) Hillegeist et al. (2004) – BSM-Prob model based on both accounting and market variables. They used a dataset (accounting, market, and firm-characteristic data) from New Generation Research (www.bankruptcydata.com), Compustat (accounting data i.e., financial ratios and diversification data) and CRSP (daily and monthly stock returns) observed in the period 1980-2006. Both matched-pair and random-sampling methods were employed to ensure comparability with the estimation procedures of the models under investigation and in addition, to remove the impact of extreme values and outliers, all variables have been winsorized at the 1st and 99th percentiles. They found that although each model that was used for comparison contained unique information regarding the probability of bankruptcy, the performance of models varied over time. They reported that the MDA model of Altman (1968) performed poorly relative to other models; the accounting based models of Ohlson (1980) and Zmijewski (1984) performed better than MDA but outperformed by others; the hazard model of Shumway (2001), outperformed other models that were based on accounting information only; Hillegeist et al. (2004) model performed adequately but was generally inferior to the Shumway model. The model proposed in this research comprised key variables from each of the five models and add a new variable that proxies for the degree of diversification within the firm. They concluded that their model outperformed other models in a variety of in-sample and out-of-sample tests. (Wu, Gaunt, & Gray, 2010).

- In 2011, Andrés et al. proposed a hybrid system which combines fuzzy c-means clustering and MARS and tested the accuracy of it using a database made up of 59,336 non-bankrupt Spanish companies and 138 distressed firms which went bankrupt during 2007. As benchmarking techniques they used DA, MARS and a BPNN. MARS is a method that can be considered as a generalization of CART. They used the five variables proposed by Altman in his seminal paper (1968).They reported that the hybrid model outperformed the other systems, both in terms of the percentage of correct classifications and in terms of the profit generated by the lending decisions. (Andrés, Lorca, Juez, & Sánchez-Lasheras, 2011).

- In 2011, Chaudhuri and De used a novel Soft Computing tool viz., Fuzzy Support Vector Machine (FSVM) to solve bankruptcy prediction problem. The test dataset comprised of 50 largest bankrupt organizations with capitalization of no less than $1 billion that filed for protection against creditors under Chapter 11 of US Bankruptcy Code in 2001–2002 after stock market crash of 2000. They reported that FSVM was found to be better capable of extracting useful information from corporate data, finding optimal feature subset and parameters. They also compared clustering power of FSVM with PNN on ripley and bankruptcy datasets and reported that FSVM outperformed PNN. (Chaudhuri & De, 2011).

In addition to the studies above, Yıldız and Akkoc's study (2009), which was surveyed under section "3. 3. Studies related to Turkey", used neuro-fuzzy as classifier, can be classified under this section.

3. 2. Feature selection and feature extraction

In prediction, although every new feature brings new perspectives that help to explain the prediction universe, every new feature also brings a new dimension and an exponential growth of complexity and number of bins. For instance if there are three features, the classifier will work in a three dimensional space. Suppose every feature can get ten different values. This means there are 10^3=1000 bins. The classifier first assigns each of the 1000 bins into a class. And after that it will classify every object into these bins. If a new feature is inserted, the new bin number will become 10^4=10.000. The negative effects of this exponential increase is called curse of dimensionality. As a result of, there exist a maximum number of features above which the performance of the classifier will decrease rather than increase.

In addition to curse of dimensionality, irrelevance, redundancy, and interaction of features should be avoided by researchers. In models only distinctive features should be used since the presence of irrelevant and redundant features may mask the distribution of truly relevant features for a target concept and hence harm the performance of classification models (Zhao, Sinha, & Ge, 2009). Also presence of irrelevant and redundant features increases the learning cost, storage requirements and utilization times of classification models (Guyon & Elisseeff, 2003). Other than feature irrelevancy and redundancy, the presence of feature interaction may also be another source for classification performance degradation. Feature interaction refers to a situation where some features are not individually related to the target concept, but are so when they are combined with other features (Zhao, Sinha, & Ge, 2009).

Three approaches have been developed to for this purpose: feature selection, feature extraction, and feature construction. Feature selection is basically selecting a ‘‘good” subset of features that retain the most useful information for a given task and discarding any other features as irrelevant and redundant information, whereas feature extraction and feature construction aim to find a set of ‘‘composite” features, which are functions of the original features (Zhao, Sinha, & Ge, 2009). As seen in Figure 6, feature selection is the selection a subset of existing features without a transformation, while feature extraction is the transformation of existing features to achieve a lower dimensional space. Principal component analysis (PCA), factor analysis, independent component analysis (ICA), and DA are examples for feature extraction techniques (Tsai, 2009).

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \end{bmatrix} \xrightarrow{Feature\ Selection} \begin{bmatrix} x_1 \\ x_4 \\ \vdots \end{bmatrix} \qquad \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \end{bmatrix} \xrightarrow{Feature\ Extraction} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \end{bmatrix} = f\left(\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \end{bmatrix}\right)$$

Figure 6: Feature selection and feature extraction(Gutierrez-Osuna)

3.2.1. Feature selection methods

Feature selection algorithms have two main components: feature search and feature subset evaluation (Liu & Motoda, 2008). The feature subset evaluation can also be classified into three categories: filter approaches, wrapper approaches and embedded approaches.

In a ***feature search***, there are 2^j possible feature subsets, where j is the number of features. An exhaustive search would definitely find the optimal solution, however it is computationally impractical. For this purpose more realistic search strategies have been studied. These strategies can be sequential or random. Sequential forward selection (starts with the empty set and sequentially adds one feature at a time), sequential backward elimination (starts with all the features and sequentially eliminates one feature at a time by eliminating the feature that contributes least to the criterion function) and bidirectional selection can be listed as examples of sequential search methods. Sequential search methods do not guarantee global optimality of the selected subsets. Random search methods such as genetic algorithms add some randomness to help to escape from a local optimum (Liu & Motoda, 2008).

Filter approaches refer to selecting feature subsets as a preprocessing step that is independent of the classifier (Li & Sun, Predicting business failure using forward ranking-order case-based reasoning, 2011). The main advantage of filter approaches is that they are fast. Also their results can be used for a larger number of classifiers since they evaluate the information in data rather than features' interactions with a specific classifier. Despite these advantages, filter approaches have some disadvantages. One of the drawbacks of the filter approach is that the resulting feature subset may not be optimal for a particular prediction model. Also they try to select large subsets since most of the filter objective functions are monotonic functions (Gutierrez-Osuna). There are techniques developed for feature filtering such as; FOCUS, LVF, RELIEF, Simba and G-flip, information theory and probabilistic reasoning based techniques. Also, in literature, for feature filtering, it is common to use a statistical technique such as; correlation matrix, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), F-ratio, Mallows Cp (minimizes the mean square error of prediction), t-test (whether there is a significant difference between two group's means) and stepwise regression (Tsai, 2009) (Rokach & Maimon, 2008).

Wrapper approaches refer to using classifier function as objective function to evaluate feature subsets by their predictive accuracy. By doing so, they aim to find an optimum feature subset for the classifier. The main advantage of wrapper approaches is their accuracy. Since the feature subset is selected as an optimum for the classifier, they generally achieve better classification rates. Also they have a mechanism to avoid over-fitting. Despite these advantages, wrapper approaches have some disadvantages. The most important disadvantage is that they are slow. Also since they try to optimize solution of a specific classifier, the feature subset they select most likely is not a good subset for another classifier (Gutierrez-Osuna).

Embedded approaches integrate the selection of features in model building (Liu & Motoda, 2008). In a way, they are similar to the wrapper approaches in the sense that the features are specifically selected for a certain learning algorithm. However, in the embedded approach the features are selected in the process of learning (Rokach & Maimon, 2008). The main advantage of embedded approaches is that they make better use of the available data by not needing to split the training data into a training and validation set (Guyon & Elisseeff, 2003).

Ensemble methodology is an approach that combines filter approaches, wrapper approaches and embedded approaches to solve some of the drawbacks of individual approaches. For instance, first due to a voting process, noisy results are filtered. Secondly, the drawback of wrappers which "cost" computing time is solved by operating a group of filters (Rokach & Maimon, 2008).

3.2.2. Limitation of feature selection methods

The usage of feature selection methodologies might have some drawbacks. First, the assumption that a large set of input features can be reduced to a small subset of relevant features is not always true; in some cases the target feature is actually affected by most of the input features, and removing features will cause a significant loss of important information (Rokach & Maimon, 2008). Second, the outcome is strongly dependent on the training set size, that is, if the training set is small, then the size of the reduced subset will be small also and relevant features might be lost (Rokach & Maimon, 2008).

Another issue arising from feature selection evaluation is feature selection bias. Using the same training data in both feature selection and classification learning may result a selection bias which can exacerbate data over-fitting and hence negatively affect classification performance. Using separate data for feature selection and for learning to overcome this problem, however, this leads to a reduction of data in both feature selection and learning. The effect of this reduction is much more harmful than the effect of feature selection bias on feature selection for classification (Liu & Motoda, 2008).

3.2.3. Literature

In 1998, Piramuthu et al. developed a feature construction methodology and used it with BPNN for bankruptcy prediction of banks and concluded that BPNN with feature construction outperformed the plain BPNN in all datasets they used. (Piramuthu, Ragavan, & Shaw, 1998).

In 2009, Tsai compared the prediction performance of five well-known feature selection methods used in bankruptcy prediction, which were t-test, correlation matrix, stepwise regression, principle component analysis and factor analysis also compared the case any feature selection was not used. BPNN was used as the prediction model. Five related credit evaluation and bankruptcy datasets were used; including Australian Credit (http://www.liacc.up.pt/ML/statlog/datasets/australian/australian.doc.html), German Credit (http://www.liacc.up.pt/ML/statlog/datasets/german/german.doc.html), Japanese Credit (http://www.ics.uci.edu/~mlearn/MLRepository.html), Bankruptcy dataset (http://www.pietruszkiewicz.com/) and UC competition datasets (http://mill.ucsd.edu/). They used 5-fold cross-validation method and reported that the t-test outperforms the other ones. (Tsai, 2009).

In 2009, Chen and Du applied BPNN and k-means techniques to 68 companies listed in the Taiwan stock exchange corporation (TSEC) where 34 of the companies were failed. 33 financial and 4 non-financial ratios were used and factor analysis was applied to extract adaptable variables. The non-financial ratios were dividend payout ratio, price-book ratio, the proportion of collateralized shares by the board of directors, and the insider holding ratio. They concluded that (i) the more factor analysis used, the less accuracy obtained; (ii) two seasons prior to the occurrence of financial distress had a better accuracy than four seasons prior to the occurrence of financial distress, the closer they got to the actual occurrence of financial distress, the higher the accuracy they obtained; (iii) factor analysis increased the rate of Type II error; (iv) the BPNN approach obtains better prediction accuracy than the k-means clustering approach. As a result, for prediction of the potential financial distress of a company, instead of traditional statistics, the usage of artificial intelligent approach was proposed.(Chen & Du, 2009).

In 2009, Zhao et al. evaluated the performance improvement due to the use of constructed features rather than the original features in bankruptcy prediction of banks by empirically comparing the performance of two sets of classifiers for bank failure prediction, one built using raw accounting variables and the other built using constructed financial ratios with the classifiers logit, decision tree (C4.5), BPNN, and k-NN. The dataset, which was obtained from the FDIC website (www.fdic.gov), covered all banks that filed bankruptcy at FDIC in 1991 and 1992 which was 121 banks in 1991 and 119 banks in 1992. For these 240 failed banks, 240 non-failed banks were selected based on three characteristics: (i) geographic location (i.e., state), (ii) size of assets, and (iii) charter type (federal chartered or state chartered). For prediction one year prior to failure, a balanced sample of 480 banks (240 failed and 240 non-failed) and for prediction two years prior to failure 468 banks (234 failed and 234 non-failed) among the 480 banks that had survived for at least two years were used. They concluded that for both periods (one year and two years prior) feature construction, guided by domain knowledge, which transforms raw accounting variables into financial ratios, significantly improved classifier performance with respect to expected misclassification cost. They also concluded that the degree of this improvement on logit and BPNN was significantly larger than that on k-NN and C4.5 decision tree. Without feature construction, the performance of BPNN was worse than that of k-NN and C4.5 decision tree and the performance of logit was worse than (in one-year prior prediction) or close to (in two-year-prior prediction) that of k-NN and C4.5 decision tree. With feature construction, the performance of logit and BPNN became much better than that of k-NN and C4.5 decision tree, and logit and BPNN became the top two performers. (Zhao, Sinha, & Ge, 2009).

In 2010, Li et al. compared four filters, i.e. MDA stepwise method, Logit stepwise method, One-way ANOVA, independent samples t-test, and the wrapper approach of genetic algorithm to generate five optimal feature subsets after data normalization using 216 companies' empirical data two years prior to failure collected from Shanghai Stock Exchange and Shenzhen Stock Exchange in China. In literature there are both evidence demonstrating CBR's applicability and inapplicability in BFP. In their study Li et al. investigated whether one of the reasons resulting in the fluctuation of CBR's predictive accuracies is its sensitiveness to 'optimal' feature subsets or not. MDA, logit and SVM were also employed as comparative models. As a result there were 7 methods namely; MDA-CBR, Logit-CBR, ANOVA-CBR, GA-CBR, MDA, Logit, SVM. For SVM, grid search technique was employed to search optimal parameter values in the candidate space with all data in this part. They also used MDA stepwise method to select optimal feature subset for SVM. For CBR, in the predetermination of k, 1NN, 3NN, ..., 19NN were tried with all features and data normalized into [0, 1]. In order to tackle with the disadvantage of hold-out method, which is its biased estimation on predictive accuracy, leave-one-out cross-validation and hold-out method were combined and a method called thirty-times hold-out method was used as assessment of predictive performances. So, for each model used, there were 30 testing accuracies which could be used to carry out significance test. From 30 financial ratios, optimal features selected by independent-sample t-test and ANOVA, which were the same, consisted of 24 features, GA consisted of 10 features, logit stepwise method consisted of 6 features, and MDA stepwise method consisted of 7 features. They reported that to select optimal feature subsets for CBR, the stepwise method of MDA was the first choice, followed by the stepwise method of logit, GA and the two filter approaches of ANOVA and t-test. If MDA stepwise method was employed to select optimal feature subset for the CBR system, there were no significant difference between CBR and the other three models, i.e. MDA, logit, SVM. If ANOVA or t-test was used as feature selection method for CBR, CBR was outperformed by the three models at the significant level of 1%. They concluded that the empirical results in this study indicated that CBR was truly sensitive to optimal feature subsets and if a true optimal feature subset was used in the CBR-based prediction system, it could produce acceptable predictive accuracy, else, the CBR system could possibly produce lower performance than other models. (Li, Huang, Sun, & Lin, 2010).

In 2010, Jardin analyzed the influence of variable selection techniques on model accuracy. He used 41 initial variables of French retail sector companies that can be investigated under seven titles: liquidity-solvency, financial structure, profit- ability, efficiency, turnover, withdrawal and contribution. Data of 250 pairs of companies in health and distress was used for training and data of 260 pairs of companies was used for evaluation. A well-balanced sample of young and old firms was designed to neutralize the effect of the young companies' higher probability of bankruptcy. In addition to well-known univariate statistical tests (t-test, F-test) six feature selection methods were compared: (i) forward search procedure, Fisher F test to interrupt the search and Wilks's lambda to compare variable subsets and determine the ''best'' one; (ii) backward stepwise search, Chi 2 as a stopping criterion and likelihood statistic as an evaluation criterion of the solutions; (iii) forward stepwise search, Chi 2 as a stopping criterion and likelihood statistic as an evaluation criterion of the solutions; (iv) a zero-order technique, backward search procedure, the evaluation criteria designed by Yacoub and Bennani (1997); (v) a first-order method, backward search procedure, the first derivatives of network parameters with respect to variables as an evaluation criterion; (vi) wrapper approach, backward search procedure. (i) was especially optimized for DA, (ii) and (iii) was for logit and the last three was the most commonly used methods especially designed for neural networks. They designed two experiments. In the first one, the accuracy of ''modelling method/ selection technique'' combinations was measured for the classifiers DA, logit and BPNN. In the second one, they applied a Kohonen map to analyze the profiles of each group of firms (healthy-unsuccessful) to test whether both groups would be represented by equal or nearly equal number of nodes or not. He claimed that the reason behind this experiment was that failing firms might continue to do business, but it was much more unusual for healthy firms to go suddenly bankrupt, so there might be sub-groups of sound companies whose financial profiles were so similar to those of failing companies that they moved the boundary between the two groups in such a way that the models tended to identify bankrupt firms as healthy, and as a consequence led to weaker results when classifying bankrupt firms. They concluded that (i) a t-test or an F-test for a selection or pre-selection of the inputs of a neural network was found to be unreliable as these tests might lead to the choice of unnecessary variables as well as to the removal of variables of great interest; (ii) in the first experiment the best BPNN achieved 93.85%, followed by that for logit with 90.77% and DA with 85.19%; (iii) in the first experiment, for logit, backward search achieved higher accuracy than forward search; (iv) variable selection based on a variance criterion (i.e., Wilks's lambda- the first feature selection model) led to poor results which showed that this feature selection model was found to be clearly ill-suited to non-linear techniques; (v) since both financial ratios and a probability of bankruptcy behave in a non-linear manner, it was found to be crucial for models to take into account this non-linearity; (vi) in the second experiment, healthy companies were coded using 52 neurons, compared with 45 neurons for bankrupt companies, which showed that healthy firms would present a much wider spectrum of profiles than failing firms; (vii) the previous conclusion was supported by the optimal number of neurons encoding sound companies in the first experiment was larger than failed companies. (Jardin, 2010).

3. 3. Studies related to Turkey

3.3.1. Development of Modern Banking in Turkey

In Turkey, banking activities were not as common as in the European Countries during Ottoman Empire administration. Instead of appearing as a result of wealth transfer gathered by the mercantilist policies to the industrial sectors in form of credits as in Europe; in Ottoman Empire banking came out as a result of fiscal troubles of the state. After the foundation of Republic of Turkey, first national bank, which is "İş Bankası", was founded in 1924 and it is followed by the Central Bank of Turkey in 1930 (Altay, 2006). The economic recessions after World War II affected banking system badly (Kurnaz, 2001). However, after liberal policies put forward at the beginning of 1950s, number of banks increased. For instance, the number of banks was 44 in 1950 and it increased 56 in 1955 and 59 in 1960 (Kurnaz, 2003). In planned economy period, banking and financial system was kept under control of governments (Kurnaz, 2001).

In 1980s, Turkish economy experienced structural changes; opening to external markets and applications of liberal policies affected banking system. Entrance into banking sector was made easier to improve banking sector to transfer monetary sources to real sector (Toprak, 1996). The interest rate limits, which were a key price in transition period to free market economy, were taken out from control of government and determination of interest rate was left to market itself and set free (Toprak, 1996). But on the contrary to expectations, four small banks and most of bankers went bankrupt in 1982 (Toprak, 1996). Thus, Central Bank restarted to arrange interest rate of deposits in 1983 (Toprak, 1996). Convertibility of Turkish lira, which brought several risks, was shaped in 1989 (Kurnaz, 2001). For instance, banks ignored main principles of fund management and inclined to foreign exchange financial sources (Çolak & Yiğidim, 2001). This inclination was ceased by the 1994 crisis. After the crisis, Treasury and Central Bank tried to establish legal infrastructure to arrange banking according to international banking rules using several tools such as sufficiency of capital and net general position ratio (Çolak & Yiğidim, 2001). In addition, coverage of insurance of saving deposit was widened and all kinds of savings deposits were insured (Çolak & Yiğidim, 2001). But, lasting of this application so long resulted in financial troubles faced after 1999 (Çolak & Yiğidim, 2001). As can be understood from Table 2, number of banks increased steadily from 1980 to 1993 and 1995 to 1999. However, together with the continuous increase in inflation, banks became intermediary institutions which gather funds from public and lend them to state or the owner of banks.

Table 2: Some selected ratios between 1980 and 2010 (TBB, 2011)

Years	Population (thousand)	Wholesale Price Index[2]	Number of Banks	Number of Branches[3]	Number of Employees	Population / Number of Branches	Loans and Receivables ($) / Population	Deposits ($) / Population
1980[4]	44.737	93,71	43	5.954	125.312	7.514	224	204
1985[4]	50.664	44,19	50	6.268	137.805	8.083	224	343
1990[4]	56.473	60,40	66	6.560	154.089	8.609	484	577
1993	59.323	71,08	70	6.241	143.983	9.505	506	635
1994	60.417	125,50	67	6.104	139.046	9.898	340	550
1995	61.532	78,90	68	6.240	144.793	9.861	476	728
1999	66.200	68,80	81	7.691	173.988	8.607	607	1.350
2000	67.804	39,00	79	7.837	170.401	8.652	751	1.503
2001	68.365	68,50	61	6.908	137.495	9.896	414	1.184
2002	69.302	29,70	54	6.106	123.271	11.350	496	1.253
2003	70.231	18,40	50	5.966	123.249	11.772	715	1.643
2010	73.723	9,00	45	9.465	178.503	7.789	4.489	5.423

Before 1999 there were several institutions related to regulation supervision of banks. Permission to open banks, abolition of permission and merging one bank with another were under control of Council of Ministers (Çolak & Yiğidim, 2001). Undersecretary of Treasury and State Ministry related to Treasury were responsible for giving recommendation to Council of Ministers about foundation of banks, abolition of banking permission, permission to public banks to open new branches (Çolak & Yiğidim, 2001). Moreover, Treasury had the authority to take actions to empower the financial structures of banks (Çolak & Yiğidim, 2001). This multi-authority on banking failed to give desirable results. Especially, political pressures on institutions increased with short-lived multi party governments. Due to political pressures, supervision of

[2] Annual % change
[3] Including foreign branches
[4] Census years. Mid-year population estimates were used for the rest of years.

banks couldn't be successful and this postponed taking necessary precautions for banks making loss (Çolak & Yiğidim, 2001).

Several arrangements related to banking sector were made after June, 1999 with the Banks Law numbered 4389 which was passed by the parliament in June 18, 1999 and it can be summarized as follows: (Çolak & Yiğidim, 2001)

- In order to regulate and make necessary arrangements in banking an "independent" institution was established under the name of "Banking Regulation and Supervisory Agency".
- Establishing new banks was made more difficult to prevent easy entrance into banking market.
- New limitations were set in credit placements of banks to reduce risks of unreturned credits.
- Sanctions in case of banks don't have sufficient capital were made heavier with new law.
- Establishing a "risk watching unit" in banks was made obligatory.

According to law regulating and supervising agency would be independent. However, the application of this couldn't be so easy. In December, 1999 several changes were made and selection of members of regulation and supervision committee was left to political parties (Çolak & Yiğidim, 2001). Although BRSA was established in 1999 to remove the political effects on regulation and supervision of banks, selection of members of committee couldn't be done easily because of political struggles and institution couldn't work until 2000 (Çolak & Yiğidim, 2001). Therefore, several changes were made in Banks Law to answer the IMF requests in May 2001 (Çolak & Yiğidim, 2001). With these changes merging of banks was encouraged and members of BRSA were changed again.

In November 2000, financial crisis broke out. In this month, the average interbank market overnight interest rate increased three times and became 110,8% and foreign exchange short position of banking sector exceeded 200% which was ten times the legal ratio, 20% (Uygur, 2001). Moreover, the fact that banks were not complying with the rules about currency and maturity mismatch was known by Central Bank of the Republic of Turkey (Uygur, 2001). Banks were claiming that they mitigate the risks caused from foreign exchange debts by forward contracts and they reported these contracts in their off-balance-sheet memorandum accounts (Uygur, 2001). But they made these contracts with domestic firms which faced the same risks that banks carried (Uygur, 2001). The program made with the IMF obligated restructuring the banking sector which was carrying too much risk (Uygur, 2001). Three months after the November crisis passed, because of a political tension in February 2001, a second speculative attack started and a currency crisis broke out (Uygur, 2001). In February 21, interbank overnight interest rate increased to maximum 6200% and average 4018% (Uygur, 2001). After the reserves of Central Bank of the Republic of Turkey dissolved 5,4 billion dollars, in the night of February 21, the currency rates set free, and in ten days the currency rates increased 40% (Uygur, 2001). These two crises and the restructuring of the banking sector cost 39,3 billion dollars and this was 26,6% of Turkish GDP (BDDK, 2003).

In these crises, some banks went bankrupt. Since all kinds of savings deposits were insured by government, according to law, the bankruptcy occurs as a transfer to SDIF of the bank. In Figure 7, Figure 8 and Figure 9 the share of the banks that were transferred to SDIF can be seen. In these figures, for unsuccessful banks, we used the share in the year that is one-year prior to bankruptcy and simply sum the rates. As for successful banks, we assumed the rest of the market is successful. Although this assumption is very rough, it sheds light to a very important fact. As seen in Figure 7, Figure 8 and Figure 9 the share of unsuccessful banks in sector for total assets is 16,68% and for total loans is 15,71. However total deposits share of unsuccessful in sector is 20,88%. This is because unsuccessful banks were weak before the crises and they needed liquid money. So they collected deposits with higher interest rates than market.

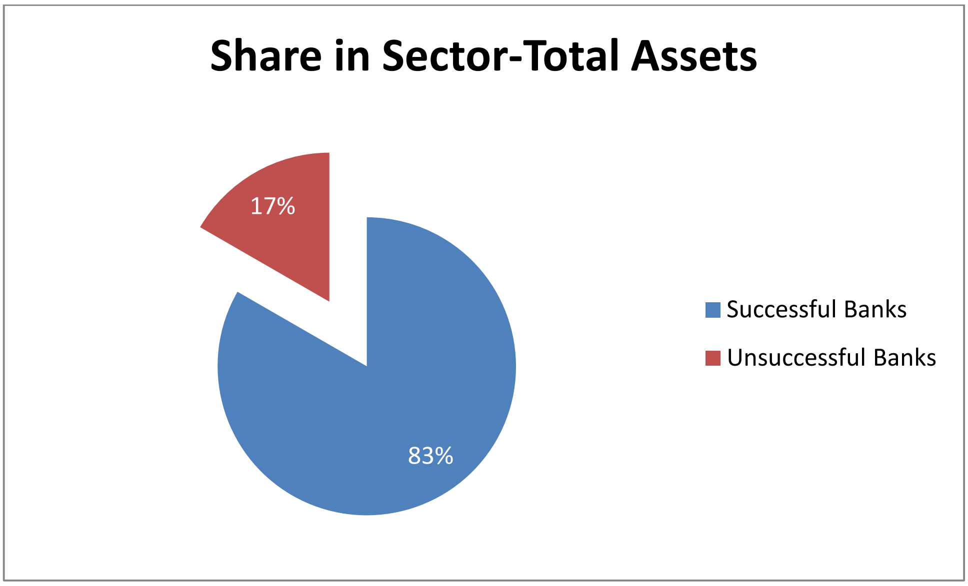

Figure 7: Share in Sector-Total Assets

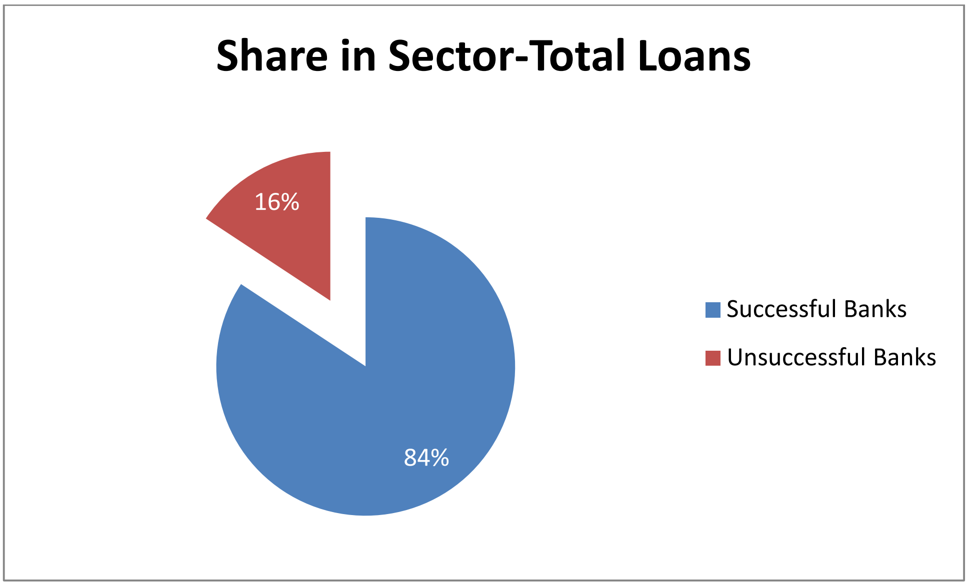

Figure 8: Share in Sector-Total Loans

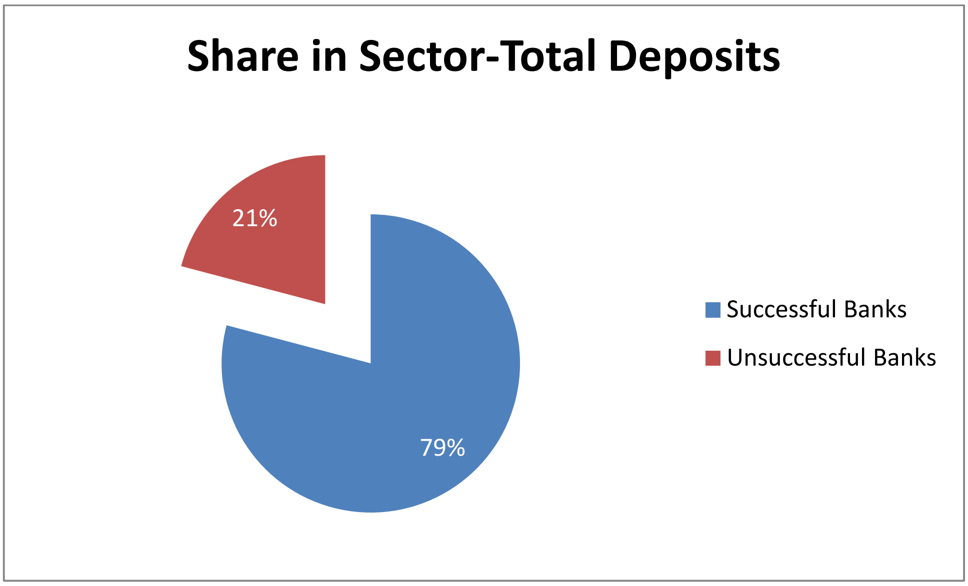

Figure 9: Share in Sector-Total Deposits

In Figure 10-Figure 15, the means of some selected ratios for successful banks, for unsuccessful banks and for total set can be seen. In these figures, for unsuccessful banks, (t-1) represents the year that is one-year prior to bankruptcy. For successful banks it represents the year 2000 since most of the bankruptcies occurred in 2001. In the same manner, (t-2) represents the year that is two-years prior to bankruptcy, for unsuccessful banks and 1999, for successful banks. By looking at these figures, it is possible to say that successful and unsuccessful banks are separated from each other.

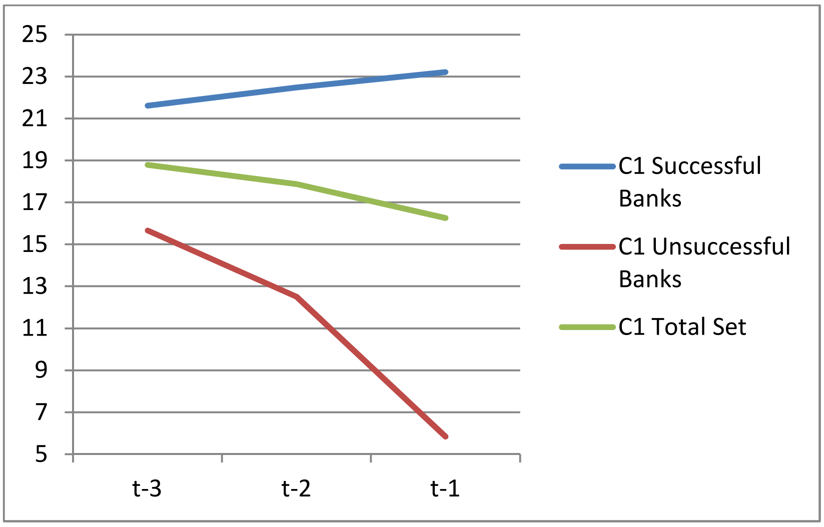

Figure 10: Standard Capital Ratio

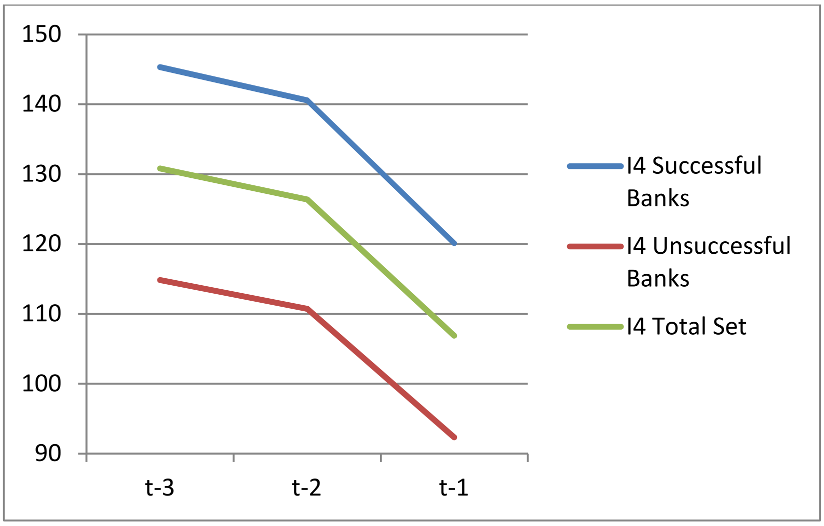

Figure 11: Total Income/Total Expenditure

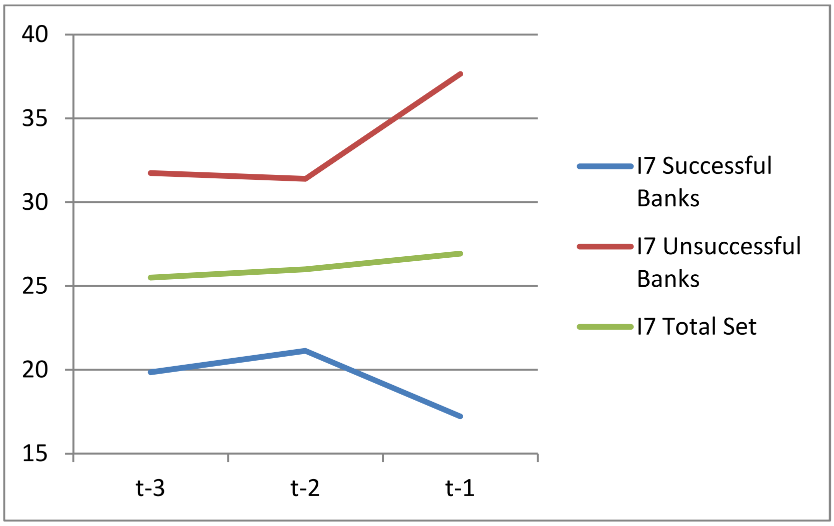

Figure 12: Interest Expenses/Average Profitable Assets

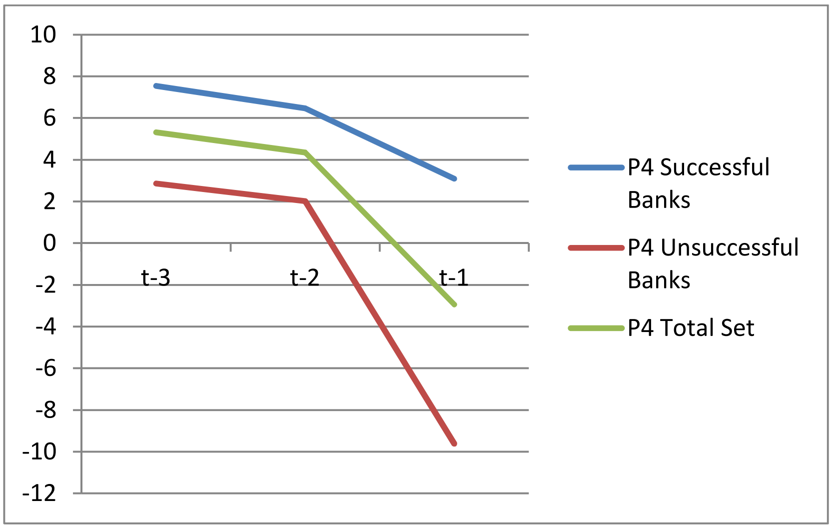

Figure 13: Income before Tax /Average Total Assets

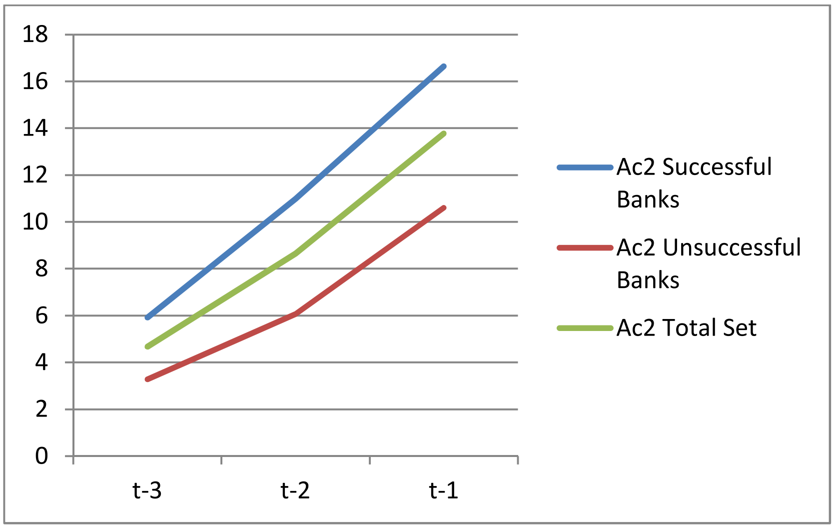

Figure 14: (Salary and Employee Benefits +Res. for Retire.)/No. of Personnel

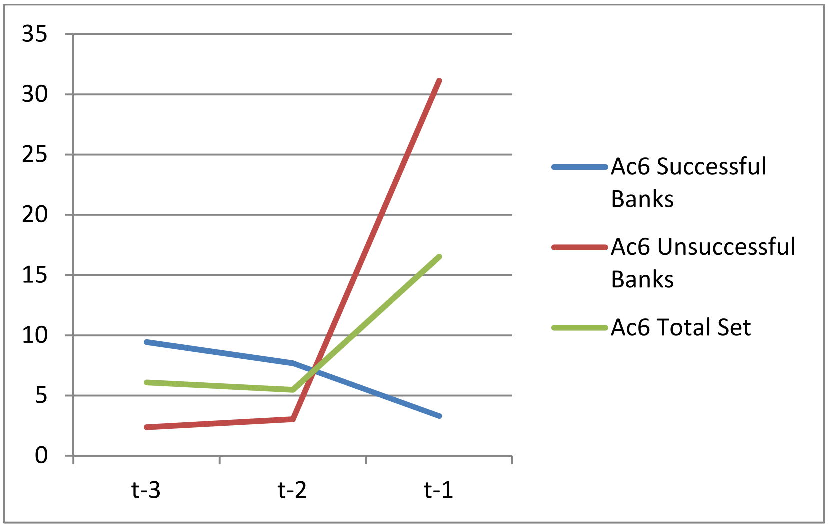

Figure 15: Provisions including Provisions for Income Tax/Total Income

3.3.2. Turkish banking system

As mentioned above Turkish banking system has an active and dynamic structure. Since Turkey does not have a stable economy, financial crises are not found strange in

Turkish economic history. Because of this, there have been some studies about bank failure prediction in Turkey. From these studies, the significant ones are reviewed in a chronological order in this section. Before going through these studies, it is useful to roughly classify the Turkish Banking System.

Turkish banking system can be classified into two groups: commercial banks and development and investment banks. As seen in Figure 16, after first grouping, banks can be classified into four groups according to ownership: State-owned banks, privately-owned banks, banks under the SDIF and foreign banks. But there is not any development and investment bank under the SDIF and also there is not any development and investment bank having branches in Turkey.

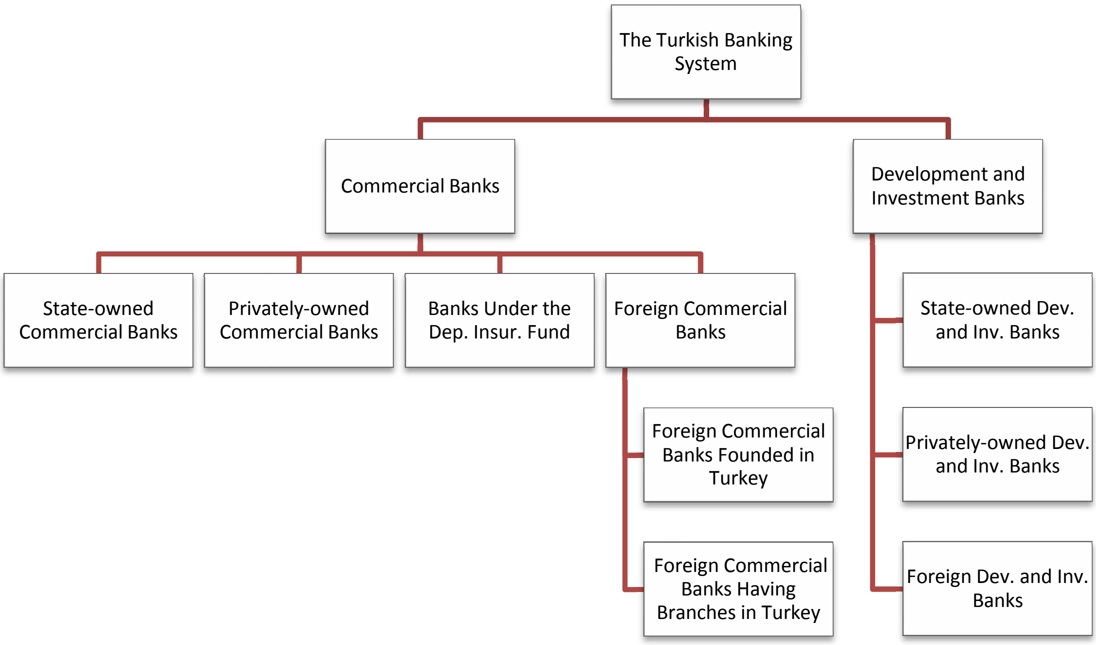

Figure 16: The Turkish Banking System

Since 1995, 21 Turkish banks transferred to SDIF. (Table 3) All of them are privately-owned commercial banks. 8 of them transferred to SDIF in 2001 and 6 of them transferred to SDIF in 1999.

Table 3: List of failed banks in Turkey after 1995 (TMSF)

Bank	Failure Date
Türk Ticaret Bankası A.Ş.	06.11.1997
Bank Ekspres A.Ş.	12.12.1998
Interbank	07.01.1999
Eskişehir Bankası T.A.Ş.	21.12.1999
Egebank A.Ş.	21.12.1999
Yurt Ticaret ve Kredi Bankası A.Ş.	21.12.1999
Türkiye Tütüncüler Bankası Yaşarbank A.Ş.	21.12.1999
Sümerbank A.Ş.	21.12.1999
Etibank A.Ş.	27.10.2000
Bank Kapital Türk A.Ş.	27.10.2000
Demirbank T.A.Ş.	06.12.2000
Ulusal Bank T.A.Ş.	28.02.2001
İktisat Bankası T.A.Ş.	15.03.2001
Sitebank A.Ş.	09.07.2001
Milli Aydın Bankası T.A.Ş. (Tarişbank)	09.07.2001
Bayındırbank A.Ş.	09.07.2001
Kentbank A.Ş.	09.07.2001
Ege Giyim Sanayicileri Bankası A.Ş.	09.07.2001
Toprakbank A.Ş.	30.11.2001
Pamukbank T.A.Ş.	18.06.2002
Türkiye İmar Bankası T.A.Ş.	03.07.2003

Banks Association of Turkey publicities 49 financial ratios of 79 failed and surviving Turkish banks for the periods 1988–2001. All of the studies covered here used these ratios issued in the website of Banks Association of Turkey: http://www.tbb.org.tr/english/bulten/yillik/2000/ratios.xls. (TBB) In addition, all of the studies covered here excluded state-owned commercial banks and development and investment banks.

3.3.3. Literature

In 2005, Canbas et al. proposed an integrated early warning system (IEWS) in three steps: (i) PCA produced three financial components using ratios from the data set of Banks Association of Turkey (ii) with these three factors they employed DA, logit and probit models (iii) by combining all these together they constructed an IEWS. Data used in this study covers the periods 1994–2001 and contains financial ratios of 40 privately owned Turkish commercial banks. They excluded State-owned Commercial Banks, Development and Investment Banks and Foreign Commercial Banks. Since the article covers 1995 - 2001, July; Toprakbank A.Ş., Pamukbank T.A.Ş. and Türkiye İmar Bankası T.A.Ş., which failed in 31.11.2001, 18.06.2002 and 03.07.2003, respectively, were classified as if they were in the successful banks group. They used data of 1, 2 and 3 years prior to the bank failure to estimate 1, 2 and 3 years before failure, respectively. For the banks failed in 2001, -1, -2 and -3 years are 2000, 1999 and 1998 respectively. Since most of the failure occurred between the period of 1998– 2001, year -1, -2 and -3 were considered as 2000, 1999 and 1998 respectively for the non-failed banks. First they applied ANOVA test to the 49 ratios of year -1 and choose 12 ratios. Secondly, they applied PCA which is a method that explores underlying patterns of relationship between the financial ratios. For PCA to be appropriate the financial ratios must be correlated to each other. To evaluate appropriateness of financial data, Bartlett's test of sphericity was performed and found that hypothesis that the correlation matrix of the financial ratios was an identity matrix can be rejected. Then all financial ratios are standardized, with a mean of 0 ($\mu = 0$) and the standard deviation of 1 ($\sigma = 1$) according to the equation:

$$z_{ak} = \frac{g_{ak} - \mu_k}{\sigma_k}, k = 1, \dots, 12, a = 1, \dots, 40$$

The standardized ratios were used to find factors in order to use in the model. To estimate jth factor (F_{aj}) for bank a the following equation was used:

$$F_{aj} = \sum_{k=1}^{m} w_{jk} z_{ak}$$

where, w_{jk} is the factor score coefficient, for the jth factor and kth ratio and z_{ak} is the standardized value of the kth ratio for bank a. After that to decide how many factors needed to represent the financial data, percentages of total variances explained by each factor were estimated (eigenvalues) and only those factors that account for variances greater than 1 (Eigen value >1) were included in the model. Three factors were selected and they were found to be explaining 78.833% of the total changes of financial conditions for the Turkish commercial banks. All three factors included all 12 ratios, but in the first factor, four capital ratios had more share, so it can be said that first factor represents capital adequacy. In the same way second factor represents income-expense structure for a bank and third one represents the liquidity factor. The authors claimed that this result showed that three factor components (capital adequacy, income-expenditure structure and liquidity) did not keep up a correspondence to the CAMELS criteria. Thirdly, these three factors were used as inputs for DA, logit and probit models and found that they have success rates of %90, %87.5 and %87.5 respectively for year -1. Lastly they talked about a combination methodology. In the first step, DAis applied. If the linear combination of factor scores of a bank is smaller than the cut-off score, which is 0 in the model, than according to model “bank will fail”. Else, in other words the bank does not fail in the first step, it passes to next step: logit. If the probability of the bank’s failure is greater than 0.5, than according to model “bank will fail”. Else the third step: probit. The bank will be classified as “survive” if and only if all three models classify the bank as it will survive in the next period. Using the combined method, for year -1, only Bayındırbank A.Ş. and Kentbank A.Ş. are misclassified and 95% success rate was achieved. (Canbas, Cabuk, & Kilic, 2005).

In 2006, for bankruptcy prediction of Turkish banks, Kilic applied a multi-criteria decision analysis method: ELECTRE TRI. As for the data, he excluded state-owned commercial banks and development and investment banks. Different from Canbas et al., he included foreign commercial banks to the sample. The data used here consists of ratios of 57 banks. 13 of them are foreign banks having branches in Turkey, which have a very small risk to be transferred to SDIF. To have a significant measure of the model, it is essential to use similar number of failed and successful banks. In this model, only %37 of the banks is failed banks. Examining the article, it is easy to see that usage of foreign banks having branches in Turkey in the model increased the success rate. Also different from Canbas et al., Toprakbank A.Ş., Pamukbank T.A.Ş. and Türkiye İmar Bankası T.A.Ş. are classified as failed banks. Kilic first chose 10 variables using values one year prior to the failure date by applying ANOVA. Second he normalized the values of the ratios to express them according to a standard measure since it is essential for ELECTRE TRI. After that, using these standardized ratios as inputs for ELECTRE TRI, he classified banks with a success rate of 93% which was better than DA, logit and probit models that Canbas et al. used. (Kılıç, 2006).

In 2008, Ravi and Pramodh applied variants of principal component neural network (PCNN) architecture trained by a threshold accepting (TA) based algorithm to bankruptcy prediction problem in commercial banks using the Spanish banks dataset and Turkish banks dataset. PCNN is a neural network architecture which has a 'principal component layer', instead of a hidden layer, and this layer consists of a few selected principal components that perform the function of hidden nodes. TA is a faster variant of the simulated annealing algorithm wherein the acceptance of a new move or solution is determined by a deterministic criterion rather than a probabilistic one. PCNN was also compared with PCA-TANN and PCA-BPNN, which have PCA as the preprocessor and have one hidden layer and also TANN and BPNN each in the 10-fold cross-validation. The comparison was made with respect to the AUC (area under the receiver operating characteristic (ROC) curve) with sensitivity on the X-axis and one-specificity on the Y-axis criterion. They reported that the proposed PCNN hybrids outperformed other classifiers in terms of AUC. The significant result was that the

PCNN trained by a TA-based algorithm improved the ‘‘generalization’’ aspect thereby circumventing the ‘over-fitting’ problem. Further, the feature subset selection (FSS) algorithm proposed in the study was found very stable and powerful. (Ravi & Pramodh, 2008).

In 2009, Yıldız and Akkoç used neuro-fuzzy method for bankruptcy prediction for Turkish banks. The data consisted of 19 unsuccessful and 21 successful banks. Although Pamukbank T.A.Ş. and Türkiye İmar Bankası T.A.Ş. are transferred to SDIF after 2001, they were classified as successful banks. As Canbas et al. they excluded State-owned Commercial Banks, Development and Investment Banks and Foreign Commercial Banks. 60% of data is used for training and 40% is used as holdout sample. They applied t-test and found that the distinctive capabilities of 23 of the 49 ratios are significant at 5% level. They used neuro-fuzzy method because of its high classification abilities as neural networks, and it does not work as a black-box like neural networks, so the decision making process of the model can be interpreted. First they applied DA and the 3 variables of the DA (“(Shareholders' Equity + Total Income) / (Deposits + Non-deposit Funds)”, “Interest Expenses / Average Non-Profitable Assets” and “Total Loans / Number of Branches”) were used in neuro-fuzzy using MATLAB – ANFIS module. Although neuro-fuzzy method achieved 81,25% success rate while DA achieved only 75%; the difference between these were not found statistically significant.(Yıldız & Akkoc, 2009).

In 2009, Chauhan et al. proposed “differential evolution trained wavelet neural network” (DEWNN), a neural network model that uses differential evolution algorithm to train a wavelet neural network. They compared the efficiency of this model on bankruptcy prediction datasets viz. US banks, Turkish banks and Spanish banks with threshold accepting trained wavelet neural network (TAWNN) and the original wavelet neural network (WNN) in the case of all data sets without feature selection and also in the case of four data sets where feature selection was performed. The Turkish dataset was from Canbas et al.’s study (2005) which covers 40 banks (22 unsuccessful - 18 healthy), the Spanish and the US dataset was obtained from Olmeda and Fernandez’s study (1997) where Spanish dataset contains 66 banks (37 unsuccessful - 29 healthy) and US dataset contains 129 banks (65 unsuccessful - 64 healthy). They used Garson's algorithm for feature selection and the whole experimentation is conducted using 10-fold cross-validation method. They reported that DEWNN and TAWNN outperformed the original WNN in terms of accuracy and sensitivity and DEWNN outscored TAWNN in terms of accuracy and sensitivity except for Turkish banks dataset.(Chauhan, Ravi, & Chandra, 2009).

In 2009, Boyacioglu et al. compared the prediction performance of 4 different neural network techniques (BPNN, competitive learning (CLNN), SOM and LVQ), support vector machines and 3 multivariate statistical methods (MDA, k-means cluster analysis and logit) for the bank failure prediction problem using 20 financial ratios with six feature groups including capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk (CAMELS) of 65 Turkish banks (21 unsuccessful-44 healthy). The data set was divided into training and validation subsets where the training set consists of randomly chosen 14 unsuccessful and 29 successful banks and the validation set consists of 7 unsuccessful and 15 successful banks. 9 of the 20 financial ratios were selected by using t-test. Then data was normalized using z-score method. They reported that BPNN and LVQ were found as the most successful prediction models. Further, SVM and multivariate statistical methods achieved satisfying prediction performance. (Boyacioglu, Kara, & Baykan, 2009).

In 2010, Ravisankar and Ravi compared three unused neural network architectures for bankruptcy prediction in banks, namely: (i) Group Method of Data Handling (GMDH), (ii) Counter Propagation Neural Network (CPNN) and (iii) fuzzy Adaptive Resonance Theory Map (fuzzy ARTMAP). The performances of these models were compared with and without feature selection using four different datasets pertaining to Spanish banks, Turkish banks, UK banks and US banks. For feature selection t-statistic, f-statistic and GMDH were used. The features selected by t-statistic and f-statistic were identical and there was a good overlap in the features selected by t-statistic and GMDH. Ten-fold cross-validation was performed throughout the study. They reported that the GMDH outperformed all the techniques with or without feature selection and the results were better than those reported in previous studies on the same datasets in terms of average accuracy, average sensitivity and average specificity. For Turkey they used 7 independent variables and reported an accuracy rate of 100%.(Ravi & Ravisankar, 2010).

CHAPTER 4

METHODOLOGY OF THE STUDY

The aim of a BFP model is to classify a number of businesses into two predefined classes (successful and unsuccessful) using historical data. As mentioned before, it has 5 steps: (i) data collection and preparation, (ii) feature selection and extraction, (iii) classifier choice, (iv) training and (v) evaluation. Data collection and preparation is probably the most time-intensive step of the BFP. Source of data and target time interval for the study are decided in this step. Especially when the target time interval for the study is not selected the past several years from the study, data collection may become the biggest challenge for the researcher. Feature selection and extraction is selecting or extracting the distinctive aspects, qualities or characteristics of an object – in this study, a bank. It is easy to see that, a case that matches important features but not less important ones will almost certainly be a better match than one that matches less important features but does not match important ones. The quality of a feature set in a model is related to its ability to discriminate examples from different classes. In a model, the objects from the same class should have similar feature values while objects from different classes have different feature values (Gutierrez-Osuna). Classifier choice may be the most crucial step for the success of a BFP model. The aim of classifiers in BFP is to classify a number of businesses into two predefined classes: successful and unsuccessful. Training is the step where classifier explores relations from the data to explain the data by minimizing overall misclassification rate or error cost function. Evaluation is the step where the trained model will be assessed or compared with other models.

The main problem in BFP is that there is no single correct way to apply all cases. There is only a best way for each case. For this reason, as seen in section 3, researchers in BFP are basically finding more accurate models by using a kind of trial-and-error process by searching optimal feature subset or classifier. In this study, 7 datasets, 9 feature selection methods and 5 classifiers were tested to find the optimal one and answers sought to the following questions: "Which classifier and feature selection method achieves best performance?", "Does the prediction accuracy increase while we got closer to the actual occurrence of bankruptcy?", "Does the usage of trend data increase the performance?", "When different feature selection methods applied, which features are selected the most?",… By doing so actually we test whether unsuccessful Turkish banks were failed following through a path or they failed instantly after a shock, which ratios affected the bank failures the most, in which variables a downward movement can be seen first and which of the banks was unsuccessfully predicted the most.

In this section, first, data collection and preparation step is reviewed. Then feature selection methods used in this study is discussed. After that classifiers used in this study are explained. Lastly training step is described as a conclusion of this section. In this study, for statistical calculations, SPSS Statistics 17.0 software was used.

4. 1. Data collection and preparation

4.2.1. Financial ratios

Financial ratios are the most important source for bankruptcy studies. Almost all of the studies surveyed in section 3 used financial ratios. Although in some studies, with financial ratios, features such as the age of the bank, the prior auditor opinion, auditor switching (indicates whether or not a bank had changed its auditor in the past one, two or three years before failure), macro-economic variables, corporate governance, stock price volatility were used and in some studies it was shown that other variables increase the performance of models; the studies showed that financial ratios are irreplaceable. In addition, instead of low-level accounting variables, most of the studies reviewed in section 3 used high-level constructs called financial ratios to eliminate the effects of some irrelevant factors in describing a bank's financial condition. For instance total loans divided by total assets represents a bank's financial situation better than total loans alone, since the effect of the bank's size is eliminated.

The financial ratios used in this study obtained from the website of Banks Association of Turkey: http://www.tbb.org.tr/english/bulten/yillik/2000/ratios.xls (TBB). The dataset originally consisted of 49 financial ratios of 79 failed and surviving Turkish banks for the periods 1988–2000. As seen in Table 3, since 1995, 21 banks transferred to SDIF. All of them are privately-owned commercial banks. 8 of them transferred to SDIF in 2001 and 6 of them transferred to SDIF in 1999. From these banks, Türkiye İmar Bankası T.A.Ş., which was transferred to SDIF in 2003, classified in the successful banks group since it was transferred to SDIF because of the fraud activities that manipulated its financial data. Since our research is based mainly on financial data, incorrect financial data will lead us to a wrong way. Pamukbank T.A.Ş., which was transferred to SDIF in 2002, also classified in successful banks group because of two reasons: (i) the share of the credits that commanding shareholder's companies used in total credits that was used from Pamukbank T.A.Ş., (ii) the credit that Fiskobirlik used (BDDK, 2002). For the first one, Pamukbank T.A.Ş. set rediscount rates (cumulative unpaid interest remainder) whichever were best for bank or commanding shareholder's group. So, it was easy to play with numbers such as overall profit rate and some ratios became unreliable. For the second one, Fiskobirlik, which is an agricultural cooperative for regulating hazelnut prices, used credits from Pamukbank T.A.Ş. in 1989 and in 1990. Till 2001, these credits were not closed by Fiskobirlik. By the mean time credits grew fast because of the macroeconomic conditions of Turkey. In 2000, Turkish Treasury Undersecretary and Pamukbank T.A.Ş. tried to agree on a rediscount rate, but there was a big difference between the rates each side proposed. This unresolved problem affected Pamukbank T.A.Ş.'s balance sheet. Because of these, our study will not cover the period after 2001 and will cover 1995-2001 period. As a result, 19 banks are in the unsuccessful banks class. To have an evenly matched dataset, equal or nearly equal number of successful banks should be chosen. Since none of the failed banks were state-owned commercial banks (4) and development and investment banks (18), as the previous studies, we excluded these banks. Another reason of this exclusion is that comparing private commercial banks with development and investment banks, which do not have permission for collecting deposit, and state-owned commercial banks, which are very different because of its capital and ownership nature, is not a very meaningful process. We also excluded foreign commercial banks (17) because the failure risk of them is much much less and also their capital and ownership nature is different from other banks chosen for this study. As mentioned before the main reason behind these exclusions is to have an evenly matched dataset, we should use an equal or nearly equal number of successful and unsuccessful banks. So, 21 successful banks were chosen. As a result, a balanced set of 40 banks (19 unsuccessful - 21 successful) were chosen. The scope of this study is in accordance with the previous studies and as many other studies, the sample size is relatively small.

For unsuccessful banks, we used financial data of one year, two years and three years prior to failure. t-1, t-2 and t-3 represent in 1, 2 and 3 years before the failure; for instance, t-1, t-2 and t-3 for a bank that failed in 2001 represent financial ratios of 2000, 1999 and 1998 respectively. For successful banks, since most of the failure occurred in 2001, t-1, t-2 and t-3 were considered as the data of 2000, 1999 and 1998 respectively.

The financial ratios set was constructed by Banks Association of Turkey which was originally consisted of 49 ratios classified into nine groups based on CAMELS rating system, namely; (i) capital ratios, (ii) assets quality, (iii) liquidity, (iv) profitability, (v) income-expenditure structure, (vi) branch ratios, (vii) activity ratios, ($viii$) share in sector and (ix) share in group. (i) Capital ratios are maybe the most critical of all since they measure the level and quality of a bank's capital base and capital base is the last line of defense against the risk of bank's insolvency (Zhao, Sinha, & Ge, 2009). (ii) Asset quality measures the level of risk of a bank's assets which effects bank profitability. Empirical evidence suggests that banks with lower asset quality are more likely to fail (Ioannidis, Pasiouras, & Zopounidis, 2010). (iii) Liquidity ratios measure a bank's ability to meet unforeseen deposit outflow, which is a combination of reluctance in interbank borrowings and rise in deposit interest rates. The recent crisis revealed the importance of liquidity measures. One of the reasons behind the strong banking infrastructure of Turkey in recent crisis is that Turkey is one of the very few countries that have regulations about liquidity (BDDK, 2009) (Resmi Gazete, 2006). (iv) Profit ratios are also very critical as some studies stated and profitability was found to be negatively related to the probability of failure (Ioannidis, Pasiouras, & Zopounidis, 2010). (v) Income-expenditure structure ratios measure the performance and the stability of a bank’s earnings stream. (vi) Branch ratios and (vii) activity ratios measure quality and efficiency of a bank’s officers and management structure. ($viii$) Share in sector which was used to measure the size of a bank which influences bank soundness due to differences between small and large banks in terms of credit constraints, diversification, and depth in management (Ioannidis, Pasiouras, & Zopounidis, 2010). (ix) Share in Group variables (Share in Group - Total Assets, Share in Group - Total Loans and Share in Group - Total Deposits) were excluded because there are many missing values in these variables (2 missing for t-1 and 8 missing for t-2 and t-3 for each of the 3 variables – total 54 missing) and because the banks we choose were in privately owned commercial banks group or in banks under SDIF group, so the difference of group has not very much importance in our analysis.

In this study, the financial ratios are represented by a coding system: “category of financial ratio”“no”_“1 for t-1, 2 for t-2, 3 for t-3”. For instance standard capital ratio is the first ratio in capital ratios category. So C1 represents standard capital ratio. t-1 value of standard capital ratio is represented by C1_1. Financial ratios and the codes used in this study are listed in a classified manner in Appendix B. The descriptive statistics for these ratios for unsuccessful banks, successful banks and total dataset for t-1, t-2 and t-3 are in Appendix C. Equations used by Banks Association of Turkey for the calculations of the financial ratios can be found in Appendix D.

4.2.2. Multiple imputation

As mentioned before, there are some missing values in the dataset. These are: 5 missing values for C1_1 and one missing value for C1_2. (C1_1: İktisat Bankası T.A.Ş., Kentbank A.Ş., Sitebank A.Ş., Toprakbank A.Ş. and Ulusal Bank T.A.Ş.; C1_2: Egebank A.Ş.) All the variables in dataset were calculated by using accounting variables which are public except C1. C1 was calculated by the banks themselves. So calculation of missing values is not an option. Because of this, to handle these missing values, multiple imputation method was used. Because, the multiple imputation method does not lessen the dataset, unlike list-wise deletion method, which is simply omitting the cases with missing data; and it does not lead to an underestimate of standard error, unlike mean substitution method, which is substituting a mean for the missing data. Multiple imputation is a method that generates imputed values on the basis of existing data. Normally, this process leads to an underestimate of the standard error, because of the less variability in the imputed data than the actual data if those values had not been missing. To prevent this, an error component drawn randomly is added to the calculated values. This solution will still underestimate the standard errors. To solve this, the multiple imputation method repeats the imputation process several times, and generates multiple sets of new data. Then the variability of the coefficients from set to set is captured and added back into the estimates (Howell, 2009).

In this study, we used SPSS Statistics 17.0 software to apply multiple imputation method. All of the financial ratios of (t-1), (t-2) and (t-3) data were used for this process. Trend variables were not used since the trend variables were generated from other variables and usage of the trend variables would increase the bias by adding the effect of some variables more than once to the model. Five imputations were used since it has shown that in many cases three to five imputations are sufficient (Howell, 2009). The imputation model was chosen by the software automatically. As a result for both C1_1 and C1_2 variables, linear regression model was chosen by the software. Five datasets were created because we chose 5 for the imputation iteration number. We derived our final set of estimates by averaging each of the estimates. The imputation process had no effect on the minimum and maximum values for both variables. The missing data were all from the unsuccessful banks. As seen in Table 4, the mean of unsuccessful banks of C1_1 and C1_2 slightly changed. But the overall set's mean a bit more affected than the unsuccessful banks', since, as mentioned, all the missing data were from unsuccessful banks.

Table 4: Descriptive statistics of multiple imputation method

			C1_1	C1_2
Unsucc. Banks	Mean	Missing	5,84	12,50
		Imputed	5,86	12,40
	Std. Deviation	Missing	13,04	19,45
		Imputed	11,10	18,91
All Set	Mean	Missing	16,26	17,87
		Imputed	14,97	17,69
	Std. Deviation	Missing	20,35	20,50
		Imputed	19,32	20,27

4.2.3. Trend analysis and other calculations

In this study, instead of low-level accounting variables, we used financial ratios to eliminate the effects of some irrelevant factors in describing a bank's financial condition. As mentioned before, for instance, total loans divided by total assets represents a bank's financial situation better than total loans alone, since the effect of the bank's size is eliminated. For this purpose, for example, among the 46 features, nine of them are constructed by dividing raw accounting variables by total assets, seven of them are constructed by dividing the variables by average (total/profitable/non-profitable) assets, four of them are constructed by dividing the variables by total income and three of them are constructed by dividing the variables by total loans. Also; the units of B1, B2, B3, B4, B6 and B7 of t-1, t-2 and t-3 years, which were Billion TL in the original dataset, are converted to Trillion TL since the values of these variables were far more different than other variables. The minimum, maximum and mean of these variables were -14098,1; 339295 and 6577,9 respectively; while the same values of overall dataset without these variables were -2597,1; 1460,4 and 31,8.

As mentioned before, one of the research questions that this study seek for an answer was whether the Turkish banks failed following through a path or they failed instantly after a shock. For this purpose, trends of individual ratios are examined. Trend is inserted into model using ratios; $Code\_12 = \frac{(t-2)value-(t-1)\ value}{(t-1)\ value}$, $Code\_23 = \frac{(t-3)\ value-\ (t-2)\ value}{(t-2)\ value}$ and $Code\_13 = \frac{(t-3)value-(t-1)\ value}{(t-1)\ value}$. Here $Code$ represents "category of financial ratio""no", for instance standard capital ratio is the first ratio in capital ratios category. So $Code$ for standard capital ratio is C1. Financial ratios and the codes used in this study are listed in a classified manner in Appendix B. When the denominator of these equations equals to "0", the denominator is omitted and the equation is used as if it was composed of just the numerator of the original equation. So, for instance, when the denominator equals to "0", $Code\_12$ equation will became: $Code\_12 = (t-2)value - (t-1)\ value$. From 5520 values of $46 \times 3 = 138$ trend variables, 42 values are altered by this method. The maximum and minimum of these altered values are 0,36 and 0; respectively. 19 of these alterations are from Ac3 variables.

The variables have no unit and used in the model as percentage except Branch Ratios and some activity ratios. The unit of B1, B2, B3, B4, B6 and B7 variables is (Trillion TL per branch); Ac2 and Ac3 variables is (Billion TL per personnel) and B5 variables is (Personnel per branch).

4.2.4. Datasets

As a result of the operations and calculations explained in section 4. 1, we prepared seven datasets to use in this study. The first dataset, which is coded as "d01", only include (t-1) financial ratios. For unsuccessful banks, this dataset includes financial ratios of 1 year prior to failure. And for successful banks it includes financial ratios of year 2000, to have a more homogenous dataset to measure the performance of models more accurately, since most of the failure occurred in 2001. In the same way, the second dataset, d02, consists of (t-2) data and the third dataset, d03, consists of (t-3) data. We prepared these two datasets to predict bank failures 2 and 3 years prior to the failure, respectively. For an unsuccessful bank that failed in 2000; d01, d02 and d03 datasets consists of financial ratios of years 1999, 1998 and 1997, respectively. For successful banks; d01, d02 and d03 datasets consists of financial ratios of years 2000, 1999 and 1998, respectively. By comparing the performances of these three datasets, we can seek answers to the question that whether the predictive ability of each model declines from year (t-1) to year (t-3). A positive answer to this question will indicate that the nearer to the time when financial distress breaks out, the more information content the financial ratios contain, so that the more strong predictive ability each model has. A negative answer to this question will be an evidence to the hypothesis that in the failure of Turkish banks, poor management was much more effective than external reasons.

In fourth dataset, d04, (t-1), (t-2) and (t-3) financial ratios was used. By doing so, we hope to increase models' performance. In the fifth dataset, d05, (t-2) and (t-3) financial ratios was used. By doing so, we hope to increase the performance of the models that aim to predict bank failures 2 years before it occurs. In the sixth dataset, d06, (t-1) financial ratios and trend analysis data (12 and 23) was used. By doing so, we hope to increase the performance of the models that aim to predict bank failures 1 year before it occurs, test whether trend data has a meaningful effect on the performance of models and test whether the Turkish banks failed following through a path or they failed instantly after a shock. In the seventh dataset, d07, (t-1) financial ratios and trend analysis data (12, 23 and 13) was used. Although the insertion of trend 13 data will harm the independence of the variables, we hope to test whether trend for two years period has an effect on the failure of the Turkish banks.

4. 2. Feature selection and extraction

Although every new feature brings new perspectives that help to explain the prediction universe, every new feature also brings a new dimension and an exponential growth of complexity. In addition, irrelevance, redundancy, and interaction of features should be avoided by researchers. For this purpose only “good” features should be used in the models. To select features standardized feature selection methods, such as ANOVA, most likely generate a better feature subset than the method of human judgments could do (Li, Huang, Sun, & Lin, 2010). But there is a trade-off between greater reduction and losing relevant features. Methods performing greater reductions start losing relevant features, which leads them to worse accuracy results. For this reason, a single method cannot be recommended for all situations (Li, Sun, & Wu, 2010).

In this study nine feature selection models were used. In the first one, f01, we did not use any feature selection methods and the models covered all data in the dataset. In the second one, f02, stepwise method of DA by minimizing Mahalanobis distance was used. Probability of F parameters for entry to and removal from the model were set to be 0,20 and 0,25, respectively. In the third model, f03, stepwise method of LR with forward LR method was used. Probability for entry to and removal from the model parameters were set to be 0,20 and 0,25, respectively and the classification cutoff parameter was set to be 0,05. In the fourth model, f04, Mann-Whitney Test, in the fifth model, f05, Wald-Wolfowitz Runs Test, in the sixth model, f06, Two-Sample Kolmogorov-Smirnov Test and in the seventh model, f07, One-way ANOVA were used with 95% confidence interval each. In the eighth model, an ensemble method with un-weighted majority voting was used. All the previous models contributed to this model and features were ranked according to their votes and most frequently selected features among these models were combined to form a new model. Features were ranked according to their votes and all the features that gather best three numbers of votes were selected. (max, max-1 and max-2) In the ninth model, f09, an ensemble model was used as f08. In this model, every method has 12 whole valued votes and limitless half valued votes. Except this, the ranking and selection methodology is the same as f08. f09 was needed because in some datasets, f08 selected too many features. f08 selected 46, 30, 23, 15 while f09 selected 22, 20, 17, 11 features for d04, d05, d06 and d07, respectively. Since some classifiers are highly sensitive to irrelevant features, by constructing f09, the effect of irrelevancy is reduced. But for d01, d02 and d03, this reduction seemed unnecessary, since f08 selected 11, 17, 11 features, respectively, so f09 was calculated for d04, d05, d06 and d07. (Table 5)

Table 5: Number of features feature selection models selected in each datasets

	f01	f02	f03	f04	f05	f06	f07	f08	f09
d01	46	6	5	24	11	19	20	11	-
d02	46	11	9	18	7	17	17	17	-
d03	46	4	6	16	5	13	10	11	-
d04	138	22	6	58	23	49	47	46	22
d05	92	27	4	34	12	30	27	30	20
d06	138	24	5	41	17	32	27	23	17
d07	184	19	4	50	24	41	32	15	11

The results of these models, the selected features in each dataset, are listed in Appendix E. The features are listed in an ordered manner according to their rate selection in Appendix F. Features selected in studies on Turkish Banking System are listed in Appendix G.

4. 3. Classifier choice

As mentioned before classifier choice may be the most crucial step for the success of a BFP model. Since there is not an optimal solution that covers all possible situations most studies used more than one classifier and compare them with each other.

In this study five classifier models were used. In the first one, c01, stepwise method of DA by minimizing Mahalanobis distance was used. Probability of F parameters for entry to and removal from the model were set to be 0,10 and 0,15, respectively. In the second model, c02, stepwise method of LR with forward LR method was used. Probability for entry to and removal from the model parameters were set to be 0,05 and 0,10, respectively and the classification cutoff parameter was set to be 0,5. In the third model, c03, decision tree method was used. The minimum number of case both in parent node and in child node parameters were set as 2. CRT was used as the growing method of the tree and Gini method was used for impurity measure. In the fourth model, c04, k-NN method was used. For distance computation Euclidean metric was used. The features were weighted according to their importance automatically and also the k values were selected automatically between 3 and 7 by SPSS Statistics 17.0 software. In the fifth model, c05, multilayer perceptron method was used. The number of units in hidden layer was selected automatically between 1 and 50 by SPSS. Batch training and scaled conjugate gradient optimization algorithm were used. The features were standardized before entering the model.

4.4. Training

Nine feature selection methods were applied to seven datasets (for d01, d02 and d03 eight feature selection methods) and 60 feature sets were constructed. Five classification methods were then applied to 60 feature sets and 300 different predictions were made. For instance, model name “d01f04c01” indicates a model that used d01 dataset (t-1 financial ratios), f04 feature selection method (Mann-Whitney Test) and c01 classifier (Stepwise Method of DA).

In Table 6, the list of datasets, feature selection methods and classifiers can be seen with the abbreviations used in this study. The problem here is that a comparison and an evaluation of the results of these 300 models were needed. For this purpose cross validation and split sample validation methods were used. Cross validation was used for validation for models that apply c01, c02 and c04 classifiers. For c03 models, both cross-validated results and split sample validated results were calculated. The reason behind this is that in BFP literature, the models that decision tree method is most likely over-fitted. Although they produce high success rates, it is not rare to see big differences between training sets and test sets. So instead of the results of the model with cross validation method, results of the model with split sample validation method were used for comparison and other evaluations. For c05, also split sample validation method was used. In split sample validation method, the data is split into two sets: training set and test set. Training set includes data of randomly selected 28 banks and test set includes data of remaining 12 banks.

Table 6: Datasets, feature selection methods and classifiers used in this study

Abbreviations	
Datasets	
d01	t-1 financial ratios
d02	t-2 financial ratios
d03	t-3 financial ratios
d04	t-1, t-2 and t-3 financial ratios
d05	t-2 and t-3 financial ratios
d06	t-1 financial ratios and trend analysis data (12 and 23)
d07	t-1 financial ratios and trend analysis data (12, 23 and 13)
Feature Selection Methods	
f01	No feature selection methods used
f02	Stepwise Method of DA
f03	Stepwise Method of LR
f04	Mann-Whitney Test (95% confidence interval)
f05	Wald-Wolfowitz Runs Test (95% confidence interval)
f06	Two-Sample Kolmogorov-Smirnov Test (95% confidence interval)
f07	One-way ANOVA (95% confidence interval)
f08	Majority Voting
f09	Majority Voting 2 (Every methodology has maximum 12 "+" votes)
Classifiers	
c01	Stepwise Method of DA
c02	Stepwise Method of LR
c03	Decision Tree
c04	Nearest Neighbor
c05	Multilayer Perceptron

CHAPTER 5

EMPIRICAL RESULTS AND DISCUSSION

The aim of a BFP model is to classify a number of businesses into two predefined classes (successful and unsuccessful) using historical data. The main problem in BFP is that there is no single correct way to apply all cases. There is only a best way for each case. So the step where the trained models assessed or compared with other models is an important step. As mentioned before, in this study, 7 datasets, 9 feature selection methods and 5 classifiers were tested to find the optimal one and answers sought to the following questions: "Which dataset, feature selection method and classifier achieves best performance?", "When different feature selection methods applied, which features are selected the most?", "Does the Turkish banks failed following through a path or they failed instantly after a shock?", "For the period covered in this study, which features affected the bank failures the most?", "Which of the banks was unsuccessfully predicted the most?".

In this study, for designing an early warning system for Turkish banking sector, 300 models were designed and 300 results were produced. The predictions that models made are listed Appendix H where banks are listed in a column-wise way and the models are listed in a row-wise way. Type I and Type II errors and overall success rates of the models are listed in Appendix I. The error rates of models constructed in this study were classified according to dataset, feature selection method and classifier used in models in Table 7, Table 8 and Table 9, respectively. In these three tables, error rates bigger than 70% are painted red, error rates that are between 50% and 70% are painted yellow and 30% and 50% are painted green. Whether the error rates in these tables were significantly different and so whether the predictive performances of datasets, feature selection methods and classifiers significantly different from each other were tested using paired samples t-test and nonparametric Wilcoxon two-related-samples test. In Table 10, Table 12 and Table 14 the p-values of paired samples t-test between each pair of datasets, feature selection methods and classifiers are presented, respectively. In these tables the green cells are significant at the confidence levels of 95% and yellow cells are significant at the confidence levels of 90%. In the same manner, in Table 11, Table 13 and Table 15 p-values of nonparametric Wilcoxon two-related-samples test between each pair of datasets, feature selection methods and classifiers are presented, respectively.

Table 7: Error rates classified according to the dataset used

	d01	d02	d03	d04	d05	d06	d07	Tot
Adabank	7,50%	42,50%	80,00%	24,44%	53,33%	4,44%	8,89%	31,00%
Akbank	0,00%	5,00%	0,00%	0,00%	2,22%	0,00%	0,00%	1,00%
A. Bank	2,50%	2,50%	27,50%	6,67%	6,67%	2,22%	0,00%	6,67%
Anadolubank	22,50%	15,00%	0,00%	6,67%	6,67%	8,89%	4,44%	9,00%
Bayındırbank	72,50%	20,00%	2,50%	22,22%	11,11%	26,67%	4,44%	22,33%
B.T. Körfez B.	0,00%	7,50%	12,50%	2,22%	4,44%	24,44%	13,33%	9,33%
Denizbank	5,00%	5,00%	0,00%	2,22%	8,89%	0,00%	2,22%	3,33%
E.G.S. Bankası	2,50%	5,00%	17,50%	2,22%	4,44%	8,89%	31,11%	10,33%
Fiba Bank	0,00%	7,50%	0,00%	6,67%	2,22%	4,44%	4,44%	3,67%
Finans Bank	15,00%	2,50%	37,50%	11,11%	13,33%	4,44%	2,22%	12,00%
İktisat B.	2,50%	5,00%	5,00%	0,00%	0,00%	4,44%	2,22%	2,67%
Kentbank	62,50%	12,50%	5,00%	11,11%	0,00%	46,67%	57,78%	28,00%
Koçbank	7,50%	7,50%	2,50%	0,00%	4,44%	6,67%	2,22%	4,33%
Milli Aydın B.	0,00%	15,00%	25,00%	6,67%	11,11%	4,44%	0,00%	8,67%
MNG Bank	2,50%	5,00%	0,00%	0,00%	4,44%	11,11%	28,89%	7,67%
Oyak Bank	2,50%	7,50%	0,00%	2,22%	2,22%	17,78%	42,22%	11,00%
Pamukbank	0,00%	45,00%	90,00%	28,89%	53,33%	6,67%	2,22%	31,67%
Sitebank A.Ş.	2,50%	5,00%	5,00%	2,22%	2,22%	4,44%	2,22%	3,33%
Şekerbank	72,50%	57,50%	70,00%	71,11%	66,67%	31,11%	20,00%	55,00%
Tekstil B.	10,00%	2,50%	5,00%	0,00%	0,00%	6,67%	2,22%	3,67%
Toprakbank	25,00%	12,50%	27,50%	13,33%	6,67%	37,78%	46,67%	24,33%
Turkish Bank	52,50%	57,50%	47,50%	48,89%	57,78%	51,11%	51,11%	52,33%
T.Dış Ticaret B.	12,50%	0,00%	0,00%	0,00%	0,00%	6,67%	6,67%	3,67%
T. E. B.	2,50%	15,00%	12,50%	8,89%	13,33%	4,44%	0,00%	8,00%
T. Garanti B.	5,00%	5,00%	0,00%	0,00%	0,00%	2,22%	0,00%	1,67%
T. İmar B.	72,50%	80,00%	77,50%	71,11%	82,22%	35,56%	13,33%	61,00%
T. İş Bankası	0,00%	2,50%	0,00%	0,00%	0,00%	2,22%	0,00%	0,67%
Ulusal Bank	10,00%	65,00%	87,50%	48,89%	68,89%	2,22%	11,11%	41,33%
YapıKredi B.	0,00%	12,50%	22,50%	0,00%	11,11%	0,00%	2,22%	6,67%
Bank Kapital	0,00%	10,00%	0,00%	2,22%	2,22%	2,22%	0,00%	2,33%
Demirbank	70,00%	47,50%	5,00%	51,11%	26,67%	40,00%	57,78%	42,67%
Etibank	7,50%	10,00%	7,50%	2,22%	2,22%	4,44%	2,22%	5,00%
Egebank	15,00%	10,00%	5,00%	2,22%	8,89%	0,00%	4,44%	6,33%
Eskişehir B.	20,00%	2,50%	32,50%	11,11%	4,44%	2,22%	0,00%	10,00%
Interbank	0,00%	2,50%	10,00%	0,00%	0,00%	0,00%	0,00%	1,67%
Sümerbank	17,50%	7,50%	2,50%	2,22%	0,00%	8,89%	0,00%	5,33%
T.T.B. YaşarB.	7,50%	7,50%	7,50%	0,00%	2,22%	2,22%	0,00%	3,67%
Yurt T.ve K. B.	0,00%	20,00%	5,00%	4,44%	4,44%	2,22%	0,00%	5,00%
Bank Ekspres	62,50%	15,00%	0,00%	15,56%	4,44%	26,67%	2,22%	17,67%
T. Ticaret B.	7,50%	2,50%	7,50%	2,22%	8,89%	0,00%	0,00%	4,00%
Max	72,50%	80,00%	90,00%	71,11%	82,22%	51,11%	57,78%	61,00%
Mean	16,94%	16,50%	18,56%	12,28%	14,06%	11,39%	10,72%	14,20%
S. Dev.	0,24	0,20	0,27	0,19	0,22	0,14	0,17	0,16

Table 8: Error rates classified according to the feature selection method used

	f01	f02	f03	f04	f05	f06	f07	f08	f09	Tot
Adabank	28,57%	22,86%	25,71%	22,86%	34,29%	31,43%	42,86%	34,29%	40,00%	31,00%
Akbank	0,00%	0,00%	2,86%	0,00%	0,00%	0,00%	0,00%	5,71%	0,00%	1,00%
A. Bank	5,71%	8,57%	20,00%	2,86%	2,86%	2,86%	8,57%	5,71%	0,00%	6,67%
Anadolubank	5,71%	5,71%	14,29%	8,57%	17,14%	11,43%	11,43%	2,86%	0,00%	9,00%
Bayındırbank	22,86%	22,86%	17,14%	28,57%	20,00%	25,71%	37,14%	14,29%	5,00%	22,33%
B.T. Körfez B.	2,86%	14,29%	14,29%	5,71%	11,43%	5,71%	14,29%	11,43%	0,00%	9,33%
Denizbank	8,57%	8,57%	0,00%	0,00%	0,00%	0,00%	5,71%	5,71%	0,00%	3,33%
E.G.S. Bankası	5,71%	14,29%	11,43%	8,57%	11,43%	11,43%	5,71%	11,43%	15,00%	10,33%
Fiba Bank	2,86%	8,57%	2,86%	5,71%	0,00%	5,71%	0,00%	5,71%	0,00%	3,67%
Finans Bank	14,29%	11,43%	22,86%	5,71%	14,29%	2,86%	20,00%	5,71%	10,00%	12,00%
İktisat B.	5,71%	5,71%	5,71%	0,00%	2,86%	0,00%	2,86%	0,00%	0,00%	2,67%
Kentbank	22,86%	20,00%	25,71%	31,43%	28,57%	31,43%	34,29%	28,57%	30,00%	28,00%
Koçbank	5,71%	2,86%	5,71%	5,71%	0,00%	0,00%	8,57%	5,71%	5,00%	4,33%
Milli Aydın B.	5,71%	20,00%	11,43%	5,71%	5,71%	8,57%	5,71%	11,43%	0,00%	8,67%
MNG Bank	11,43%	2,86%	5,71%	8,57%	2,86%	11,43%	5,71%	8,57%	15,00%	7,67%
Oyak Bank	5,71%	8,57%	11,43%	14,29%	5,71%	14,29%	11,43%	11,43%	20,00%	11,00%
Pamukbank	31,43%	25,71%	28,57%	28,57%	37,14%	37,14%	34,29%	31,43%	30,00%	31,67%
Sitebank A.Ş.	0,00%	8,57%	11,43%	0,00%	8,57%	0,00%	0,00%	0,00%	0,00%	3,33%
Şekerbank	40,00%	40,00%	65,71%	51,43%	57,14%	51,43%	62,86%	68,57%	60,00%	55,00%
Tekstil B.	5,71%	5,71%	5,71%	5,71%	0,00%	0,00%	2,86%	2,86%	5,00%	3,67%
Toprakbank	22,86%	40,00%	28,57%	20,00%	20,00%	22,86%	14,29%	20,00%	35,00%	24,33%
Turkish Bank	40,00%	31,43%	48,57%	54,29%	54,29%	57,14%	60,00%	60,00%	75,00%	52,33%
T.Dış Ticaret B.	2,86%	5,71%	5,71%	2,86%	8,57%	0,00%	5,71%	0,00%	0,00%	3,67%
T. E. B.	14,29%	2,86%	11,43%	11,43%	0,00%	5,71%	17,14%	5,71%	0,00%	8,00%
T. Garanti B.	0,00%	0,00%	5,71%	0,00%	0,00%	0,00%	2,86%	5,71%	0,00%	1,67%
T. İmar B.	51,43%	45,71%	48,57%	65,71%	74,29%	57,14%	68,57%	71,43%	70,00%	61,00%
T. İş Bankası	0,00%	0,00%	2,86%	0,00%	0,00%	0,00%	0,00%	2,86%	0,00%	0,67%
Ulusal Bank	40,00%	31,43%	37,14%	42,86%	51,43%	48,57%	37,14%	42,86%	40,00%	41,33%
YapıKredi B.	2,86%	0,00%	8,57%	11,43%	8,57%	5,71%	14,29%	2,86%	5,00%	6,67%
Bank Kapital	0,00%	5,71%	2,86%	2,86%	5,71%	2,86%	0,00%	0,00%	0,00%	2,33%
Demirbank	37,14%	37,14%	34,29%	48,57%	60,00%	45,71%	34,29%	51,43%	30,00%	42,67%
Etibank	5,71%	5,71%	0,00%	5,71%	5,71%	2,86%	8,57%	8,57%	0,00%	5,00%
Egebank	5,71%	2,86%	2,86%	11,43%	5,71%	11,43%	14,29%	0,00%	0,00%	6,33%
Eskişehir B.	8,57%	5,71%	14,29%	11,43%	14,29%	11,43%	14,29%	5,71%	0,00%	10,00%
Interbank	0,00%	0,00%	0,00%	2,86%	8,57%	0,00%	2,86%	0,00%	0,00%	1,67%
Sümerbank	2,86%	0,00%	5,71%	8,57%	11,43%	8,57%	5,71%	0,00%	5,00%	5,33%
T.T.B. YaşarB.	2,86%	0,00%	2,86%	2,86%	8,57%	2,86%	11,43%	0,00%	0,00%	3,67%
Yurt T.ve K. B.	8,57%	5,71%	0,00%	5,71%	8,57%	5,71%	5,71%	2,86%	0,00%	5,00%
Bank Ekspres	8,57%	20,00%	20,00%	20,00%	28,57%	14,29%	14,29%	17,14%	15,00%	17,67%
T. Ticaret B.	2,86%	5,71%	0,00%	2,86%	14,29%	2,86%	5,71%	0,00%	0,00%	4,00%
Max	51,43%	45,71%	65,71%	65,71%	74,29%	57,14%	68,57%	71,43%	75,00%	61,00%
Mean	12,21%	12,57%	14,71%	14,29%	16,21%	13,93%	16,29%	14,21%	12,75%	14,20%
S. Dev.	0,14	0,13	0,15	0,17	0,19	0,17	0,18	0,19	0,20	0,16

Table 9: Error rates classified according to the classifier used

	c01	c02	c03	c04	c05	Tot	Tot-c04	Combined
Adabank	40,00%	30,00%	26,67%	40,00%	18,33%	31,00%	28,75%	71,25%
Akbank	0,00%	0,00%	3,33%	1,67%	0,00%	1,00%	0,83%	99,17%
A. Bank	6,67%	6,67%	3,33%	11,67%	5,00%	6,67%	5,42%	94,58%
Anadolubank	6,67%	0,00%	16,67%	20,00%	1,67%	9,00%	6,25%	93,75%
Bayındırbank	20,00%	31,67%	25,00%	16,67%	18,33%	22,33%	23,75%	23,75%
B.T. Körfez B.	10,00%	6,67%	18,33%	11,67%	0,00%	9,33%	8,75%	91,25%
Denizbank	0,00%	0,00%	5,00%	6,67%	5,00%	3,33%	2,50%	97,50%
E.G.S. Bankası	13,33%	13,33%	3,33%	20,00%	1,67%	10,33%	7,92%	7,92%
Fiba Bank	1,67%	0,00%	10,00%	6,67%	0,00%	3,67%	2,92%	97,08%
Finans Bank	11,67%	3,33%	10,00%	31,67%	3,33%	12,00%	7,08%	92,92%
İktisat B.	0,00%	5,00%	0,00%	6,67%	1,67%	2,67%	1,67%	1,67%
Kentbank	36,67%	45,00%	8,33%	40,00%	10,00%	28,00%	25,00%	25,00%
Koçbank	1,67%	0,00%	16,67%	3,33%	0,00%	4,33%	4,58%	95,42%
Milli Aydın B.	3,33%	6,67%	15,00%	11,67%	6,67%	8,67%	7,92%	7,92%
MNG Bank	16,67%	10,00%	0,00%	8,33%	3,33%	7,67%	7,50%	92,50%
Oyak Bank	18,33%	11,67%	11,67%	13,33%	0,00%	11,00%	10,42%	89,58%
Pamukbank	40,00%	25,00%	30,00%	48,33%	15,00%	31,67%	27,50%	72,50%
Sitebank A.Ş.	0,00%	5,00%	5,00%	5,00%	1,67%	3,33%	2,92%	2,92%
Şekerbank	63,33%	40,00%	41,67%	76,67%	53,33%	55,00%	49,58%	50,42%
Tekstil B.	3,33%	0,00%	8,33%	5,00%	1,67%	3,67%	3,33%	96,67%
Toprakbank	23,33%	48,33%	8,33%	33,33%	8,33%	24,33%	22,08%	22,08%
Turkish Bank	73,33%	41,67%	26,67%	83,33%	36,67%	52,33%	44,58%	55,42%
T.Dış Ticaret B.	0,00%	3,33%	3,33%	11,67%	0,00%	3,67%	1,67%	98,33%
T. E. B.	5,00%	0,00%	8,33%	25,00%	1,67%	8,00%	3,75%	96,25%
T. Garanti B.	0,00%	0,00%	3,33%	5,00%	0,00%	1,67%	0,83%	99,17%
T. İmar B.	66,67%	55,00%	46,67%	81,67%	55,00%	61,00%	55,83%	44,17%
T. İş Bankası	0,00%	0,00%	1,67%	1,67%	0,00%	0,67%	0,42%	99,58%
Ulusal Bank	40,00%	46,67%	35,00%	61,67%	23,33%	41,33%	36,25%	36,25%
YapıKredi B.	3,33%	0,00%	6,67%	23,33%	0,00%	6,67%	2,50%	97,50%
Bank Kapital	1,67%	6,67%	1,67%	1,67%	0,00%	2,33%	2,50%	2,50%
Demirbank	51,67%	61,67%	38,33%	38,33%	23,33%	42,67%	43,75%	43,75%
Etibank	0,00%	10,00%	5,00%	8,33%	1,67%	5,00%	4,17%	4,17%
Egebank	1,67%	18,33%	6,67%	3,33%	1,67%	6,33%	7,08%	7,08%
Eskişehir B.	0,00%	21,67%	25,00%	3,33%	0,00%	10,00%	11,67%	11,67%
Interbank	0,00%	1,67%	1,67%	5,00%	0,00%	1,67%	0,83%	0,83%
Sümerbank	0,00%	16,67%	6,67%	3,33%	0,00%	5,33%	5,83%	5,83%
T.T.B. YaşarB.	0,00%	8,33%	1,67%	8,33%	0,00%	3,67%	2,50%	2,50%
Yurt T.ve K. B.	1,67%	6,67%	3,33%	10,00%	3,33%	5,00%	3,75%	3,75%
Bank Ekspres	6,67%	21,67%	31,67%	20,00%	8,33%	17,67%	17,08%	17,08%
T. Ticaret B.	0,00%	6,67%	3,33%	8,33%	1,67%	4,00%	2,92%	2,92%
Max	73,33%	61,67%	46,67%	83,33%	55,00%	61,00%	55,83%	
Mean	14,21%	15,38%	13,08%	20,54%	7,79%	14,20%	12,61%	
S. Dev.	0,21	0,18	0,13	0,22	0,14	0,16	15,04%	

In Table 7, the means of error rates of models are listed in a classified manner according to the dataset used. The models that used d07 achieved the smallest of the means of error rates. d06, d04 and d05 follow d07. Then d02, d01 and d03 came. As seen from these results, models that used trend data achieved better mean of error rates. After that the models that used more than one year's data but not trend data came. Models that used only a single year's data achieved the worst mean of error rates.

In Table 10 the p-values of paired samples t-test between each pair of datasets and in

Table 11 p-values of nonparametric Wilcoxon two-related-samples test between each pair of datasets are presented. d04 is significantly different from d01, d02 and d03; d05 is significantly different from d02 and d03; d06 and d07 is significantly different from d01 and d02 at least at the confidence level of 90% in both paired samples t-test and nonparametric Wilcoxon two-related-samples test. There is no significant difference between d01, d02 and d03. Also, the interaction in d07 (trend 12 and 23 features include all the knowledge that trend 13 includes) did not affect the performance of the models very much.

Since there is no significant difference between the mean of the performances of models that has d01, d02 and d03 as their dataset, it is possible to say that successful and unsuccessful banks were separated from each other not one year prior to the failure, but at least three years prior to the failure. The prediction accuracy did not increase significantly while we got closer to the actual occurrence of bankruptcy. This shows that instead of an instant shock, banks failed following through a path. This also can be shown as evidence to the claim that instead of external reasons and fast change in the financial environment, the banks have failed because of internal reasons mostly caused by mismanagement. From the papers reviewed in section 3, this subject is studied only in Arena's (2008) paper. These result is parallel with the ones that Arena (2008) found, which were for both East Asia and Latin America crises, bank-level fundamentals significantly affect the likelihood of collapse of banks and systemic shocks (both macroeconomic and liquidity) that triggered the crises mainly destabilized the weak banks ex ante. All the papers reviewed in section 3 that studied more than one period's data (used not only (t-1) data but also for instance (t-3) data), found that the prediction accuracy increases while we got closer to the actual occurrence of bankruptcy. From the papers that used Turkish data Canbas et al. (2005) also found the same result. However, since neither of them constructed as much models as this study, none of them tested if the increase in the prediction accuracy while we got closer to the actual occurrence of bankruptcy is significant.

In addition, since both d06 and d07, which contains (t-1) financial ratios and trend analysis data, significantly outperformed d01, which only contains (t-1) financial ratios, it is evident that trend data is useful for BFP of Turkish banks for the period covered in this study. Also, since d04 (t-1, t-2 and t-3 financial ratios) outperformed d01 (t-1 financial ratios), d02 (t-2 financial ratios) and d03 (t-3 financial ratios) and d05 (t-2 and t-3 financial ratios) outperformed d02 and d03; it is obvious that models that used more than one period's data or trend data, which is also calculated using more than one period's data, outperformed models that used only a single period's data. In addition, neither of the studies reviewed in section 3 used trend data or more than one period's data in the same model.

Table 10: p-values of paired samples t-test between each pair of datasets

Datasets	d01	d02	d03	d04	d05	d06
d02	0,8949	-	-	-	-	-
d03	0,7494	0,4362	-	-	-	-
d04	0,0876	0,0003	0,0352	-	-	-
d05	0,4589	0,0267	0,0215	0,2337	-	-
d06	0,0244	0,0743	0,1114	0,7187	0,4346	-
d07	0,0791	0,0987	0,1114	0,6293	0,4026	0,6839

Table 11: p-values of nonparametric Wilcoxon two-related-samples test between each pair of datasets

Datasets	d01	d02	d03	d04	d05	d06
d02	1,0000	-	-	-	-	-
d03	0,5974	0,7889	-	-	-	-
d04	0,0267	0,0004	0,0128	-	-	-
d05	0,3802	0,0251	0,0409	0,2626	-	-
d06	0,0432	0,0521	0,3647	0,7764	0,8500	-
d07	0,0274	0,0141	0,1090	0,3631	0,1339	0,3220

In Table 8, the means of error rates of models are listed in a classified manner according to the feature selection method used. The models that used f01 achieved the smallest of the means of error rates. f02, f09 and f06 follow f01. Then f08, f04, f03, f05 and f07 came. As seen from these results, models that used no feature selection method achieved better mean of error rates. Although f09 came third, f09 was applied only to the datasets d04-d07 which achieved better mean of absolute values of errors than datasets d01-d03. The performance of the ensemble feature selection method, f08, which accomplished only the fifth best mean of absolute values of errors, was a disappointment since in most studies a linear combination of different techniques would give a smaller error than any of the individual techniques working in stand-alone mode. Also the performance of the models that used no feature selection methods, f01, was a surprise since in literature, a usage of a feature selection method improved results in most of the problems considered while reducing the number of features.

In Table 12 the p-values of paired samples t-test between each pair of feature selection methods and in Table 13 p-values of nonparametric Wilcoxon two-related-samples test between each pair of feature selection methods are presented. f01 is significantly different from f03, f04, f05, f06 and f07; f02 is significantly different from f05 and f07; f04 is significantly different from f05 and f07; f05 is significantly different from f06, f08 and f09; f06 is significantly different from f07; f07 is significantly different from f08 and f09 at least at the level of 90% in both paired samples t-test and nonparametric Wilcoxon two-related-samples test. According to paired samples t-test f02 and f03 and according to nonparametric Wilcoxon two-related-samples test f03 and f09 are significantly different from each other at least at the confidence level of 90% although the other method did not find the difference significant. It means that f01 outperformed f03, f04, f05, f06 and f07; f02 outperformed f05 and f07; f04 outperformed f05 and f07; f06 outperformed f05 and f07; f08 outperformed f05 and f07; f09 outperformed f05 and f07.

As seen in section 3.2.3, there is no optimal feature selection method; every situation has its own best feature selection method. Also some methods produce better results when they are used with specific classifiers. It is interesting that in no other study reviewed in section 3.2.3, models that no feature selection method was used achieved smallest mean of absolute values of errors rate and significantly outperformed most of the models that other feature selection methods used. The only similar (not the same) result was obtained by Chen and Du (2009); in their study they reported that the more factor analysis used, the less accuracy obtained.

Table 12: p-values of paired samples t-test between each pair of feature selection methods

Feature S.	f01	f02	f03	f04	f05	f06	f07	f08
f02	0,7196	-	-	-	-	-	-	-
f03	0,0258	0,0661	-	-	-	-	-	-
f04	0,0273	0,2112	0,7179	-	-	-	-	-
f05	0,0045	0,0279	0,2902	0,0507	-	-	-	-
f06	0,0682	0,3221	0,5109	0,5355	0,0245	-	-	-
f07	0,0007	0,0322	0,2065	0,0440	0,9561	0,0294	-	-
f08	0,1199	0,2971	0,6849	0,9395	0,0701	0,7619	0,0835	-
f09	0,7296	0,9233	0,1913	0,2544	0,0273	0,3413	0,0184	0,1810

Table 13: p-values of nonparametric Wilcoxon two-related-samples test between each pair of feature selection methods

Feature S.	f01	f02	f03	f04	f05	f06	f07	f08
f02	1,0000	-	-	-	-	-	-	-
f03	0,0369	0,1124	-	-	-	-	-	-
f04	0,0381	0,1800	0,8584	-	-	-	-	-
f05	0,0041	0,0319	0,4632	0,0585	-	-	-	-
f06	0,0975	0,3661	0,7105	0,3265	0,0397	-	-	-
f07	0,0011	0,0258	0,1884	0,0563	0,7560	0,0328	-	-
f08	0,2495	0,7342	0,4470	0,8211	0,0389	0,8290	0,0846	-
f09	0,7407	0,4308	0,0699	0,1551	0,0170	0,3589	0,0072	0,1220

In Table 9, the means of error rates of models are listed in a classified manner according to the classifier used. The models that used c05 achieved the smallest of the means of error rates. c03 and c01 follow c05. Then c02 and c04 came. As seen from these results, models that used BPNN achieved best mean of error rates while models that used k-NN achieved worst mean of error rates. Although c03 seemed to achieve second best mean of error rates, as seen in Appendix J, there is difference between test sample success rates and training sample success rates and also between test sample success rates and 10-fold Cross Validation-Resubstitution success rates at least at the confidence level of 95% in both paired samples t-test and nonparametric Wilcoxon two-related-samples test. So we concluded that in our case decision tree method over-fitted and had bad generalization ability. In none of the studies reviewed in section 3, neither the significance of the difference between test sample success rates and training sample success rates nor the significance of the difference between test sample success rates and 10-fold Cross Validation-Resubstitution success rates were tested for models that Decision Tree method was used as classifier.

In Table 14 the p-values of paired samples t-test between each pair of classifiers and in Table 15 p-values of nonparametric Wilcoxon two-related-samples test between each pair of classifiers are presented. c05 outperformed all other models and all of the models outperformed c04 at least at the confidence level of 95% in both paired samples t-test and nonparametric Wilcoxon two-related-samples test. There is no significant difference between c01, c02 and c03. This is parallel with the literature since the most chosen classifier by the studies reviewed in section 3 is neural networks while k-NN is one of the least chosen classifier.

Table 14: p-values of paired samples t-test between each pair of classifiers

Calssifiers	c01	c02	c03	c04
c02	0,5092	-	-	-
c03	0,6000	0,2350	-	-
c04	0,0000	0,0293	0,0035	-
c05	0,0003	0,0001	0,0002	0,0000

Table 15: p-values of nonparametric Wilcoxon two-related-samples test between each pair of classifiers

Calssifiers	c01	c02	c03	c04
c02	0,3379	-	-	-
c03	0,9075	0,4001	-	-
c04	0,0000	0,0213	0,0053	-
c05	0,0004	0,0001	0,0002	0,0000

Selected features in each dataset are listed in Appendix E. The features are listed in an ordered manner according to their rate of selection in Appendix F. In Table 16 feature selection rates are presented in a classified manner according to feature category and data type. As seen in table, from (t-3) variables, Activity Ratios are the most selected ratios. This means that feature selection methods used in this study found Activity Ratios the more distinctive than other (t-3) variables. Then Profitability Ratios came. Activity Ratios selection rate decreases while we got closer from (t-3) to the (t-1) from 44,93% to 18,28%. Profitability Ratios first increase from 32,61% to 44,20%, then decrease to 31,18%. Branch Ratios, which also measure quality and efficiency of a bank like Activity Ratios, move differently from Activity Ratios. First their selection rate decrease from 12,42% to 9,32%, then increase to 26,27%. Capital Ratios and Income-Expenditure Structure Ratios increase while we got closer from (t-3) to the (t-1). Capital Ratios increase from 10,14% to 55,38% and Income-Expenditure Structure Ratios increase from 20,55% to 40,47%. For the selection ratio of Assets Quality Ratios, trend of from (t-2) to (t-1), which is Trend12 ratio and has a value of 20,31%, and (t-2) ratio, which has a value of 21,74%, are also noteworthy. Share in Sector Ratios and Liquidity Ratios do not have a noticeable selection value.

Table 16: Feature selection rates classified according to feature category and data type

	t-1	t-2	t-3	Trend12	Trend23	Trend13	Total
Activity Ratios	18,28%	30,43%	44,93%	39,58%	15,63%	43,75%	30,20%
Assets Quality	1,61%	21,74%	5,43%	20,31%	4,69%	0,00%	9,19%
Branch Ratios	26,27%	9,32%	12,42%	0,89%	4,46%	1,79%	12,09%
Capital Ratios	55,38%	46,38%	10,14%	5,21%	16,67%	12,50%	29,63%
Inc.-Exp. Structure	40,47%	34,78%	20,55%	8,52%	4,55%	9,09%	24,01%
Liquidity	17,20%	7,25%	10,14%	0,00%	4,17%	0,00%	8,55%
Profitability	31,18%	44,20%	32,61%	4,17%	5,21%	10,42%	25,36%
Share in Sector	6,45%	11,59%	0,00%	6,25%	0,00%	0,00%	4,84%
Total	29,03%	28,64%	19,38%	10,73%	7,34%	11,14%	20,36%

As seen in Table 16 and mentioned in the previous paragraph, the feature selection methods used in this study found that some ratios of some datasets are more distinctive than other ratios. Based on the findings of the feature selection methods used in this study, it can be said for the banks and the timeline that the scope of this study covers that a downward movement can be seen first in the values of the Activity Ratios followed by the values of the Profitability Ratios and finally the Capital Ratios and Income-Expenditure Structure Ratios, when a bank is heading towards bankruptcy. Although both Branch Ratios and Activity Ratios measure quality and efficiency of a bank's officers and management structure, only Activity Ratios showed a noteworthy distinctive ability. Share in sector, which was used to measure the size of a bank which influences bank soundness due to differences between small and large banks in terms of credit constraints, diversification, and depth in management, did not show a noteworthy distinctive ability since before 2000, Turkish banking sector did not diversified and showed the same character. Assets Quality Ratios, which measure the level of risk of a bank's assets, and Liquidity Ratios, which measure a bank's ability to meet unforeseen deposit outflow, did not show a noteworthy distinctive ability. We believe that the reason behind this is that other ratios such as Profitability Ratios and Income-Expenditure Structure Ratios contain the information that Assets Quality Ratios and Liquidity Ratios contain since as mentioned before Assets Quality Ratios primarily affect bank profitability and Liquidity Ratios primarily affect rise in deposit interest. As a result, when a bank is heading towards bankruptcy, a downward movement affects first the quality and efficiency of the bank's officers and management structure (Activity Ratios), followed by the profitability of the bank (Profit Ratios) and finally the performance and the stability of a bank's earnings stream (Income-Expenditure Structure Ratios) and the level and quality of a bank's capital base which is the last line of defense (Capital Ratios). Although Pompe and Bilderbeek (2005) tested whether a downward movement can first be seen in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and finally the liquidity ratios, when a bank is heading towards bankruptcy; they could not find any evidence that support their hypothesis.

In the models some banks are classified more accurately than others. The "Tot" columns of Table 7, Table 8 and Table 9 are equal because they represent the overall model in each table. As mentioned before, in these three tables, error rates bigger than 70% are painted red, error rates that are between 50% and 70% are painted yellow and 30% and 50% are painted green. The total error rate of Türkiye İmar Bankası T.A.Ş. is the largest error rate, which is 61,00%. Şekerbank T.A.Ş. and Turkish Bank A.Ş. follow T. İmar Bankası which have error rates 55,00% and 52,33, respectively. And finally, Demirbank T.A.Ş., Ulusal Bank T.A.Ş., Pamukbank T.A.Ş. and Adabank A.Ş. have also noteworthy error rates which were 42,67%, 41,33%, 31,67% and 31,00%, respectively. In Table 9, we extracted the misleading effects of c04 in the column "Tot-c04". In that prediction, only the error rate of Türkiye İmar Bankası T.A.Ş. exceeded 50% which was 55,83%. The error rate of Şekerbank T.A.Ş. was 49,58%, Turkish Bank A.Ş. was 44,58%, Demirbank T.A.Ş. was 43,75% and Ulusal Bank T.A.Ş. was 36,25%. In this classification, the error rates of Pamukbank T.A.Ş. and Adabank A.Ş. are not noteworthy.

From the studies reviewed in section 3.3.3, only Canbas et al. (2005) and Kilic (2006) presented the results about which banks they predicted correct and which banks they predicted wrong. Canbas et al. (2005) classified Bayındırbank A.Ş., Kentbank A.Ş., Pamukbank T.A.Ş., Türkiye İmar Bankası T.A.Ş. and Ulusal Bank T.A.Ş. wrong when the applied DA; Bayındırbank A.Ş., Demirbank T.A.Ş., Kentbank A.Ş. and Türkiye İmar Bankası T.A.Ş. wrong when the applied logit and probit. Kilic (2006) classified Bank Ekspres A.Ş., Demirbank T.A.Ş., Pamukbank T.A.Ş. and Şekerbank T.A.Ş. wrong when the applied ELECTRE TRI. The only bank classified wrong when the misleading effects of k-NN was extracted, Türkiye İmar Bankası T.A.Ş. was classified wrong in all the models Canbas et al. (2005) constructed. From the banks that were correctly classified but with a relatively high error rate Demirbank T.A.Ş., Şekerbank T.A.Ş. and Ulusal Bank T.A.Ş. were also classified wrong in some models that were in Canbas et al.'s (2005) and Kilic's (2006) studies.

If the models that has c01, c02, c03 or c05 as classifiers linear combined with un-weighted majority voting as an ensemble model, since in most studies, a linear combination of different techniques would give a smaller error than any of the individual techniques working in stand-alone mode; the new model unsuccessfully predicted only one bank from 40 banks datasets cover, which gives an error rate of 2,5% (predicted Türkiye İmar Bankası T.A.Ş. as an unsuccessful bank). As seen in Table 9's "Combined" column, the new model also gives ratios of probability of banks' being successful. Although Türkiye İmar Bankası T.A.Ş. was successful bank according to the scope of this study, as shown in Table 3, it failed in the date 03.07.2003 which was not in the scope of this study. According to the combined model, from sound banks Şekerbank T.A.Ş. and Turkish Bank A.Ş. had a very high probability of being unsuccessful. This is a sign of the trouble they pass through in the crises in 2000 and 2001. Also Demirbank T.A.Ş. and Ulusal Bank T.A.Ş. had a very high probability of being successful. Although the combined model needs too much calculation and construction of 240 models, in this computerized world, it is not a significant problem.

In Table 17, the accuracy of the models presented in papers reviewed in section 3 can be seen. Studies that achieved are highlighted in the table. Although there are three models that achieved better accuracy than the combined model (100% accuracy); the only bank that was predicted wrong in this study, Türkiye İmar Bankası T.A.Ş., which was successful bank according to the scope of this study, failed in 03.07.2003 as shown in Table 3. Also, as seen in Appendix I, from 300 models constructed here, 19 achieved 100% accuracy too. Although it achieved less accuracy, the combined model is more trustworthy, since the reason behind the 100% accuracy achievement of 19 models may be the randomness in validation set selection or over-fitting. But in the combined model, since it includes 240 different models, the effect of these two reasons is lessened. This claim is also true for the models in the literature that achieved 100% accuracy. The validation method in those models was 10-fold cross-validation which can change the accuracy results of models due to fold selection. In the construction of our models that used 10-fold cross-validation, when we run the model more than one time we saw that the accuracy rate changes. Although the software automatically select the folds, by running more than one time the best accuracy rate can be achieved. So we only run once every model in this study and the real randomness is achieved by combination of 240 models.

Table 17: Accuracy of the models presented in papers reviewed in section 3.3.3

Authors	Year	Method	Acc.%	Validation
Canbas, Cabuk and Kilic	2005	DA	90	-
Canbas, Cabuk and Kilic	2005	logit	87,5	-
Canbas, Cabuk and Kilic	2005	probit	87,5	-
Kilic	2006	ELECTRE TRI	93	-
Ravi and Pramodh	2008	PCNN-WFS-LTF	100	10-fold
Ravi and Pramodh	2008	PCA-TANN	97,5	10-fold
Ravi and Pramodh	2008	TANN	92,5	10-fold
Ravi and Pramodh	2008	PCNN-WOFS-LTF	97,5	10-fold
Ravi and Pramodh	2008	PCA-BPNN	85	10-fold
Ravi and Pramodh	2008	BPNN	87,5	10-fold
Ravi and Pramodh	2008	PCNN-WOFS-STF	92,5	10-fold
Ravi and Pramodh	2008	PCNN-WFS-STF	90	10-fold
Yıldız and Akkoç	2009	neuro-fuzzy	81,25	-
Chauhan, Ravi and Chandra	2009	DEWNN	95	10-fold
Chauhan, Ravi and Chandra	2009	TAWNN	100	10-fold
Chauhan, Ravi and Chandra	2009	WNN	95	10-fold
Boyacioglu, Kara and Baykan	2009	BPNN	95,5	Split Sample
Boyacioglu, Kara and Baykan	2009	CLNN	68,18	Split Sample
Boyacioglu, Kara and Baykan	2009	SOM	63,63	Split Sample
Boyacioglu, Kara and Baykan	2009	LVQ	83,72	Split Sample
Boyacioglu, Kara and Baykan	2009	SVM	90,9	Split Sample
Boyacioglu, Kara and Baykan	2009	MDA	68,18	Split Sample
Boyacioglu, Kara and Baykan	2009	k-means	81,81	Split Sample
Boyacioglu, Kara and Baykan	2009	logit	81,81	Split Sample
Ravisankar and Ravi	2010	GMDH	100	10-fold
Ravisankar and Ravi	2010	CPNN	95	10-fold
Ravisankar and Ravi	2010	fuzzy ARTMAP	95	10-fold

CHAPTER 6

SUMMARY AND COCNCLUSION

Early Warning Systems (EWSs) for banking sectors are used to measure the risk of banking crises that generally result in a rundown of bank deposits and widespread failures of financial institutions. A banking crisis has very serious negative economic effects economically and socially. Because of this, EWSs offering systematic methods to predict crises are important, even though they do not provide perfect accuracy. An extensive amount of effort has been spent on the research for the development of EWSs for banking sectors since 1970s. In countries with a small number of banks, like Turkey with 48 banks (BDDK (2011)), every bank may be considered to have a systematic importance since, the failure of any individual bank may carry a potential threat to lead to a banking crisis. Therefore this thesis concentrated on the analyses of EWSs for Turkey.

The EWSs can be considered as Business Failure Prediction (BFP) models. The aim of a BFP model is to classify a number of businesses into two predefined classes (successful and unsuccessful) using historical data. It has 5 steps: (i) data collection and preparation, (ii) feature selection and extraction, (iii) classifier choice, (iv) training and (v) evaluation. The main problem in BFP models is that there is no single correct method to apply to all cases. There is only a best method for each case. For this reason, researchers in BFP are basically trying to find more accurate models by using a trial-and-error process and by searching optimal feature subset or classifier. In this study, 7 datasets, 9 feature selection methods and 5 classifiers were tested.

The findings of the study is summarized below in items (i)-(x).

(i) Successful and unsuccessful banks were separated from each other not one year prior to the failure, but at least three years prior to the failure. The prediction accuracy did not increase significantly while we got closer to the actual occurrence of bankruptcy. This can be shown as evidence to the claim that instead of external reasons and fast change in the financial environment, the banks have failed because of internal reasons mostly caused by mismanagement. All the papers reviewed in section 3 that studied more than one period's data (used not only (t-1) data but also for instance (t-3) data), found that the prediction accuracy increases while we got closer to the actual occurrence of bankruptcy. From the papers that used Turkish data Canbas et al. (2005) also found the same result. However, since neither of them constructed as much models as this study, none of them tested if the increase in the prediction accuracy while we got closer to the actual occurrence of bankruptcy is significant. (ii) Datasets that contain (t-1) financial ratios and trend analysis data, significantly outperformed dataset that only contains (t-1) financial ratios. Also datasets that contain (t-1) financial ratios and trend analysis data achieved the smallest mean of absolute values of errors rate. So it is possible to say that, trend data is useful for BFP of Turkish banks for the period covered in this study. (iii) Since dataset that contains (t-1), (t-2) and (t-3) financial ratios outperformed datasets that only contain (t-1) financial ratios, (t-2) financial ratios and (t-3) financial ratios; dataset that contains (t-2) and (t-3) financial ratios outperformed datasets that only contain (t-2) financial ratios and (t-3) financial ratios; and also datasets that contain (t-1) financial ratios and trend analysis data outperformed dataset that only contains (t-1) financial ratios, it is obvious that models that used more than one period's data or trend data, which is also calculated using more than one period's data, outperformed models that used only a single period's data. In addition, neither of the studies reviewed in section 3 used trend data or more than one period's data in the same model.

(iv) The results listed above show that instead of an instant shock, banks failed following through a path. This also can be shown as evidence to the claim that instead of external reasons and fast change in the financial environment, the banks have failed because of internal reasons mostly caused by mismanagement. From the papers reviewed in section 3, this subject is studied only in Arena's (2008) paper. These results are parallel with the study by Arena, (2008), which analyzes both East Asia and Latin America crises. The bank-level fundamentals significantly affect the likelihood of collapse of banks and systemic shocks (both macroeconomic and liquidity) that triggered the crises mainly destabilized the weak banks ex ante. (v) The feature selection methods used in this study showed that some ratios of some datasets are more distinctive than other ratios. Based on the findings of the feature selection methods used in this study, it can be said for the banks and the timeline that the scope of this study covers that a downward movement affects first the quality and efficiency of the bank's officers and management structure (Activity Ratios), followed by the profitability of the bank (Profit Ratios) and finally the performance and the stability of a bank's earnings stream (Income-Expenditure Structure Ratios) and the level and quality of a bank's capital base which is the last line of defense (Capital Ratios). A downward movement can be seen first in the values of the Activity Ratios followed by the values of the Profitability Ratios and finally the Capital Ratios and Income-Expenditure Structure Ratios, when a bank is heading towards bankruptcy. Although Pompe and Bilderbeek (2005) tested whether a downward movement can first be seen in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and finally the liquidity ratios, when a bank is heading towards bankruptcy; they could not find any evidence that support their hypothesis.

(vi) Models that no feature selection method was used achieved smallest mean of absolute values of errors rate and significantly outperformed most of the models that other feature selection methods used. As seen in section 3.2.3, there is no optimal feature selection method; every situation has its own best feature selection method. Also some methods produce better results when they are used with specific classifiers. It is interesting that in no other study reviewed in section 3.2.3, models that no feature selection method was used achieved smallest mean of absolute values of errors rate and significantly outperformed most of the models that other feature selection methods used. The only <u>similar</u> (not the same) result was obtained by Chen and Du (2009); in their study they reported that the more factor analysis used, the less accuracy obtained. (vii) Models that BPNN were used as classifier outperformed models that other classification methods used. Models that k-NN was used as classifier were outperformed by models that other classification methods used. This is parallel with the literature since the most chosen classifier by the studies reviewed in section 3 is neural networks while k-NN is one of the least chosen classifier. ($viii$) Models that Decision Tree method was used as classifier there is significant difference between test sample success rates and training sample success rates and also between test sample success rates and 10-fold Cross Validation-Resubstitution success rates at least at the confidence level of 95% in both paired samples t-test and nonparametric Wilcoxon two-related-samples test. So we concluded that in our case decision tree method over-fitted and had bad generalization ability. In none of the studies reviewed in section 3, neither the significance of the difference between test sample success rates and training sample success rates nor the significance of the difference between test sample success rates and 10-fold Cross Validation-Resubstitution success rates were tested for models that Decision Tree method was used as classifier.

(ix) The total error rate of Türkiye İmar Bankası T.A.Ş. is the largest error rate, which is 61,00%. Şekerbank T.A.Ş. and Turkish Bank A.Ş. follow T. İmar Bankası which have error rates 55,00% and 52,33, respectively. And finally, Demirbank T.A.Ş., Ulusal Bank T.A.Ş., Pamukbank T.A.Ş. and Adabank A.Ş. have also noteworthy error rates which were 42,67%, 41,33%, 31,67% and 31,00%, respectively. (x) If misleading effects of k-NN was extracted, only the error rate of Türkiye İmar Bankası T.A.Ş. exceeded 50% which was 55,83%. The error rate of Şekerbank T.A.Ş. was 49,58%, Turkish Bank A.Ş. was 44,58%, Demirbank T.A.Ş. was 43,75% and Ulusal Bank T.A.Ş. was 36,25%. From the studies reviewed in section 3.3.3, only Canbas et al. (2005) and Kilic (2006) presented the results about which banks they predicted correct and which banks they predicted wrong. Canbas et al. (2005) classified Bayındırbank A.Ş., Kentbank A.Ş., Pamukbank T.A.Ş., Türkiye İmar Bankası T.A.Ş. and Ulusal Bank T.A.Ş. wrong when the applied DA; Bayındırbank A.Ş., Demirbank T.A.Ş., Kentbank A.Ş. and Türkiye İmar Bankası T.A.Ş. wrong when the applied logit and probit. Kilic (2006) classified Bank Ekspres A.Ş., Demirbank T.A.Ş., Pamukbank T.A.Ş. and Şekerbank T.A.Ş. wrong when the applied ELECTRE TRI. The only bank classified wrong when the misleading effects of k-NN was extracted, Türkiye İmar Bankası T.A.Ş. was classified wrong in all the models Canbas et al. (2005) constructed. From the banks that were correctly classified but with a relatively high error rate Demirbank T.A.Ş., Şekerbank T.A.Ş. and Ulusal Bank T.A.Ş. were also classified wrong in some models that were in Canbas et al.'s (2005) and Kilic's (2006) studies.

An ensemble model, a linear combination with un-weighted majority voting of all models constructed in this study except the models that used k-NN as their classifier was proposed in this study. The new model gives ratios of probability of banks' being successful and it only predicted Türkiye İmar Bankası T.A.Ş. as an unsuccessful bank, and correctly predicted other 39 banks that this study covers. Although there are three models in the literature reviewed in this study that achieved better accuracy than the combined model (100% accuracy); the only bank that was predicted wrong in this study, Türkiye İmar Bankası T.A.Ş., which was successful bank according to the scope of this study, failed in 03.07.2003. Also, from 300 models constructed here, 19 achieved 100% accuracy too. Although it achieved less accuracy, the combined model is more trustworthy, since the reason behind the 100% accuracy achievement of 19 models may be the randomness in validation set selection or over-fitting. But in the combined model, since it includes 240 different models, the effect of these two reasons is lessened. This claim is also true for the models in the literature that achieved 100% accuracy. The validation method in those models was 10-fold cross-validation which can change the accuracy results of models due to fold selection. According to the combined model, from sound banks Şekerbank T.A.Ş. and Turkish Bank A.Ş. had a very high probability of being unsuccessful. This is a sign of the trouble they pass through in the crises in 2000 and 2001. Also Demirbank T.A.Ş. and Ulusal Bank T.A.Ş. had a very high probability of being successful. Although the combined model needs too much calculation and construction of 240 models, in this computerized world, it is not a significant problem.

In this research, we use Turkish data as input for our models. The observations and results of this study are restricted to Turkish data for the period 1995-2001, feature selection methods and classifiers used in this study. It is useful to employ other countries' data - for instance the data of the recent global crisis - and see whether the results listed above can be generalized for different countries and different time periods.

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Appendix A. Financial Soundness Indicators[5]

Core Set	
Deposit-taking institutions (banks)	
Capital adequacy	Regulatory capital to risk-weighted assets
	Regulatory Tier I capital to risk-weighted assets
	Nonperforming loans net of provisions to capital
Asset quality	Nonperforming loans to total gross loans
	Sectoral distribution of loans to total loans
Earnings and profitability	Return on assets
	Return on equity
	Interest margin to gross income
	Noninterest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio)
	Liquid assets to short-term liabilities
Sensitivity to market risk	Net open position in foreign exchange to capital
Encouraged Set	
Deposit-taking institutions (banks)	Capital to assets
	Large exposures to capital
	Geographical distribution of loans to total loans
	Gross asset position in financial derivatives to capital
	Gross liability position in financial derivatives to capital
	Trading income to total income
	Personnel expenses to noninterest expenses
	Spread between reference lending and deposit rates
	Spread between highest and lowest interbank rate
	Customer deposits to total (non-interbank) loans
	Foreign currency-denominated loans to total loans
	Foreign currency-denominated liabilities to total liabilities
	Net open position in equities to capital
Other financial corporations	Assets to total financial system assets
	Assets to GDP
Nonfinancial corporations sector	Total debt to equity
	Return on equity
	Earnings to interest and principal expenses
	Net foreign exchange exposure to equity
	Number of applications for protection from creditors
Households	Household debt to GDP
	Household debt service and principal payments to income
Market liquidity	Average bid-ask spread in the securities market[6]
	Average daily turnover ratio in the securities market
Real estate markets	Residential real estate prices
	Commercial real estate prices
	Residential real estate loans to total loans
	Commercial real estate loans to total loans

[5] (International Monetary Fund, 2009)
[6] Or in other markets that are most relevant to bank liquidity, such as foreign exchange markets.

Appendix B. Financial Ratios

Category	Code	Ratio
Capital Ratios	C1	Standard Capital Ratio
	C2	(Shareholders' Equity + T.Income)/Total Assets
	C3	(Shareholders' Equity + T.Income)/(Deposits + Non-deposit Funds)
	C4	Net Working Capital/Total Assets
	C5	(Shareholders' Equity + T.Income)/(T.Assets + Contin.and Com.)
	C6	Fx Position/Shareholders' Equity
Assets Quality	A1	Total Loans/Total Assets
	A2	Non Performing Loans/Total Loans
	A3	Permanent Assets/Total Assets
	A4	Fx Assets/Fx Liabilities
Liquidity	L1	Liquid Assets/Total Assets
	L2	Liquity Assets/(Deposits + Non-deposit Funds)
	L3	Fx Liquid Assets/Fx Liabilities
Profitability	P1	Net Income(Loss)/Average Total Assets
	P2	Net Income(Loss)/Average Total Assets
	P3	Net Income(Loss)/Average Share-in Capital
	P4	Income Before Tax /Average Total Assets
	P5	Provision for Loan Losses/Total Loans
	P6	Provision for Loan Losses /Total Assets
Income-Expenditure Structure	I1	Net Interest Income After Provision/Average Total Assets
	I2	Interest Income/Interest Expenses
	I3	Non-Interest Income/Non-Interest Expenses
	I4	Total Income/Total Expenditure
	I5	Interest Income/Average Profitable Assets
	I6	Interest Expenses/Average Non-Profitable Assets
	I7	Interest Expenses/Average Profitable Assets
	I8	Interest Income/Total Income
	I9	Non-Interest Income/Total Income
	I10	Interest Expenses/Total Expenses
	I11	Non-Interest Expenses/Total Expenses
Branch Ratios	B1	Total Assets / No. of Branches
	B2	Total Deposits / No. of Branches
	B3	TL Deposits / No. of Branches
	B4	Fx Deposits / No. of Branches
	B5	No. of Personnel / No. of Branches
	B6	Total Loans / No. of Branches
	B7	Net Income / No. of Branches
Activity Ratios	Ac1	(Salaries and Emp'ee Benefits + Reserve for Retirement)/Total Assets
	Ac2	(Salaries and Emp'ee Benefits + Reserve for Retirement)/No. of Pers.
	Ac3	Reserve for Seniority Pay/No. of Personnel
	Ac4	Operational Expenses/Total Assets
	Ac5	Provisions except Provisions for Income Tax/Total Income
	Ac6	Provisions including Provisions for Income Tax/Total Income
Share in Sector	S1	Share in Sector-Total Assets
	S2	Share in Sector-Total Loans
	S3	Share in Sector-Total Deposits

Appendix C. Descriptive Statistics of Financial Ratios

t-1												
	Successful Banks				Unsuccessful Banks				Total Set			
	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.
C1_1	6,71	96,00	23,21	21,60	-36,10	22,40	5,84	13,04	-36,10	96,00	16,26	20,35
C2_1	5,28	46,73	17,29	10,60	-120,39	14,12	-1,94	30,72	-120,39	46,73	8,15	24,24
C3_1	5,84	94,70	25,06	21,31	-60,08	17,66	2,81	18,50	-60,08	94,70	14,49	22,75
C4_1	-1,04	34,36	9,18	9,27	-133,63	8,79	-12,00	36,79	-133,63	34,36	-0,88	27,99
C5_1	1,28	26,01	7,84	6,76	-32,71	8,71	0,17	10,25	-32,71	26,01	4,20	9,32
C6_1	-11,48	669,05	188,88	186,25	-493,67	804,12	205,21	293,47	-493,67	804,12	196,64	240,02
A1_1	0,64	59,09	31,74	14,11	3,10	60,67	33,54	12,24	0,64	60,67	32,60	13,12
A2_1	0,00	19,65	3,84	4,67	0,00	397,54	42,24	102,97	0,00	397,54	22,08	72,68
A3_1	1,27	63,72	17,22	14,22	2,18	59,63	15,50	14,35	1,27	63,72	16,40	14,12
A4_1	15,98	109,45	69,66	23,65	29,33	98,17	62,97	22,77	15,98	109,45	66,48	23,19
L1_1	10,10	92,69	44,25	20,99	4,07	70,34	32,70	16,25	4,07	92,69	38,76	19,54
L2_1	20,46	152,49	57,71	29,57	3,39	75,39	37,36	19,32	3,39	152,49	48,04	26,95
L3_1	14,77	109,27	39,82	23,68	7,07	80,50	33,00	16,23	7,07	109,27	36,58	20,52
P1_1	-4,79	6,31	2,24	2,45	-106,87	7,01	-10,07	26,01	-106,87	7,01	-3,60	18,82
P2_1	-18,55	121,67	28,26	30,23	-1492,52	273,30	-88,87	384,97	-1492,52	273,30	-27,37	269,03
P3_1	-18,86	156,33	44,51	41,65	-2597,04	140,07	-193,46	619,09	-2597,04	156,33	-68,52	438,48
P4_1	-4,79	8,65	3,09	3,12	-106,87	11,20	-9,62	26,28	-106,87	11,20	-2,95	19,11
P5_1	0,00	10,07	1,69	2,47	0,07	226,08	21,17	58,43	0,00	226,08	10,94	40,94
P6_1	0,00	3,10	0,47	0,66	0,02	62,88	5,35	15,30	0,00	62,88	2,79	10,69
I1_1	0,31	20,74	10,25	6,09	-61,70	20,11	4,29	18,43	-61,70	20,74	7,42	13,60
I2_1	102,18	329,23	206,18	69,56	66,68	231,37	146,23	43,20	66,68	329,23	177,70	65,29

I3_1	-123,56	121,98	13,24	68,20	-290,23	64,38	-42,61	87,62	-290,23	121,98	-13,29	82,01
I4_1	91,70	170,41	120,09	17,55	-2,51	146,34	92,30	31,82	-2,51	170,41	106,89	28,69
I5_1	22,71	52,39	32,66	8,39	24,96	130,33	51,09	27,47	22,71	130,33	41,41	21,71
I6_1	9,37	29,89	15,49	5,91	13,22	65,65	25,83	11,86	9,37	65,65	20,40	10,50
I7_1	9,35	37,81	17,23	6,64	16,79	103,14	37,65	23,64	9,35	103,14	26,93	19,67
I8_1	67,23	143,09	98,74	21,31	-1360,4	168,74	32,07	338,02	-1360,4	168,74	67,07	232,60
I9_1	-43,09	32,77	1,26	21,31	-68,74	1460,39	67,93	338,02	-68,74	1460,39	32,93	232,60
I10_1	28,96	86,90	60,38	12,96	51,18	91,47	69,56	11,22	28,96	91,47	64,74	12,88
I11_1	13,10	71,04	39,62	12,96	8,53	48,82	30,44	11,22	8,53	71,04	35,26	12,88
B1_1	0,76	114,78	19,23	23,25	0,77	44,57	9,27	9,19	0,76	114,78	14,50	18,48
B2_1	0,46	61,69	10,10	12,44	0,66	29,41	7,36	6,83	0,46	61,69	8,80	10,14
B3_1	0,13	6,50	2,21	1,78	0,24	18,19	3,62	4,53	0,13	18,19	2,88	3,41
B4_1	0,33	55,18	7,89	11,23	0,32	11,22	3,74	2,66	0,32	55,18	5,92	8,50
B5_1	6,55	44,50	22,60	10,05	13,44	43,90	21,81	7,30	6,55	44,50	22,22	8,75
B6_1	0,00	23,33	5,89	5,41	0,20	3,76	2,27	0,96	0,00	23,33	4,17	4,33
B7_1	-0,70	2,74	0,44	0,64	-14,10	0,86	-1,78	4,45	-14,10	2,74	-0,61	3,26
Ac1_1	0,91	8,82	2,77	1,72	1,24	7,15	2,97	1,42	0,91	8,82	2,87	1,57
Ac2_1	4,20	42,00	16,64	8,12	1,27	20,49	10,61	5,88	1,27	42,00	13,77	7,69
Ac3_1	0,00	0,96	0,36	0,34	0,00	0,59	0,21	0,22	0,00	0,96	0,29	0,30
Ac4_1	1,34	13,18	3,79	2,62	2,15	9,56	3,93	1,79	1,34	13,18	3,86	2,24
Ac5_1	0,00	4,82	1,81	1,56	0,42	293,02	31,14	67,68	0,00	293,02	15,74	48,33
Ac6_1	0,50	8,14	3,29	2,46	0,42	293,02	31,15	67,68	0,42	293,02	16,52	48,12
S1_1	0,05	7,47	2,09	2,64	0,08	2,35	0,88	0,65	0,05	7,47	1,51	2,04
S2_1	0,00	8,61	2,44	3,28	0,03	2,22	0,83	0,63	0,00	8,61	1,67	2,53
S3_1	0,02	6,80	1,85	2,41	0,10	2,95	1,10	0,82	0,02	6,80	1,49	1,85

t-2												
	Successful Banks				Unsuccessful Banks				Total Set			
	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.
C1_2	8,05	108,00	22,48	20,70	-5,10	88,00	12,50	19,45	-5,10	108,00	17,87	20,50
C2_2	5,90	25,64	12,81	5,14	0,48	14,47	7,86	3,08	0,48	25,64	10,46	4,92
C3_2	6,48	36,07	16,53	7,93	0,51	18,18	9,25	3,93	0,51	36,07	13,07	7,27
C4_2	-0,21	17,41	7,00	4,58	-10,74	9,52	3,04	4,03	-10,74	17,41	5,12	4,72
C5_2	2,07	15,60	5,88	3,56	0,35	8,32	3,92	1,92	0,35	15,60	4,95	3,03
C6_2	-27,00	1132,70	244,32	307,91	-42,92	1110,73	285,45	265,51	-42,92	1132,70	263,86	285,63
A1_2	0,01	57,57	27,97	14,41	5,81	58,29	35,97	12,63	0,01	58,29	31,77	14,02
A2_2	0,00	150,00	10,58	32,20	0,14	27,85	4,73	6,79	0,00	150,00	7,80	23,70
A3_2	1,20	30,99	12,01	8,48	0,76	13,12	5,80	3,55	0,76	30,99	9,06	7,25
A4_2	23,20	102,49	76,13	22,14	27,50	109,72	75,89	19,04	23,20	109,72	76,02	20,46
L1_2	22,65	91,06	49,31	18,78	19,13	66,03	41,36	13,38	19,13	91,06	45,53	16,72
L2_2	25,70	106,61	61,50	21,76	22,42	78,76	48,19	16,24	22,42	106,61	55,18	20,25
L3_2	15,89	101,83	42,80	23,16	13,58	73,02	41,23	18,01	13,58	101,83	42,05	20,63
P1_2	0,18	8,87	4,40	2,41	-10,72	6,89	1,42	3,32	-10,72	8,87	2,98	3,22
P2_2	3,00	178,38	58,64	40,91	-265,90	131,84	17,94	75,06	-265,90	178,38	39,31	62,31
P3_2	3,52	230,81	89,64	55,98	-114,15	148,56	35,01	51,24	-114,15	230,81	63,69	59,85
P4_2	0,18	13,65	6,46	3,55	-10,72	8,38	2,02	3,64	-10,72	13,65	4,35	4,20
P5_2	0,00	6,15	1,51	1,64	0,00	9,85	1,26	2,26	0,00	9,85	1,39	1,94
P6_2	0,00	2,10	0,44	0,51	0,00	3,76	0,43	0,85	0,00	3,76	0,44	0,68
I1_2	-5,11	27,43	11,46	7,11	-4,26	23,14	9,26	5,72	-5,11	27,43	10,42	6,50
I2_2	83,12	462,78	220,31	99,21	96,95	240,67	151,84	32,83	83,12	462,78	187,79	82,12

I3_2	-237,36	197,33	9,08	100,91	-225,29	95,70	-21,73	68,64	-237,36	197,33	-5,55	87,40
I4_2	100,66	182,49	140,54	25,07	80,03	141,79	110,70	12,00	80,03	182,49	126,37	24,83
I5_2	25,74	58,13	37,66	8,43	30,10	66,37	45,10	10,68	25,74	66,37	41,20	10,16
I6_2	5,90	42,82	18,94	9,63	16,43	52,09	25,65	8,70	5,90	52,09	22,13	9,70
I7_2	6,02	51,57	21,13	11,72	19,62	63,86	31,39	12,18	6,02	63,86	26,01	12,88
I8_2	69,42	162,09	100,81	21,48	77,00	128,61	104,35	11,88	69,42	162,09	102,49	17,46
I9_2	-62,09	30,58	-0,81	21,48	-28,61	23,00	-4,35	11,88	-62,09	30,58	-2,49	17,46
I10_2	35,42	90,62	69,88	13,94	53,55	91,19	77,33	9,00	35,42	91,19	73,42	12,30
I11_2	9,38	64,58	30,12	13,94	8,81	46,45	22,67	9,00	8,81	64,58	26,58	12,30
B1_2	0,44	339,30	29,97	74,85	0,37	117,45	11,28	25,92	0,37	339,30	21,09	57,21
B2_2	0,27	295,61	22,40	64,56	0,31	30,93	5,11	6,61	0,27	295,61	14,19	47,27
B3_2	0,00	87,45	5,58	18,83	0,17	21,36	2,22	4,71	0,00	87,45	3,99	13,96
B4_2	0,27	208,16	16,82	46,21	0,13	9,57	2,89	2,22	0,13	208,16	10,20	33,87
B5_2	0,46	999,00	68,18	213,53	10,52	46,20	22,42	8,08	0,46	999,00	46,44	154,75
B6_2	0,00	144,51	10,40	30,97	0,11	6,82	2,19	1,69	0,00	144,51	6,50	22,59
B7_2	0,00	4,86	0,68	1,04	-0,35	5,59	0,37	1,27	-0,35	5,59	0,53	1,15
Ac1_2	0,78	7,67	2,53	1,49	0,52	6,25	2,32	1,32	0,52	7,67	2,43	1,40
Ac2_2	3,13	29,90	10,98	5,83	0,58	13,13	6,07	3,91	0,58	29,90	8,65	5,53
Ac3_2	-1,69	0,68	0,18	0,48	0,00	0,40	0,12	0,14	-1,69	0,68	0,15	0,36
Ac4_2	1,03	11,11	3,29	2,12	0,77	7,67	2,99	1,57	0,77	11,11	3,15	1,86
Ac5_2	-3,62	12,07	1,85	2,82	0,04	11,48	1,68	2,58	-3,62	12,07	1,77	2,68
Ac6_2	0,06	24,16	7,67	5,82	0,34	11,48	3,02	2,70	0,06	24,16	5,46	5,12
S1_2	0,06	6,79	1,98	2,43	0,07	2,57	1,02	0,73	0,06	6,79	1,52	1,87
S2_2	0,00	8,95	2,24	3,14	0,07	2,05	0,90	0,61	0,00	8,95	1,60	2,39
S3_2	0,05	7,24	1,82	2,34	0,09	3,28	1,13	0,89	0,05	7,24	1,49	1,81

t-3												
	Successful Banks				Unsuccessful Banks				Total Set			
	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.	Min.	Max.	Mean	S.Dev.
C1_3	9,69	53,58	21,61	12,09	-0,05	66,00	15,67	14,10	-0,05	66,00	18,79	13,25
C2_3	6,38	36,06	13,52	7,02	5,88	29,28	11,88	6,12	5,88	36,06	12,74	6,58
C3_3	7,13	65,84	18,40	13,20	6,80	45,94	15,71	11,19	6,80	65,84	17,12	12,21
C4_3	-0,56	30,91	8,09	6,25	-16,41	11,67	4,60	6,00	-16,41	30,91	6,43	6,31
C5_3	2,42	16,96	6,74	3,95	2,85	19,14	6,27	4,05	2,42	19,14	6,52	3,95
C6_3	-39,41	745,04	167,35	206,94	12,27	920,27	169,52	201,34	-39,41	920,27	168,38	201,67
A1_3	9,12	62,34	32,56	13,67	9,00	58,00	36,26	14,04	9,00	62,34	34,32	13,80
A2_3	0,00	9,42	2,53	2,65	0,00	24,38	4,01	5,89	0,00	24,38	3,23	4,49
A3_3	0,18	25,28	7,32	6,13	1,26	41,58	7,98	9,37	0,18	41,58	7,63	7,74
A4_3	55,93	106,30	83,40	14,34	38,51	98,02	77,06	16,09	38,51	106,30	80,39	15,34
L1_3	22,80	80,46	48,75	16,45	21,64	79,54	40,47	13,50	21,64	80,46	44,82	15,51
L2_3	27,01	91,61	62,45	20,76	26,10	100,49	50,74	18,25	26,10	100,49	56,89	20,24
L3_3	17,23	86,82	47,76	18,78	14,63	84,47	39,25	16,39	14,63	86,82	43,72	17,98
P1_3	0,32	15,78	5,35	3,76	-9,43	12,09	2,22	4,16	-9,43	15,78	3,86	4,21
P2_3	4,18	170,24	67,91	44,84	-64,43	250,38	38,98	63,49	-64,43	250,38	54,17	55,73
P3_3	6,12	1393,30	163,68	289,94	-69,52	281,69	47,66	75,41	-69,52	1393,30	108,57	221,76
P4_3	0,32	21,46	7,53	5,14	-9,43	16,15	2,85	4,87	-9,43	21,46	5,31	5,48
P5_3	0,00	7,95	1,30	1,76	0,00	4,06	0,57	0,98	0,00	7,95	0,96	1,48
P6_3	0,00	2,11	0,43	0,50	0,00	1,68	0,23	0,41	0,00	2,11	0,33	0,47
I1_3	-2,24	47,92	16,12	10,80	-2,93	29,07	10,64	8,01	-2,93	47,92	13,52	9,85
I2_3	90,97	838,50	271,08	171,52	91,20	310,21	168,83	59,45	90,97	838,50	222,51	139,26

I3_3	-482,38	179,84	-29,57	125,93	-202,09	190,65	-8,64	84,89	-482,38	190,65	-19,63	107,57
I4_3	100,96	212,31	145,29	31,88	68,55	202,39	114,84	25,43	68,55	212,31	130,83	32,51
I5_3	26,04	76,82	41,66	12,63	31,16	71,63	46,86	12,01	26,04	76,82	44,13	12,46
I6_3	4,19	43,66	18,64	9,25	12,09	55,91	26,94	11,31	4,19	55,91	22,58	10,98
I7_3	3,62	49,59	19,86	11,29	11,16	65,90	31,73	15,24	3,62	65,90	25,50	14,44
I8_3	79,66	181,62	108,41	23,35	63,32	129,78	102,19	17,33	63,32	181,62	105,46	20,69
I9_3	-81,62	20,34	-8,41	23,35	-29,78	36,68	-2,19	17,33	-81,62	36,68	-5,46	20,69
I10_3	31,57	88,56	66,75	15,23	43,33	91,16	72,65	15,03	31,57	91,16	69,55	15,24
I11_3	11,44	68,43	33,25	15,23	8,84	56,67	27,35	15,03	8,84	68,43	30,45	15,24
B1_3	0,53	161,98	14,25	34,80	0,13	32,55	4,50	7,11	0,13	161,98	9,62	25,86
B2_3	0,08	140,01	10,11	29,99	0,07	16,45	2,69	3,56	0,07	140,01	6,59	21,93
B3_3	0,02	57,82	3,52	12,46	0,05	2,57	0,79	0,64	0,02	57,82	2,22	9,04
B4_3	0,06	82,18	6,59	17,62	0,03	15,03	1,90	3,28	0,03	82,18	4,37	13,03
B5_3	1,11	936,00	66,20	199,59	13,45	49,25	24,48	8,88	1,11	936,00	46,38	144,60
B6_3	0,07	57,37	4,85	12,19	0,02	3,70	1,26	0,97	0,02	57,37	3,15	8,94
B7_3	0,00	2,51	0,38	0,55	-0,07	2,84	0,21	0,64	-0,07	2,84	0,30	0,59
Ac1_3	0,78	6,96	2,59	1,30	0,93	17,96	3,35	3,93	0,78	17,96	2,95	2,86
Ac2_3	1,77	11,39	5,92	2,35	0,29	7,09	3,28	2,23	0,29	11,39	4,67	2,63
Ac3_3	0,00	0,74	0,21	0,21	0,00	0,24	0,06	0,08	0,00	0,74	0,14	0,17
Ac4_3	1,10	9,52	3,30	1,75	1,32	19,61	4,20	4,30	1,10	19,61	3,73	3,21
Ac5_3	0,01	13,48	3,17	2,98	0,02	4,84	1,07	1,31	0,01	13,48	2,18	2,54
Ac6_3	0,01	29,12	9,44	6,84	0,02	10,74	2,36	2,60	0,01	29,12	6,08	6,32
S1_3	0,08	6,59	1,93	2,44	0,05	3,12	0,94	0,85	0,05	6,59	1,46	1,91
S2_3	0,02	8,58	2,13	3,01	0,02	1,92	0,80	0,63	0,02	8,58	1,50	2,30
S3_3	0,02	7,10	1,85	2,44	0,05	4,22	1,03	1,05	0,02	7,10	1,46	1,93

Appendix D. Formulas Used in the Calculation of Ratios

Liquid Assets = Cash + Due from Banks + Central Bank + Other Financial Institutions + Interbank + Securities + Reserve Requirements

Average Total Assets = (Total Assets (1^{st} Year) + Total Assets (2^{nd} Year)) / 2

Average Shareholders' Equity = (Shareholders' Equity (1^{st} Year)) + Shareholders' Equity (2^{nd} Year)) / 2

Average Share-in Capital = (Share-in Capital (1^{st} Year) + Share-in Capital (2^{nd} Year)) / 2

Non-deposits Funds = Interbank + Central Bank + Other Funds Borrowed + Funds + Securities Issued

Contingencies and Commitments = Total Contingencies and Commitments- Other Contingencies and Commitments

Net Working Capital = Shareholders' Equity + Total Income (Current + Previous) - Permanent Assets except Affiliated Securities

Total Profit = Current Year's Profit + Previous Years' Profit

FX Position = FX Liabilities - FX Assets

Permanent Assets = Non-performing Assets (net) + Equity Participations + Affiliated Securities and Companies + Fixed Assets

Profitable Assets = Loans + Securities Portfolio + Banks + Interbank + Government Bonds Account for Legal Reserves

Non-Profitable Assets = Deposits + Non-deposit Funds

Total Income = Interest Income + Non-Interest Income

Total Expenditures = Interest Expenses + Non-Interest Expenses

Interest Income = Interest on (Loans + Securities Portfolio + Deposits in other Banks + Interbank Funds Sold) + Other Interest Income

Other Interest Income = Income from Reserve Requirements + Other

Interest Expenses = Interest on (Deposits + Non-Deposits Funds Borrowed) + Other Interest Expenses

Other Interest Expenses = Interest on Interbank Funds Borrowed + Interest on Securities Issued + Other

Net Interest Income After Provision for Loan Losses = Interest Income - Interest Expenses - Provisions for Loan Losses

Non-Interest Income = Income from Commissions (net) + Income from FX Transactions (net) + Income from Capital Market Transactions (net) + Other Non-Interest Income

Income from Commissions (net) = Fees and Commissions Received - Fees and Commissions Paid

Income from FX Transactions (net) = Income from FX Transactions - Loss from FX Transactions

Income from Capital Market Transactions (net) = Income from Capital Market Transactions - Loss from Capital Market Transactions

Other Non-Interest Income = Dividends from Equity Participations and Affiliated Companies + Extraordinary Income + Other

Non-Interest Expenses = Salaries & Employee Benefits + Res. for Retire. Pay + Other Provisions + Taxes and Duties + Rental Expenses + Depreciation & Amortization + Other

Other Non-Interest Expenses = Extraordinary Expenses + Other

Operational Expenses = Salaries and Benefits + Reserve for Retirement + Rental Expenses + Depreciation and Amortization

Provisions = Reserves for Retirement Pay + Provision for Loan Losses + Provisions for Taxes + Other Provisions

Income before Tax = Net Interest Income after Provision for Loan Losses + Non-Interest Income - Non-Interest Expenses

Net Income (Loss) = Income before Tax - Provisions for Income Tax

Appendix E. Selected Features for each Dataset

d01

Variables	f01	f02	f03	f04	f05	f06	f07	f08
C1_1	+		+	+	+	+	+	6
C2_1	+			+	+	+	+	5
C3_1	+		+	+	+	+	+	6
C4_1	+			+		+	+	4
C5_1	+			-		-	+	4
C6_1	+							1
A1_1	+							1
A2_1	+							1
A3_1	+							1
A4_1	+							1
L1_1	+							1
L2_1	+	+		-		-	-	5
L3_1	+							1
P1_1	+			+	+	+	-	5
P2_1	+				+			2
P3_1	+			-		-		3
P4_1	+			+	+	+	-	5
P5_1	+							1
P6_1	+							1
I1_1	+	+						2
I2_1	+	+		-	+	-	+	6
I3_1	+	+	+	-			-	5
I4_1	+			+		+	+	4
I5_1	+			+		-	+	4
I6_1	+		+	+	+	+	+	6
I7_1	+			+	+	+	+	5
I8_1	+							1
I9_1	+							1
I10_1	+			-			-	3
I11_1	+			-			-	3
B1_1	+			-		-		3
B2_1	+							1
B3_1	+							1
B4_1	+	+		-				3
B5_1	+							1
B6_1	+	+	+	-	+	+	+	7
B7_1	+			+		+	-	4
Ac1_1	+							1
Ac2_1	+			-			+	3
Ac3_1	+							1
Ac4_1	+							1
Ac5_1	+			+	+	+		4
Ac6_1	+			-		-		3
S1_1	+							1
S2_1	+						-	2
S3_1	+							1
Total	46	6	5	24	11	19	20	11

d02

Variables	f01	f02	f03	f04	f05	f06	f07	f08
C1_2	+			+	+	+		4
C2_2	+			+	+	+	+	5
C3_2	+			+		+	+	4
C4_2	+			+		-	+	4
C5_2	+						-	2
C6_2	+							1
A1_2	+	+						2
A2_2	+		+					2
A3_2	+	+		-		-	+	5
A4_2	+							1
L1_2	+							1
L2_2	+						-	2
L3_2	+							1
P1_2	+			+		+	+	4
P2_2	+		+	-		-	-	5
P3_2	+	+		+		+	+	5
P4_2	+		+	+	+	+	+	6
P5_2	+							1
P6_2	+							1
I1_2	+							1
I2_2	+	+		-	+	+	+	6
I3_2	+							1
I4_2	+			+	+	+	+	5
I5_2	+	+	+	-		-	-	6
I6_2	+			+		+	-	4
I7_2	+	+	+	+		+	+	6
I8_2	+							1
I9_2	+							1
I10_2	+							1
I11_2	+	+						2
B1_2	+							1
B2_2	+	+						2
B3_2	+	+						2
B4_2	+							1
B5_2	+							1
B6_2	+							1
B7_2	+			-	+	+		4
Ac1_2	+							1
Ac2_2	+			+		-	+	4
Ac3_2	+			-				2
Ac4_2	+							1
Ac5_2	+		+					2
Ac6_2	+		+	+	+	+	+	6
S1_2	+		+					2
S2_2	+	+	+					3
S3_2	+	+						2
Total	46	11	9	18	7	17	17	17

d03

Variables	f01	f02	f03	f04	f05	f06	f07	f08
C1_3	+			+	+	+		4
C2_3	+							1
C3_3	+							1
C4_3	+							1
C5_3	+							1
C6_3	+		+					2
A1_3	+		+					2
A2_3	+	+						2
A3_3	+							1
A4_3	+	+						2
L1_3	+							1
L2_3	+							1
L3_3	+				+			2
P1_3	+			+		+	+	4
P2_3	+			-				2
P3_3	+			+		+		3
P4_3	+			+	+	+	+	5
P5_3	+					+		2
P6_3	+							1
I1_3	+							1
I2_3	+			-			+	3
I3_3	+							1
I4_3	+			+		+	+	4
I5_3	+							1
I6_3	+			+		+	+	4
I7_3	+		+	+		+	+	5
I8_3	+							1
I9_3	+							1
I10_3	+							1
I11_3	+							1
B1_3	+			-				2
B2_3	+							1
B3_3	+							1
B4_3	+			-				2
B5_3	+		+					2
B6_3	+		+					2
B7_3	+			+	+	+		4
Ac1_3	+							1
Ac2_3	+	+		+		+	+	5
Ac3_3	+			+		+	+	4
Ac4_3	+							1
Ac5_3	+			+		+	+	4
Ac6_3	+	+	+	+	+	+	+	7
S1_3	+							1
S2_3	+							1
S3_3	+							1
Total	46	4	6	16	5	13	10	11

d04

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
C1_1	+			+	-	+	-	5	4
C2_1	+	+		+	+	+	-	6	6
C3_1	+		+	+	+	+	+	6	6
C4_1	+			+		-	-	4	3
C5_1	+			-		-	-	4	3
C6_1	+							1	1
A1_1	+							1	1
A2_1	+							1	1
A3_1	+							1	1
A4_1	+		+					2	2
L1_1	+							1	1
L2_1	+			-		-	-	4	3
L3_1	+							1	1
P1_1	+			-	-	+	-	5	4
P2_1	+				-			2	2
P3_1	+			-		-		3	2
P4_1	+			-	+	-	-	5	4
P5_1	+	+						2	2
P6_1	+							1	1
I1_1	+							1	1
I2_1	+			-	-	-	-	5	3
I3_1	+	+		-			-	4	3
I4_1	+			+		-	+	4	4
I5_1	+			-		-	-	4	3
I6_1	+			+	-	+	+	5	5
I7_1	+		+	+	+	+	+	6	6
I8_1	+							1	1
I9_1	+							1	1
I10_1	+	+		-			-	4	3
I11_1	+			-			-	3	2
B1_1	+			-		-		3	2
B2_1	+							1	1
B3_1	+							1	1
B4_1	+			-				2	2
B5_1	+	+						2	2
B6_1	+	+		-	+	+	-	6	5
B7_1	+			-		-	-	4	3
Ac1_1	+							1	1
Ac2_1	+			-			-	3	2
Ac3_1	+							1	1
Ac4_1	+							1	1
Ac5_1	+			-	-	-		4	3
Ac6_1	+			-		-		3	2
S1_1	+							1	1
S2_1	+						-	2	2
S3_1	+							1	1
C1_2	+			+	+	+		4	4
C2_2	+			-	-	-	+	5	4
C3_2	+			-		-	+	4	3
C4_2	+			-		-	-	4	3
C5_2	+						-	2	2
C6_2	+							1	1
A1_2	+							1	1

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
A2_2	+	+						2	2
A3_2	+			-		-	-	4	3
A4_2	+	+						2	2
L1_2	+							1	1
L2_2	+	+					-	3	3
L3_2	+							1	1
P1_2	+			-		-	+	4	3
P2_2	+			-		-	-	4	3
P3_2	+			-		-	-	4	3
P4_2	+			+	-	+	+	5	5
P5_2	+							1	1
P6_2	+	+						2	2
I1_2	+							1	1
I2_2	+			-	+	-	-	5	4
I3_2	+	+						2	2
I4_2	+	+		+	+	+	+	6	6
I5_2	+	+		-		-	-	5	4
I6_2	+	+		-		-	-	5	4
I7_2	+		+	-		+	-	5	4
I8_2	+							1	1
I9_2	+							1	1
I10_2	+							1	1
I11_2	+							1	1
B1_2	+							1	1
B2_2	+							1	1
B3_2	+							1	1
B4_2	+							1	1
B5_2	+							1	1
B6_2	+							1	1
B7_2	+			-	+	-		4	3
Ac1_2	+							1	1
Ac2_2	+	+		-		-	-	5	4
Ac3_2	+			-				2	2
Ac4_2	+							1	1
Ac5_2	+							1	1
Ac6_2	+	+		-	-	+	-	6	5
S1_2	+	+						2	2
S2_2	+							1	1
S3_2	+							1	1
C1_3	+			-	-	-		4	3
C2_3	+							1	1
C3_3	+							1	1
C4_3	+							1	1
C5_3	+							1	1
C6_3	+							1	1
A1_3	+							1	1
A2_3	+	+						2	2
A3_3	+							1	1
A4_3	+							1	1
L1_3	+	+						2	2
L2_3	+	+						2	2
L3_3	+				-			2	2
P1_3	+			-		-	-	4	3
P2_3	+			-				2	2
P3_3	+			-		-		3	2

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
P4_3	+			-	+	-	-	5	4
P5_3	+					-		2	2
P6_3	+							1	1
I1_3	+	+						2	2
I2_3	+			-			-	3	2
I3_3	+							1	1
I4_3	+			-		-	+	4	3
I5_3	+							1	1
I6_3	+			-		-	-	4	3
I7_3	+		+	-		-	-	5	4
I8_3	+							1	1
I9_3	+							1	1
I10_3	+							1	1
I11_3	+							1	1
B1_3	+			-				2	2
B2_3	+							1	1
B3_3	+							1	1
B4_3	+			-				2	2
B5_3	+							1	1
B6_3	+							1	1
B7_3	+			-	-	-		4	3
Ac1_3	+							1	1
Ac2_3	+			-		-	+	4	3
Ac3_3	+			-		-	-	4	3
Ac4_3	+	+						2	2
Ac5_3	+			-		-	-	4	3
Ac6_3	+		+	+	+	+	+	6	6
S1_3	+							1	1
S2_3	+							1	1
S3_3	+							1	1
Total	138	22	6	58	23	49	47	46	22

d05

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
C1_2	+			+	+	+		4	4
C2_2	+	+		+	+	+	+	6	6
C3_2	+			+		+	+	4	4
C4_2	+	+	+	-		-	-	6	5
C5_2	+						-	2	2
C6_2	+	+						2	2
A1_2	+	+						2	2
A2_2	+							1	1
A3_2	+	+		-		-	+	5	4
A4_2	+							1	1
L1_2	+	+						2	2
L2_2	+						-	2	2
L3_2	+							1	1
P1_2	+			+		+	+	4	4
P2_2	+			-		-	-	4	3
P3_2	+	+		+		-	+	5	5
P4_2	+			+	+	+	+	5	5
P5_2	+	+						2	2
P6_2	+							1	1
I1_2	+							1	1
I2_2	+			-	+	-	-	5	4
I3_2	+							1	1
I4_2	+			+	+	+	+	5	5
I5_2	+		+	-		-	-	5	4
I6_2	+			-		+	-	4	3
I7_2	+			+		+	-	4	4
I8_2	+							1	1
I9_2	+							1	1
I10_2	+							1	1
I11_2	+	+						2	2
B1_2	+							1	1
B2_2	+							1	1
B3_2	+							1	1
B4_2	+							1	1
B5_2	+							1	1
B6_2	+							1	1
B7_2	+			-	+	+		4	4
Ac1_2	+	+						2	2
Ac2_2	+			+		-	+	4	4
Ac3_2	+	+		-				3	3
Ac4_2	+	+						2	2
Ac5_2	+							1	1
Ac6_2	+	+		-	+	+	+	6	6
S1_2	+	+						2	2
S2_2	+	+						2	2
S3_2	+	+						2	2
C1_3	+			-	+	-		4	3
C2_3	+							1	1
C3_3	+							1	1
C4_3	+							1	1
C5_3	+							1	1
C6_3	+		+					2	2
A1_3	+							1	1

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
A2_3	+							1	1
A3_3	+							1	1
A4_3	+	+						2	2
L1_3	+	+						2	2
L2_3	+							1	1
L3_3	+	+			+			3	3
P1_3	+			-		-	-	4	3
P2_3	+	+		-				3	3
P3_3	+	+		-		-		4	3
P4_3	+			-	+	-	-	5	4
P5_3	+					-		2	2
P6_3	+	+						2	2
I1_3	+							1	1
I2_3	+	+		-			-	4	3
I3_3	+							1	1
I4_3	+	+		+		+	+	5	5
I5_3	+							1	1
I6_3	+			-		-	-	4	3
I7_3	+	+		-		-	-	5	4
I8_3	+							1	1
I9_3	+							1	1
I10_3	+							1	1
I11_3	+							1	1
B1_3	+			-				2	2
B2_3	+							1	1
B3_3	+							1	1
B4_3	+			-				2	2
B5_3	+							1	1
B6_3	+							1	1
B7_3	+			-	+	-		4	3
Ac1_3	+	+						2	2
Ac2_3	+	+		+		-	+	5	5
Ac3_3	+			-		-	-	4	3
Ac4_3	+							1	1
Ac5_3	+			+		-	-	4	3
Ac6_3	+		+	+	+	+	+	6	6
S1_3	+							1	1
S2_3	+							1	1
S3_3	+							1	1
Total	92	27	4	34	12	30	27	30	20

d06

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
C1_1	+			+	+	+	+	5	5
C2_1	+			+	+	+	+	5	5
C3_1	+		+	+	+	+	+	6	6
C4_1	+			+		+	-	4	4
C5_1	+			-		-	+	4	3
C6_1	+							1	1
A1_1	+							1	1
A2_1	+							1	1
A3_1	+							1	1
A4_1	+	+						2	2
L1_1	+							1	1
L2_1	+			-		-	-	4	3
L3_1	+							1	1
P1_1	+			+	-	+	-	5	4
P2_1	+				-			2	2
P3_1	+			-		-		3	2
P4_1	+			+	+	+	-	5	5
P5_1	+							1	1
P6_1	+							1	1
I1_1	+							1	1
I2_1	+	+		-	+	-	+	6	5
I3_1	+			-			-	3	2
I4_1	+			+		+	+	4	4
I5_1	+			-		-	+	4	3
I6_1	+	+		+	+	+	+	6	6
I7_1	+			+	+	+	+	5	5
I8_1	+							1	1
I9_1	+							1	1
I10_1	+			-			-	3	2
I11_1	+			-			-	3	2
B1_1	+			-		-		3	2
B2_1	+							1	1
B3_1	+							1	1
B4_1	+			-				2	2
B5_1	+	+						2	2
B6_1	+	+		-	+	+	+	6	6
B7_1	+			+		-	-	4	3
Ac1_1	+							1	1
Ac2_1	+			-			-	3	2
Ac3_1	+							1	1
Ac4_1	+	+						2	2
Ac5_1	+	+		+	+	+		5	5
Ac6_1	+			-		-		3	2
S1_1	+							1	1
S2_1	+	+					-	3	3
S3_1	+							1	1
C1_12	+							1	1
C2_12	+							1	1
C3_12	+							1	1
C4_12	+							1	1
C5_12	+				-			2	2
C6_12	+					-		2	2
A1_12	+		+	-		-	-	5	4

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
A2_12	+			-				2	2
A3_12	+							1	1
A4_12	+							1	1
L1_12	+							1	1
L2_12	+							1	1
L3_12	+							1	1
P1_12	+	+						2	2
P2_12	+							1	1
P3_12	+							1	1
P4_12	+							1	1
P5_12	+			-				2	2
P6_12	+							1	1
I1_12	+			-	+	-		4	3
I2_12	+							1	1
I3_12	+	+						2	2
I4_12	+							1	1
I5_12	+					-		2	2
I6_12	+							1	1
I7_12	+							1	1
I8_12	+					-		2	2
I9_12	+	+						2	2
I10_12	+							1	1
I11_12	+							1	1
B1_12	+							1	1
B2_12	+							1	1
B3_12	+							1	1
B4_12	+							1	1
B5_12	+							1	1
B6_12	+	+						2	2
B7_12	+							1	1
Ac1_12	+			-			+	3	3
Ac2_12	+	+	+	+		-	+	6	6
Ac3_12	+							1	1
Ac4_12	+			-			-	3	2
Ac5_12	+			-	+	+		4	4
Ac6_12	+			-	+	-	-	5	4
S1_12	+							1	1
S2_12	+			-				2	2
S3_12	+							1	1
C1_23	+	+						2	2
C2_23	+			-		-		3	2
C3_23	+	+		-		-		4	3
C4_23	+							1	1
C5_23	+			-		-		3	2
C6_23	+							1	1
A1_23	+		+					2	2
A2_23	+							1	1
A3_23	+			-				2	2
A4_23	+							1	1
L1_23	+							1	1
L2_23	+	+						2	2
L3_23	+		+					2	2
P1_23	+							1	1
P2_23	+	+						2	2
P3_23	+							1	1

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
P4_23	+							1	1
P5_23	+				+			2	2
P6_23	+							1	1
I1_23	+							1	1
I2_23	+	+						2	2
I3_23	+							1	1
I4_23	+	+						2	2
I5_23	+	+						2	2
I6_23	+							1	1
I7_23	+							1	1
I8_23	+			-			-	3	2
I9_23	+	+						2	2
I10_23	+							1	1
I11_23	+							1	1
B1_23	+				+			2	2
B2_23	+							1	1
B3_23	+							1	1
B4_23	+							1	1
B5_23	+	+						2	2
B6_23	+							1	1
B7_23	+	+						2	2
Ac1_23	+							1	1
Ac2_23	+	+		-		-	-	5	4
Ac3_23	+							1	1
Ac4_23	+							1	1
Ac5_23	+							1	1
Ac6_23	+			-		-		3	2
S1_23	+							1	1
S2_23	+							1	1
S3_23	+							1	1
Total	138	24	5	41	17	32	27	23	17

d07

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
C1_1	+			+	-	+	+	5	5
C2_1	+			+	+	+	-	5	5
C3_1	+			+	+	+	+	5	5
C4_1	+			+		-	-	4	3
C5_1	+			-		-	-	4	3
C6_1	+							1	1
A1_1	+							1	1
A2_1	+							1	1
A3_1	+							1	1
A4_1	+							1	1
L1_1	+							1	1
L2_1	+			-		-	-	4	3
L3_1	+							1	1
P1_1	+			+	-	+	-	5	4
P2_1	+				-			2	2
P3_1	+			-		-		3	2
P4_1	+			+	+	+	-	5	5
P5_1	+							1	1
P6_1	+							1	1
I1_1	+							1	1
I2_1	+			-	-	-	+	5	4
I3_1	+			-			-	3	2
I4_1	+	+	+	+		-	+	6	6
I5_1	+			-		-	+	4	3
I6_1	+			+	-	+	+	5	5
I7_1	+			+	+	+	+	5	5
I8_1	+							1	1
I9_1	+							1	1
I10_1	+			-			-	3	2
I11_1	+			-			-	3	2
B1_1	+			-		-		3	2
B2_1	+							1	1
B3_1	+							1	1
B4_1	+			-				2	2
B5_1	+							1	1
B6_1	+		+	-	+	+	+	6	6
B7_1	+			+		-	-	4	3
Ac1_1	+							1	1
Ac2_1	+			-			-	3	2
Ac3_1	+							1	1
Ac4_1	+	+						2	2
Ac5_1	+			+	-	-		4	3
Ac6_1	+			-		-		3	2
S1_1	+							1	1
S2_1	+						-	2	2
S3_1	+		+					2	2
C1_12	+							1	1
C2_12	+							1	1
C3_12	+							1	1
C4_12	+	+						2	2
C5_12	+				-			2	2
C6_12	+					-		2	2
A1_12	+	+		-		-	-	5	4

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
A2_12	+			-				2	2
A3_12	+							1	1
A4_12	+							1	1
L1_12	+							1	1
L2_12	+							1	1
L3_12	+							1	1
P1_12	+							1	1
P2_12	+							1	1
P3_12	+							1	1
P4_12	+							1	1
P5_12	+			-				2	2
P6_12	+	+						2	2
I1_12	+			-	+	-		4	3
I2_12	+							1	1
I3_12	+							1	1
I4_12	+							1	1
I5_12	+					-		2	2
I6_12	+							1	1
I7_12	+							1	1
I8_12	+					-		2	2
I9_12	+	+						2	2
I10_12	+							1	1
I11_12	+	+						2	2
B1_12	+							1	1
B2_12	+							1	1
B3_12	+							1	1
B4_12	+							1	1
B5_12	+							1	1
B6_12	+							1	1
B7_12	+							1	1
Ac1_12	+	+		-			+	4	4
Ac2_12	+			+		-	+	4	4
Ac3_12	+							1	1
Ac4_12	+			-			-	3	2
Ac5_12	+			-	+	+		4	4
Ac6_12	+			-	+	-	-	5	4
S1_12	+	+						2	2
S2_12	+			-				2	2
S3_12	+							1	1
C1_23	+							1	1
C2_23	+			-		-		3	2
C3_23	+	+		-		-		4	3
C4_23	+							1	1
C5_23	+			-		-		3	2
C6_23	+							1	1
A1_23	+							1	1
A2_23	+							1	1
A3_23	+			-				2	2
A4_23	+							1	1
L1_23	+							1	1
L2_23	+							1	1
L3_23	+							1	1
P1_23	+	+						2	2
P2_23	+	+						2	2
P3_23	+							1	1

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
P4_23	+							1	1
P5_23	+				-			2	2
P6_23	+							1	1
I1_23	+							1	1
I2_23	+							1	1
I3_23	+							1	1
I4_23	+							1	1
I5_23	+							1	1
I6_23	+							1	1
I7_23	+							1	1
I8_23	+			-			-	3	2
I9_23	+							1	1
I10_23	+							1	1
I11_23	+							1	1
B1_23	+				-			2	2
B2_23	+							1	1
B3_23	+							1	1
B4_23	+							1	1
B5_23	+	+						2	2
B6_23	+							1	1
B7_23	+							1	1
Ac1_23	+							1	1
Ac2_23	+			-		-	-	4	3
Ac3_23	+	+						2	2
Ac4_23	+							1	1
Ac5_23	+							1	1
Ac6_23	+	+		-		-		4	3
S1_23	+							1	1
S2_23	+							1	1
S3_23	+							1	1
C1_13	+							1	1
C2_13	+				-	-		3	2
C3_13	+							1	1
C4_13	+	+		-		-		4	3
C5_13	+							1	1
C6_13	+			-				2	2
A1_13	+							1	1
A2_13	+							1	1
A3_13	+							1	1
A4_13	+							1	1
L1_13	+							1	1
L2_13	+							1	1
L3_13	+							1	1
P1_13	+				-			2	2
P2_13	+					-		2	2
P3_13	+					-		2	2
P4_13	+							1	1
P5_13	+							1	1
P6_13	+			-		-		3	2
I1_13	+			-	+	+		4	4
I2_13	+							1	1
I3_13	+	+						2	2
I4_13	+							1	1
I5_13	+			-			-	3	2
I6_13	+							1	1

Variables	f01	f02	f03	f04	f05	f06	f07	f08	f09
I7_13	+							1	1
I8_13	+			-			-	3	2
I9_13	+							1	1
I10_13	+							1	1
I11_13	+							1	1
B1_13	+							1	1
B2_13	+							1	1
B3_13	+							1	1
B4_13	+							1	1
B5_13	+							1	1
B6_13	+							1	1
B7_13	+				-			2	2
Ac1_13	+							1	1
Ac2_13	+	+	+	+	+	-	+	7	7
Ac3_13	+							1	1
Ac4_13	+							1	1
Ac5_13	+	+		+	+	+	+	6	6
Ac6_13	+			+	+	+	-	5	5
S1_13	+							1	1
S2_13	+							1	1
S3_13	+							1	1
Total	184	19	4	50	24	41	32	15	11

Appendix F. Selected Features' Selection Ratio (Ordered)

Variable	# dataset	# selected	%	Variable	# dataset	# selected	%
Ac2_13	1	8	100%	Ac2_23	2	9	56,25%
Ac6_3	3	21	91,30%	C1_3	3	12	52,17%
B6_1	4	28	90,32%	P1_3	3	12	52,17%
Ac5_13	1	7	87,50%	I6_3	3	12	52,17%
Ac6_2	3	20	86,96%	B7_3	3	12	52,17%
C3_1	4	26	83,87%	Ac3_3	3	12	52,17%
I6_1	4	25	80,65%	Ac5_3	3	12	52,17%
C2_2	3	18	78,26%	L2_1	4	16	51,61%
P4_2	3	18	78,26%	Ac5_1	4	16	51,61%
I2_2	3	18	78,26%	Ac5_12	2	8	50,00%
I4_2	3	18	78,26%	C4_1	4	15	48,39%
I5_2	3	18	78,26%	C5_1	4	14	45,16%
C1_1	4	24	77,42%	I5_1	4	14	45,16%
C2_1	4	24	77,42%	B7_1	4	14	45,16%
I7_1	4	24	77,42%	I1_12	2	7	43,75%
Ac6_13	1	6	75,00%	C3_23	2	7	43,75%
P4_1	4	23	74,19%	I3_1	4	13	41,94%
I2_1	4	23	74,19%	C4_13	1	3	37,50%
I7_2	3	17	73,91%	I1_13	1	3	37,50%
P4_3	3	17	73,91%	P3_3	3	8	34,78%
I7_3	3	17	73,91%	I2_3	3	8	34,78%
P1_1	4	22	70,97%	I10_1	4	10	32,26%
A1_12	2	11	68,75%	Ac1_12	2	5	31,25%
Ac6_12	2	11	68,75%	Ac6_23	2	5	31,25%
C4_2	3	15	65,22%	P3_1	4	8	25,81%
A3_2	3	15	65,22%	I11_1	4	8	25,81%
P3_2	3	15	65,22%	B1_1	4	8	25,81%
Ac2_2	3	15	65,22%	Ac2_1	4	8	25,81%
Ac2_3	3	15	65,22%	Ac6_1	4	8	25,81%
I4_1	4	20	64,52%	Ac4_12	2	4	25,00%
Ac2_12	2	10	62,50%	C2_23	2	4	25,00%
C1_2	3	14	60,87%	C5_23	2	4	25,00%
I6_2	3	14	60,87%	I8_23	2	4	25,00%
I4_3	3	14	60,87%	C2_13	1	2	25,00%
C3_2	3	13	56,52%	P6_13	1	2	25,00%
P1_2	3	13	56,52%	I5_13	1	2	25,00%
P2_2	3	13	56,52%	I8_13	1	2	25,00%
B7_2	3	13	56,52%	L2_2	3	4	17,39%

Variable	# dataset	# selected	%	Variable	# dataset	# selected	%
Ac3_2	3	4	17,39%	Ac4_1	4	2	6,45%
L3_3	3	4	17,39%	C4_12	2	1	6,25%
P2_3	3	4	17,39%	P1_12	2	1	6,25%
B4_1	4	5	16,13%	P6_12	2	1	6,25%
S2_1	4	5	16,13%	I3_12	2	1	6,25%
C5_2	3	3	13,04%	I11_12	2	1	6,25%
S1_2	3	3	13,04%	B6_12	2	1	6,25%
S2_2	3	3	13,04%	S1_12	2	1	6,25%
P5_3	3	3	13,04%	C1_23	2	1	6,25%
B1_3	3	3	13,04%	A1_23	2	1	6,25%
B4_3	3	3	13,04%	L2_23	2	1	6,25%
P2_1	4	4	12,90%	L3_23	2	1	6,25%
C5_12	2	2	12,50%	P1_23	2	1	6,25%
C6_12	2	2	12,50%	I2_23	2	1	6,25%
A2_12	2	2	12,50%	I4_23	2	1	6,25%
P5_12	2	2	12,50%	I5_23	2	1	6,25%
I5_12	2	2	12,50%	I9_23	2	1	6,25%
I8_12	2	2	12,50%	B7_23	2	1	6,25%
I9_12	2	2	12,50%	Ac3_23	2	1	6,25%
S2_12	2	2	12,50%	C6_2	3	1	4,35%
A3_23	2	2	12,50%	A4_2	3	1	4,35%
P2_23	2	2	12,50%	L1_2	3	1	4,35%
P5_23	2	2	12,50%	P5_2	3	1	4,35%
B1_23	2	2	12,50%	P6_2	3	1	4,35%
B5_23	2	2	12,50%	I3_2	3	1	4,35%
C6_13	1	1	12,50%	B2_2	3	1	4,35%
P1_13	1	1	12,50%	B3_2	3	1	4,35%
P2_13	1	1	12,50%	Ac1_2	3	1	4,35%
P3_13	1	1	12,50%	Ac4_2	3	1	4,35%
I3_13	1	1	12,50%	Ac5_2	3	1	4,35%
B7_13	1	1	12,50%	A1_3	3	1	4,35%
A1_2	3	2	8,70%	L2_3	3	1	4,35%
A2_2	3	2	8,70%	P6_3	3	1	4,35%
I11_2	3	2	8,70%	I1_3	3	1	4,35%
S3_2	3	2	8,70%	B5_3	3	1	4,35%
C6_3	3	2	8,70%	B6_3	3	1	4,35%
A2_3	3	2	8,70%	Ac1_3	3	1	4,35%
A4_3	3	2	8,70%	Ac4_3	3	1	4,35%
L1_3	3	2	8,70%	P5_1	4	1	3,23%
A4_1	4	2	6,45%	I1_1	4	1	3,23%
B5_1	4	2	6,45%	S3_1	4	1	3,23%

Appendix G. Selected Features in the Literature

Variables	2005 Canbas, Cabuk, Kilic	2006 Kilic	2008 Ravi, Pramodh	2009 Yıldız, Akkoç	2009 Chauhan, Ravi, Chandra	2009 Boyacioglu, Kara, Baykan	2010 Ravisankar, Ravi	Total
C1_1					+		+	2
C2_1	+	+	+		+			4
C3_1	+	+	+	+	+		+	6
C4_1	+	+	+		+			4
C5_1	+		+				+	3
C6_1								0
A1_1								0
A2_1								0
A3_1								0
A4_1						+		1
L1_1	+	+					+	3
L2_1			+		+		++	4
L3_1								0
P1_1								0
P2_1								0
P3_1								0
P4_1		+						1
P5_1								0
P6_1								0
I1_1								0
I2_1	+	+	+				+	4
I3_1								0
I4_1		+						1
I5_1								0
I6_1	+			+			+	3
I7_1	+		+				++	4
I8_1								0
I9_1								0
I10_1		+			+		++	4
I11_1		+						1
B1_1		+						1
B2_1								0
B3_1								0
B4_1								0
B5_1								0
B6_1	+			+				2
B7_1	+							1
Ac1_1								0
Ac2_1	+						++	3
Ac3_1								0
Ac4_1								0
Ac5_1								0
Ac6_1								0
S1_1								0
S2_1								0
S3_1								0
Total	10	10	7	3	6	1	6	7

Appendix H. Results of the Models

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
Observed	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d01f01c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f01c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	0	1	1	0	1	0
d01f01c03	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f01c04	1	1	1	1	1	1	1	0	1	1	0	1	1	0	0	0	1	0	0	1	0	0	0	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1	1
d01f01c05	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f02c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f02c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1	0
d01f02c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f02c04	1	1	1	0	0	1	0	0	1	0	0	0	1	0	1	1	1	0	0	1	1	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f02c05	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f03c01	1	1	1	0	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f03c02	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	1	0	1	0	0	1	0
d01f03c03	1	1	1	1	1	1	1	0	1	1	0	0	0	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f03c04	1	1	1	0	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f03c05	1	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f04c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f04c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	0	0	1	0
d01f04c03	1	1	1	1	1	1	1	0	1	0	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f04c04	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	0	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d01f04c05	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d01f05c01	1	1	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f05c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	1	1	0	1	1	0	1	1
d01f05c03	0	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d01f05c04	1	1	1	0	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f05c05	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f06c01	1	1	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f06c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	0	1	1	0	1	1
d01f06c03	1	1	1	0	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	1	1	0	1	0	0	1	0
d01f06c04	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d01f06c05	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d01f07c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f07c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	0	0	1	0
d01f07c03	1	1	1	1	1	1	1	0	1	0	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	0	1	0	0	1	0	0	0	0	1	0
d01f07c04	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f07c05	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d01f08c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f08c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	1	0
d01f08c03	1	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d01f08c04	1	1	0	0	0	1	0	0	1	1	0	0	1	0	1	1	1	0	0	0	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d01f08c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d02f01c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	0	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d02f01c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	1	0	0
d02f01c03	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d02f01c04	0	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0
d02f01c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	0	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0
d02f02c01	1	1	1	1	0	1	1	0	0	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0
d02f02c02	0	1	1	1	1	1	1	0	1	1	0	1	1	0	1	0	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d02f02c03	1	1	1	1	0	1	1	0	1	1	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	1	0
d02f02c04	0	1	1	0	0	0	1	0	1	1	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d02f02c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d02f03c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f03c02	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	0	0	0
d02f03c03	1	1	1	1	0	1	1	0	1	1	0	0	1	1	1	0	0	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d02f03c04	0	0	1	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
d02f03c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d02f04c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f04c02	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	0	1	1	0
d02f04c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	0	0	0	1	1	0	1	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0
d02f04c04	1	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d02f04c05	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0
d02f05c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f05c02	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
d02f05c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f05c04	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f05c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d02f06c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f06c02	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	0	1	1	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d02f06c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f06c04	1	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d02f06c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d02f07c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f07c02	0	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0
d02f07c03	0	1	0	0	1	0	0	0	1	0	0	0	0	0	1	1	1	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
d02f07c04	0	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0
d02f07c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d02f08c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f08c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d02f08c03	1	0	1	1	0	0	1	0	0	1	0	0	0	1	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d02f08c04	1	1	1	1	0	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0
d02f08c05	1	1	1	1	0	1	0	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d03f01c01	0	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d03f01c02	0	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f01c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f01c04	0	1	1	1	0	1	1	0	1	0	0	0	0	0	1	1	0	0	0	1	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d03f01c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d03f02c01	0	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d03f02c02	0	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f02c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f02c04	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f02c05	1	1	0	1	0	1	1	0	1	1	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d03f03c01	0	1	1	1	0	0	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0

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Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d03f03c02	0	1	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d03f03c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f03c04	0	1	0	1	0	0	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d03f03c05	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f04c01	0	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f04c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f04c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f04c04	0	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	0	1	0	0	1	0	1	1	1	1	0	0	0	0	1	1	1	0	1	0	0	0
d03f04c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f05c01	0	1	1	1	0	0	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d03f05c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f05c03	1	1	1	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	0	1	0	0	1	0	0	1	0	1
d03f05c04	1	1	0	1	0	1	1	1	1	0	0	1	1	0	1	1	0	0	0	1	1	1	1	1	1	0	1	1	0	0	0	0	0	1	1	0	1	0	0	1
d03f05c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d03f06c01	0	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f06c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f06c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f06c04	0	1	0	1	0	0	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d03f06c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f07c01	0	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f07c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f07c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f07c04	1	1	0	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	1	1	0	0	1	0	1	0	1	1	0	0	0	1	1	0	1	1	1	1	0	1
d03f07c05	0	1	1	1	0	1	1	0	1	1	1	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0

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Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d03f08c01	0	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d03f08c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d03f08c03	1	1	1	1	0	1	1	0	1	1	0	0	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	0	0	1	0	1	0	0	0	0	0	0
d03f08c04	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d03f08c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d04f01c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f01c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d04f01c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d04f01c04	1	1	1	1	1	1	1	0	0	0	0	0	1	0	1	1	0	0	0	1	0	1	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d04f01c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f02c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f02c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f02c03	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	1	0
d04f02c04	1	1	1	1	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	0	0	0	0	0	1	0	0
d04f02c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f03c01	1	1	0	1	0	0	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d04f03c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1	0	0	0	0	0	0
d04f03c03	1	1	1	0	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0
d04f03c04	0	1	0	1	1	1	1	0	1	0	0	1	1	0	1	1	0	0	0	1	1	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0
d04f03c05	1	1	0	1	1	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0
d04f04c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d04f04c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f04c03	1	1	1	0	1	1	1	0	0	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	1	0	0	1	0	0	1	0
d04f04c04	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d04f04c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f05c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f05c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f05c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f05c04	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	1
d04f05c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f06c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f06c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f06c03	1	1	1	1	0	1	1	0	0	1	0	0	1	1	1	0	1	0	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0
d04f06c04	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f06c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f07c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d04f07c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f07c03	1	1	1	0	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0	0
d04f07c04	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d04f07c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f08c01	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d04f08c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f08c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	1	0
d04f08c04	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f08c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d04f09c01	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d04f09c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d04f09c03	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d04f09c04	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d04f09c05	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f01c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f01c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	1	1	1	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0
d05f01c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f01c04	1	1	1	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f01c05	1	1	1	1	0	1	0	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f02c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
d05f02c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f02c03	1	1	1	1	0	1	0	1	1	1	0	0	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	1
d05f02c04	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f02c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1
d05f03c01	1	1	0	1	0	1	1	0	1	0	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0
d05f03c02	1	1	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d05f03c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d05f03c04	0	1	1	1	0	1	1	0	1	0	0	0	1	1	1	1	0	0	0	1	1	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0
d05f03c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f04c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f04c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1
d05f04c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	0	1	0	1	1	0	1	1	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f04c04	0	1	1	0	0	1	1	0	1	1	0	0	1	0	0	1	1	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d05f04c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f05c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f05c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d05f05c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f05c04	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d05f05c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f06c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f06c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f06c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0
d05f06c04	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
d05f06c05	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d05f07c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f07c02	0	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0
d05f07c03	0	1	0	0	1	0	0	0	1	0	0	0	0	0	1	1	1	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
d05f07c04	0	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1
d05f07c05	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0
d05f08c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f08c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f08c03	1	0	1	1	0	0	1	0	0	1	0	0	0	1	1	1	1	0	1	1	0	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d05f08c04	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	1	0	0
d05f08c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f09c01	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f09c02	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d05f09c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f09c04	0	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d05f09c05	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d06f01c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0

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Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d06f01c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f01c03	1	1	1	1	1	1	1	0	1	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f01c04	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	0	1	1	1	1	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0
d06f01c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f02c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f02c02	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f02c03	1	1	1	1	0	0	1	0	0	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	0	1	0	0	1	0	0	0	0	0	0	1	0
d06f02c04	1	1	1	1	1	0	1	1	0	1	1	0	1	0	1	0	1	0	0	1	0	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f02c05	1	1	1	1	0	1	1	0	1	0	0	0	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d06f03c01	1	1	1	1	0	0	1	0	1	1	0	0	0	0	1	1	1	0	0	1	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f03c02	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f03c03	1	1	1	0	1	0	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f03c04	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	1	0	0	0	0
d06f03c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	0	0	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f04c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f04c02	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f04c03	1	1	1	1	0	1	1	0	1	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d06f04c04	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d06f04c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f05c01	1	1	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0
d06f05c02	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0
d06f05c03	0	1	1	0	0	0	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1	0	1	0	0	1	0
d06f05c04	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	0	0	1	0	0	0	1	1	1	1	0	1	1	1	0	0	0	0	0	0	1	1	0
d06f05c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0

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Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d06f06c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f06c02	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f06c03	1	1	1	0	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f06c04	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f06c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f07c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f07c02	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f07c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	1	0	1	0
d06f07c04	0	1	1	1	0	0	1	0	1	0	0	1	1	0	1	1	0	0	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f07c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f08c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f08c02	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f08c03	1	1	1	1	1	0	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f08c04	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f08c05	1	1	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f09c01	1	1	1	1	0	1	1	0	1	1	0	0	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d06f09c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d06f09c03	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0
d06f09c04	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d06f09c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f01c01	1	1	1	1	0	0	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f01c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f01c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f01c04	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d07f01c05	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f02c01	1	1	1	1	0	0	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f02c02	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f02c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	0
d07f02c04	1	1	1	1	0	0	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f02c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f03c01	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f03c02	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f03c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f03c04	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f03c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f04c01	1	1	1	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f04c02	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f04c03	1	1	1	1	0	0	1	0	0	1	0	1	1	0	1	0	1	0	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f04c04	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f04c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f05c01	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f05c02	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d07f05c03	1	1	1	0	0	0	1	0	1	1	0	0	1	0	1	0	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f05c04	1	1	1	0	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d07f05c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	0	1	1	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f06c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f06c02	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f06c03	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	0

Code	Adabank A.Ş.	Akbank T.A.Ş.	Alternatif Bank A.Ş.	Anadolubank A.Ş.	Bayındırbank A.Ş.	B. Türk Körfez Bankası A.Ş.	Denizbank A.Ş.	E.G.S. Bankası A.Ş.	Fiba Bank A.Ş.	Finans Bank A.Ş.	İktisat Bankası T.A.Ş.	Kentbank A.Ş.	Koçbank A.Ş.	Milli Aydın Bankası T.A.Ş.	MNG Bank A.Ş.	Oyak Bank A.Ş.	Pamukbank T.A.Ş.	Sitebank A.Ş.	Şekerbank T.A.Ş.	Tekstil Bankası A.Ş.	Toprakbank A.Ş.	Turkish Bank A.Ş.	T. Dış Ticaret Bankası A.Ş.	T. Ekonomi Bankası A.Ş.	T. Garanti Bankası A.Ş.	T. İmar Bankası T.A.Ş.	Türkiye İş Bankası A.Ş.	Ulusal Bank T.A.Ş.	Yapı ve Kredi Bankası A.Ş.	Bank Kapital Türk A.Ş.	Demirbank T.A.Ş.	Etibank A.Ş.	Egebank A.Ş.	Eskişehir Bankası T.A.Ş.	Interbank	Sümerbank A.Ş.	T. T. B. Yaşarbank A.Ş.	Yurt T. K. Bankası A.Ş.	Bank Ekspres A.Ş.	Türk Ticaret Bankası A.Ş.
d07f06c04	1	1	1	1	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f06c05	1	1	1	1	0	1	1	1	1	1	0	0	1	0	1	1	1	0	1	1	0	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f07c01	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	0	1	0	1	1	0	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
d07f07c02	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f07c03	0	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0
d07f07c04	0	1	1	1	0	0	1	0	1	0	0	1	1	0	1	0	1	0	0	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f07c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f08c01	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f08c02	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f08c03	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f08c04	1	1	1	1	0	1	1	1	1	1	0	1	1	0	1	0	1	0	0	1	1	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
d07f08c05	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f09c01	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f09c02	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
d07f09c03	1	1	1	1	0	1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
d07f09c04	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	1	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
d07f09c05	1	1	1	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0

Appendix I. Type I and Type II Errors and Overall Success Rates of the Models

Code	# var	Type I	Type II	Overall Success
d01f01c01	46	7,50%	7,50%	85,00%
d01f01c02	46	0,00%	22,50%	77,50%
d01f01c03	46	7,50%	7,50%	85,00%
d01f01c04	46	15,00%	15,00%	70,00%
d01f01c05	46	5,00%	7,50%	87,50%
d01f02c01	6	7,50%	7,50%	85,00%
d01f02c02	6	5,00%	15,00%	80,00%
d01f02c03	6	12,50%	2,50%	85,00%
d01f02c04	6	15,00%	5,00%	80,00%
d01f02c05	6	5,00%	7,50%	87,50%
d01f03c01	5	10,00%	5,00%	85,00%
d01f03c02	5	0,00%	22,50%	77,50%
d01f03c03	5	5,00%	7,50%	87,50%
d01f03c04	5	22,50%	2,50%	75,00%
d01f03c05	5	10,00%	2,50%	87,50%
d01f04c01	24	7,50%	7,50%	85,00%
d01f04c02	24	0,00%	22,50%	77,50%
d01f04c03	24	10,00%	7,50%	82,50%
d01f04c04	24	10,00%	7,50%	82,50%
d01f04c05	24	5,00%	2,50%	92,50%
d01f05c01	11	10,00%	10,00%	80,00%
d01f05c02	11	2,50%	30,00%	67,50%
d01f05c03	11	10,00%	2,50%	87,50%
d01f05c04	11	15,00%	2,50%	82,50%
d01f05c05	11	5,00%	7,50%	87,50%
d01f06c01	19	10,00%	10,00%	80,00%
d01f06c02	19	0,00%	25,00%	75,00%
d01f06c03	19	2,50%	15,00%	82,50%
d01f06c04	19	5,00%	10,00%	85,00%
d01f06c05	19	5,00%	7,50%	87,50%
d01f07c01	20	7,50%	7,50%	85,00%
d01f07c02	20	0,00%	22,50%	77,50%
d01f07c03	20	10,00%	10,00%	80,00%
d01f07c04	20	7,50%	7,50%	85,00%

Code	# var	Type I	Type II	Overall Success
d01f07c05	20	2,50%	5,00%	92,50%
d01f08c01	11	7,50%	7,50%	85,00%
d01f08c02	11	0,00%	15,00%	85,00%
d01f08c03	11	10,00%	2,50%	87,50%
d01f08c04	11	17,50%	2,50%	80,00%
d01f08c05	11	5,00%	0,00%	95,00%
d02f01c01	46	12,50%	2,50%	85,00%
d02f01c02	46	10,00%	5,00%	85,00%
d02f01c03	46	7,50%	2,50%	90,00%
d02f01c04	46	15,00%	5,00%	80,00%
d02f01c05	46	2,50%	5,00%	92,50%
d02f02c01	11	5,00%	2,50%	92,50%
d02f02c02	11	5,00%	7,50%	87,50%
d02f02c03	11	0,00%	12,50%	87,50%
d02f02c04	11	20,00%	2,50%	77,50%
d02f02c05	11	10,00%	2,50%	87,50%
d02f03c01	9	15,00%	5,00%	80,00%
d02f03c02	9	0,00%	20,00%	80,00%
d02f03c03	9	10,00%	2,50%	87,50%
d02f03c04	9	25,00%	2,50%	72,50%
d02f03c05	9	7,50%	0,00%	92,50%
d02f04c01	18	12,50%	5,00%	82,50%
d02f04c02	18	2,50%	30,00%	67,50%
d02f04c03	18	12,50%	5,00%	82,50%
d02f04c04	18	15,00%	2,50%	82,50%
d02f04c05	18	0,00%	5,00%	95,00%
d02f05c01	7	12,50%	5,00%	82,50%
d02f05c02	7	0,00%	45,00%	55,00%
d02f05c03	7	5,00%	5,00%	90,00%
d02f05c04	7	12,50%	5,00%	82,50%
d02f05c05	7	0,00%	2,50%	97,50%
d02f06c01	17	12,50%	5,00%	82,50%
d02f06c02	17	2,50%	30,00%	67,50%
d02f06c03	17	2,50%	5,00%	92,50%
d02f06c04	17	12,50%	2,50%	85,00%
d02f06c05	17	0,00%	0,00%	100,00%
d02f07c01	17	12,50%	5,00%	82,50%
d02f07c02	17	10,00%	7,50%	82,50%
d02f07c03	17	30,00%	2,50%	67,50%
d02f07c04	17	22,50%	5,00%	72,50%

Code	# var	Type I	Type II	Overall Success
d02f07c05	17	10,00%	0,00%	90,00%
d02f08c01	17	12,50%	5,00%	82,50%
d02f08c02	17	12,50%	5,00%	82,50%
d02f08c03	17	12,50%	5,00%	82,50%
d02f08c04	17	7,50%	10,00%	82,50%
d02f08c05	17	7,50%	0,00%	92,50%
d03f01c01	46	15,00%	5,00%	80,00%
d03f01c02	46	10,00%	7,50%	82,50%
d03f01c03	46	2,50%	5,00%	92,50%
d03f01c04	46	22,50%	5,00%	72,50%
d03f01c05	46	7,50%	2,50%	90,00%
d03f02c01	4	15,00%	5,00%	80,00%
d03f02c02	4	10,00%	7,50%	82,50%
d03f02c03	4	2,50%	5,00%	92,50%
d03f02c04	4	10,00%	20,00%	70,00%
d03f02c05	4	5,00%	5,00%	90,00%
d03f03c01	6	20,00%	2,50%	77,50%
d03f03c02	6	7,50%	5,00%	87,50%
d03f03c03	6	5,00%	5,00%	90,00%
d03f03c04	6	22,50%	2,50%	75,00%
d03f03c05	6	12,50%	2,50%	85,00%
d03f04c01	16	12,50%	5,00%	82,50%
d03f04c02	16	10,00%	5,00%	85,00%
d03f04c03	16	10,00%	5,00%	85,00%
d03f04c04	16	20,00%	15,00%	65,00%
d03f04c05	16	12,50%	2,50%	85,00%
d03f05c01	5	20,00%	2,50%	77,50%
d03f05c02	5	10,00%	5,00%	85,00%
d03f05c03	5	7,50%	20,00%	72,50%
d03f05c04	5	15,00%	20,00%	65,00%
d03f05c05	5	7,50%	7,50%	85,00%
d03f06c01	13	12,50%	5,00%	82,50%
d03f06c02	13	10,00%	5,00%	85,00%
d03f06c03	13	12,50%	2,50%	85,00%
d03f06c04	13	25,00%	2,50%	72,50%
d03f06c05	13	12,50%	2,50%	85,00%
d03f07c01	10	12,50%	5,00%	82,50%
d03f07c02	10	10,00%	5,00%	85,00%
d03f07c03	10	10,00%	5,00%	85,00%
d03f07c04	10	17,50%	22,50%	60,00%

Code	# var	Type I	Type II	Overall Success
d03f07c05	10	12,50%	5,00%	82,50%
d03f08c01	11	12,50%	5,00%	82,50%
d03f08c02	11	10,00%	5,00%	85,00%
d03f08c03	11	2,50%	10,00%	87,50%
d03f08c04	11	20,00%	2,50%	77,50%
d03f08c05	11	12,50%	2,50%	85,00%
d04f01c01	138	2,50%	0,00%	97,50%
d04f01c02	138	7,50%	2,50%	90,00%
d04f01c03	138	10,00%	5,00%	85,00%
d04f01c04	138	15,00%	5,00%	80,00%
d04f01c05	138	0,00%	0,00%	100,00%
d04f02c01	22	12,50%	7,50%	80,00%
d04f02c02	22	5,00%	7,50%	87,50%
d04f02c03	22	0,00%	15,00%	85,00%
d04f02c04	22	10,00%	17,50%	72,50%
d04f02c05	22	0,00%	0,00%	100,00%
d04f03c01	6	20,00%	2,50%	77,50%
d04f03c02	6	5,00%	5,00%	90,00%
d04f03c03	6	2,50%	2,50%	95,00%
d04f03c04	6	17,50%	12,50%	70,00%
d04f03c05	6	5,00%	12,50%	82,50%
d04f04c01	58	7,50%	7,50%	85,00%
d04f04c02	58	5,00%	5,00%	90,00%
d04f04c03	58	5,00%	10,00%	85,00%
d04f04c04	58	10,00%	5,00%	85,00%
d04f04c05	58	7,50%	5,00%	87,50%
d04f05c01	23	10,00%	0,00%	90,00%
d04f05c02	23	5,00%	5,00%	90,00%
d04f05c03	23	5,00%	0,00%	95,00%
d04f05c04	23	10,00%	5,00%	85,00%
d04f05c05	23	2,50%	0,00%	97,50%
d04f06c01	49	10,00%	5,00%	85,00%
d04f06c02	49	5,00%	5,00%	90,00%
d04f06c03	49	7,50%	5,00%	87,50%
d04f06c04	49	12,50%	5,00%	82,50%
d04f06c05	49	5,00%	0,00%	95,00%
d04f07c01	47	7,50%	7,50%	85,00%
d04f07c02	47	5,00%	5,00%	90,00%
d04f07c03	47	2,50%	7,50%	90,00%
d04f07c04	47	12,50%	2,50%	85,00%

Code	# var	Type I	Type II	Overall Success
d04f07c05	47	0,00%	0,00%	100,00%
d04f08c01	46	7,50%	7,50%	85,00%
d04f08c02	46	5,00%	5,00%	90,00%
d04f08c03	46	0,00%	7,50%	92,50%
d04f08c04	46	10,00%	5,00%	85,00%
d04f08c05	46	12,50%	2,50%	85,00%
d04f09c01	22	12,50%	0,00%	87,50%
d04f09c02	22	5,00%	5,00%	90,00%
d04f09c03	22	7,50%	7,50%	85,00%
d04f09c04	22	15,00%	2,50%	82,50%
d04f09c05	22	5,00%	2,50%	92,50%
d05f01c01	92	0,00%	0,00%	100,00%
d05f01c02	92	12,50%	7,50%	80,00%
d05f01c03	92	2,50%	5,00%	92,50%
d05f01c04	92	22,50%	2,50%	75,00%
d05f01c05	92	7,50%	2,50%	90,00%
d05f02c01	27	0,00%	2,50%	97,50%
d05f02c02	27	0,00%	0,00%	100,00%
d05f02c03	27	7,50%	15,00%	77,50%
d05f02c04	27	7,50%	7,50%	85,00%
d05f02c05	27	5,00%	2,50%	92,50%
d05f03c01	4	12,50%	5,00%	82,50%
d05f03c02	4	5,00%	2,50%	92,50%
d05f03c03	4	7,50%	5,00%	87,50%
d05f03c04	4	15,00%	10,00%	75,00%
d05f03c05	4	0,00%	0,00%	100,00%
d05f04c01	34	12,50%	2,50%	85,00%
d05f04c02	34	5,00%	2,50%	92,50%
d05f04c03	34	7,50%	5,00%	87,50%
d05f04c04	34	20,00%	2,50%	77,50%
d05f04c05	34	2,50%	0,00%	97,50%
d05f05c01	12	12,50%	2,50%	85,00%
d05f05c02	12	12,50%	5,00%	82,50%
d05f05c03	12	2,50%	5,00%	92,50%
d05f05c04	12	17,50%	2,50%	80,00%
d05f05c05	12	5,00%	2,50%	92,50%
d05f06c01	30	12,50%	2,50%	85,00%
d05f06c02	30	12,50%	5,00%	82,50%
d05f06c03	30	2,50%	5,00%	92,50%
d05f06c04	30	17,50%	2,50%	80,00%

Code	# var	Type I	Type II	Overall Success
d05f06c05	30	0,00%	5,00%	95,00%
d05f07c01	27	12,50%	2,50%	85,00%
d05f07c02	27	10,00%	10,00%	80,00%
d05f07c03	27	30,00%	2,50%	67,50%
d05f07c04	27	20,00%	7,50%	72,50%
d05f07c05	27	2,50%	10,00%	87,50%
d05f08c01	30	12,50%	2,50%	85,00%
d05f08c02	30	12,50%	5,00%	82,50%
d05f08c03	30	12,50%	5,00%	82,50%
d05f08c04	30	10,00%	7,50%	82,50%
d05f08c05	30	10,00%	2,50%	87,50%
d05f09c01	20	12,50%	2,50%	85,00%
d05f09c02	20	12,50%	5,00%	82,50%
d05f09c03	20	12,50%	2,50%	85,00%
d05f09c04	20	12,50%	5,00%	82,50%
d05f09c05	20	12,50%	2,50%	85,00%
d06f01c01	138	0,00%	0,00%	100,00%
d06f01c02	138	2,50%	2,50%	95,00%
d06f01c03	138	7,50%	5,00%	87,50%
d06f01c04	138	5,00%	17,50%	77,50%
d06f01c05	138	0,00%	0,00%	100,00%
d06f02c01	24	0,00%	0,00%	100,00%
d06f02c02	24	5,00%	5,00%	90,00%
d06f02c03	24	10,00%	5,00%	85,00%
d06f02c04	24	12,50%	10,00%	77,50%
d06f02c05	24	7,50%	5,00%	87,50%
d06f03c01	5	12,50%	0,00%	87,50%
d06f03c02	5	2,50%	2,50%	95,00%
d06f03c03	5	5,00%	5,00%	90,00%
d06f03c04	5	2,50%	17,50%	80,00%
d06f03c05	5	7,50%	2,50%	90,00%
d06f04c01	41	5,00%	7,50%	87,50%
d06f04c02	41	7,50%	7,50%	85,00%
d06f04c03	41	7,50%	2,50%	90,00%
d06f04c04	41	5,00%	7,50%	87,50%
d06f04c05	41	0,00%	0,00%	100,00%
d06f05c01	17	10,00%	10,00%	80,00%
d06f05c02	17	5,00%	12,50%	82,50%
d06f05c03	17	12,50%	10,00%	77,50%
d06f05c04	17	7,50%	15,00%	77,50%

Code	# var	Type I	Type II	Overall Success
d06f05c05	17	7,50%	5,00%	87,50%
d06f06c01	32	5,00%	7,50%	87,50%
d06f06c02	32	7,50%	7,50%	85,00%
d06f06c03	32	2,50%	2,50%	95,00%
d06f06c04	32	5,00%	7,50%	87,50%
d06f06c05	32	5,00%	0,00%	95,00%
d06f07c01	27	5,00%	7,50%	87,50%
d06f07c02	27	7,50%	7,50%	85,00%
d06f07c03	27	2,50%	7,50%	90,00%
d06f07c04	27	17,50%	2,50%	80,00%
d06f07c05	27	0,00%	0,00%	100,00%
d06f08c01	23	5,00%	7,50%	87,50%
d06f08c02	23	7,50%	7,50%	85,00%
d06f08c03	23	10,00%	5,00%	85,00%
d06f08c04	23	5,00%	5,00%	90,00%
d06f08c05	23	7,50%	0,00%	92,50%
d06f09c01	17	7,50%	5,00%	87,50%
d06f09c02	17	0,00%	0,00%	100,00%
d06f09c03	17	2,50%	10,00%	87,50%
d06f09c04	17	5,00%	7,50%	87,50%
d06f09c05	17	5,00%	0,00%	95,00%
d07f01c01	184	2,50%	0,00%	97,50%
d07f01c02	184	0,00%	0,00%	100,00%
d07f01c03	184	2,50%	0,00%	97,50%
d07f01c04	184	2,50%	17,50%	80,00%
d07f01c05	184	2,50%	5,00%	92,50%
d07f02c01	19	2,50%	0,00%	97,50%
d07f02c02	19	0,00%	0,00%	100,00%
d07f02c03	19	0,00%	2,50%	97,50%
d07f02c04	19	7,50%	10,00%	82,50%
d07f02c05	19	0,00%	0,00%	100,00%
d07f03c01	4	7,50%	10,00%	82,50%
d07f03c02	4	5,00%	7,50%	87,50%
d07f03c03	4	5,00%	2,50%	92,50%
d07f03c04	4	2,50%	10,00%	87,50%
d07f03c05	4	0,00%	0,00%	100,00%
d07f04c01	50	2,50%	7,50%	90,00%
d07f04c02	50	7,50%	10,00%	82,50%
d07f04c03	50	10,00%	2,50%	87,50%
d07f04c04	50	5,00%	10,00%	85,00%

Code	# var	Type I	Type II	Overall Success
d07f04c05	50	0,00%	0,00%	100,00%
d07f05c01	24	5,00%	10,00%	85,00%
d07f05c02	24	5,00%	5,00%	90,00%
d07f05c03	24	7,50%	2,50%	90,00%
d07f05c04	24	5,00%	10,00%	85,00%
d07f05c05	24	7,50%	2,50%	90,00%
d07f06c01	41	5,00%	7,50%	87,50%
d07f06c02	41	7,50%	10,00%	82,50%
d07f06c03	41	5,00%	2,50%	92,50%
d07f06c04	41	7,50%	7,50%	85,00%
d07f06c05	41	2,50%	5,00%	92,50%
d07f07c01	32	2,50%	7,50%	90,00%
d07f07c02	32	7,50%	10,00%	82,50%
d07f07c03	32	7,50%	7,50%	85,00%
d07f07c04	32	20,00%	2,50%	77,50%
d07f07c05	32	0,00%	0,00%	100,00%
d07f08c01	15	7,50%	10,00%	82,50%
d07f08c02	15	7,50%	10,00%	82,50%
d07f08c03	15	10,00%	2,50%	87,50%
d07f08c04	15	7,50%	7,50%	85,00%
d07f08c05	15	0,00%	5,00%	95,00%
d07f09c01	11	7,50%	10,00%	82,50%
d07f09c02	11	7,50%	10,00%	82,50%
d07f09c03	11	15,00%	0,00%	85,00%
d07f09c04	11	7,50%	7,50%	85,00%
d07f09c05	11	2,50%	2,50%	95,00%

Appendix J. Split-Sample and Cross Validation Results for Decision Tree Models

c03	Type I	Type II	Overall Success	Evaluation Methodology
d01f01	50,00%	25,00%	66,70%	Test Sample
d01f01	5,90%	9,10%	92,90%	Training Sample
d01f01	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d01f02	42,90%	0,00%	70,00%	Test Sample
d01f02	14,30%	6,20%	90,00%	Training Sample
d01f02	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d01f03	33,30%	33,30%	66,70%	Test Sample
d01f03	0,00%	12,50%	93,50%	Training Sample
d01f03	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d01f04	20,00%	80,00%	50,00%	Test Sample
d01f04	0,00%	14,30%	93,30%	Training Sample
d01f04	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d01f05	28,60%	16,70%	76,90%	Test Sample
d01f05	14,30%	0,00%	92,60%	Training Sample
d01f05	9,50%	5,30%	92,50%	10-fold Cross Validation-Resubstitution
d01f06	20,00%	80,00%	50,00%	Test Sample
d01f06	0,00%	14,30%	93,30%	Training Sample
d01f06	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d01f07	37,50%	40,00%	61,50%	Test Sample
d01f07	7,70%	14,30%	88,90%	Training Sample
d01f07	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d01f08	33,30%	50,00%	62,50%	Test Sample
d01f08	13,30%	0,00%	93,80%	Training Sample
d01f08	9,50%	5,30%	92,50%	10-fold Cross Validation-Resubstitution
d02f01	20,00%	25,00%	76,90%	Test Sample
d02f01	6,20%	0,00%	96,30%	Training Sample
d02f01	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d02f02	28,60%	33,30%	70,00%	Test Sample
d02f02	0,00%	18,70%	90,00%	Training Sample
d02f02	0,00%	10,50%	95,00%	10-fold Cross Validation-Resubstitution
d02f03	33,30%	0,00%	77,80%	Test Sample
d02f03	13,30%	6,20%	90,30%	Training Sample
d02f03	14,30%	10,50%	87,50%	10-fold Cross Validation-Resubstitution
d02f04	33,30%	33,30%	66,70%	Test Sample

c03	Type I	Type II	Overall Success	Evaluation Methodology
d02f04	16,70%	6,20%	89,30%	Training Sample
d02f04	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d02f05	28,60%	0,00%	85,70%	Test Sample
d02f05	0,00%	16,70%	92,30%	Training Sample
d02f05	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d02f06	0,00%	0,00%	100,00%	Test Sample
d02f06	5,30%	14,30%	90,90%	Training Sample
d02f06	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d02f07	9,10%	83,30%	52,20%	Test Sample
d02f07	22,20%	0,00%	88,20%	Training Sample
d02f07	9,50%	5,30%	92,50%	10-fold Cross Validation-Resubstitution
d02f08	57,10%	50,00%	45,50%	Test Sample
d02f08	7,10%	0,00%	96,60%	Training Sample
d02f08	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d03f01	0,00%	28,60%	85,70%	Test Sample
d03f01	7,10%	0,00%	96,20%	Training Sample
d03f01	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d03f02	14,30%	25,00%	81,80%	Test Sample
d03f02	0,00%	6,70%	96,60%	Training Sample
d03f02	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d03f03	12,50%	14,30%	86,70%	Test Sample
d03f03	7,70%	8,30%	92,00%	Training Sample
d03f03	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d03f04	66,70%	12,50%	64,30%	Test Sample
d03f04	0,00%	9,10%	96,20%	Training Sample
d03f04	19,00%	0,00%	90,00%	10-fold Cross Validation-Resubstitution
d03f05	37,50%	83,30%	42,90%	Test Sample
d03f05	0,00%	23,10%	88,50%	Training Sample
d03f05	14,30%	10,50%	87,50%	10-fold Cross Validation-Resubstitution
d03f06	60,00%	0,00%	72,70%	Test Sample
d03f06	12,50%	7,70%	89,70%	Training Sample
d03f06	19,00%	0,00%	90,00%	10-fold Cross Validation-Resubstitution
d03f07	42,90%	25,00%	63,60%	Test Sample
d03f07	7,10%	6,70%	93,10%	Training Sample
d03f07	19,00%	0,00%	90,00%	10-fold Cross Validation-Resubstitution
d03f08	20,00%	33,30%	71,40%	Test Sample
d03f08	0,00%	10,00%	96,20%	Training Sample
d03f08	19,00%	0,00%	90,00%	10-fold Cross Validation-Resubstitution
d04f01	37,50%	33,30%	63,60%	Test Sample
d04f01	7,70%	6,20%	93,10%	Training Sample

c03	Type I	Type II	Overall Success	Evaluation Methodology
d04f01	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d04f02	0,00%	66,70%	44,40%	Test Sample
d04f02	0,00%	15,40%	93,50%	Training Sample
d04f02	10,50%	9,50%	90,00%	10-fold Cross Validation-Resubstitution
d04f03	16,70%	14,30%	84,60%	Test Sample
d04f03	0,00%	0,00%	100,00%	Training Sample
d04f03	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d04f04	25,00%	50,00%	60,00%	Test Sample
d04f04	5,90%	7,70%	93,30%	Training Sample
d04f04	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d04f05	33,30%	0,00%	80,00%	Test Sample
d04f05	5,60%	0,00%	97,10%	Training Sample
d04f05	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d04f06	38,50%	33,30%	61,50%	Test Sample
d04f06	0,00%	0,00%	100,00%	Training Sample
d04f06	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d04f07	20,00%	33,30%	72,70%	Test Sample
d04f07	7,70%	0,00%	96,60%	Training Sample
d04f07	4,80%	0,00%	97,50%	10-fold Cross Validation-Resubstitution
d04f08	0,00%	33,30%	81,80%	Test Sample
d04f08	0,00%	7,70%	96,60%	Training Sample
d04f08	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d04f09	25,00%	37,50%	68,80%	Test Sample
d04f09	7,70%	0,00%	95,80%	Training Sample
d04f09	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d05f01	17,70%	33,30%	75,00%	Test Sample
d05f01	0,00%	0,00%	100,00%	Training Sample
d05f01	0,00%	15,80%	92,50%	10-fold Cross Validation-Resubstitution
d05f02	50,00%	57,10%	45,50%	Test Sample
d05f02	5,90%	16,70%	89,70%	Training Sample
d05f02	0,00%	10,50%	95,00%	10-fold Cross Validation-Resubstitution
d05f03	42,90%	0,00%	70,00%	Test Sample
d05f03	0,00%	12,50%	93,30%	Training Sample
d05f03	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d05f04	17,70%	0,00%	88,90%	Test Sample
d05f04	13,30%	12,50%	87,10%	Training Sample
d05f04	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d05f05	12,50%	16,70%	85,70%	Test Sample
d05f05	0,00%	7,70%	96,20%	Training Sample
d05f05	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution

c03	Type I	Type II	Overall Success	Evaluation Methodology
d05f06	0,00%	20,00%	85,70%	Test Sample
d05f06	5,30%	7,10%	93,90%	Training Sample
d05f06	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d05f07	83,30%	9,10%	52,20%	Test Sample
d05f07	22,20%	0,00%	88,20%	Training Sample
d05f07	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d05f08	57,10%	50,00%	45,50%	Test Sample
d05f08	7,10%	0,00%	96,60%	Training Sample
d05f08	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d05f09	60,00%	0,00%	62,50%	Test Sample
d05f09	12,50%	6,20%	90,60%	Training Sample
d05f09	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d06f01	28,60%	50,00%	63,60%	Test Sample
d06f01	7,10%	0,00%	96,60%	Training Sample
d06f01	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d06f02	44,40%	38,60%	62,50%	Test Sample
d06f02	0,00%	0,00%	100,00%	Training Sample
d06f02	9,50%	0,00%	95,00%	10-fold Cross Validation-Resubstitution
d06f03	0,00%	25,00%	90,00%	Test Sample
d06f03	13,30%	6,70%	90,00%	Training Sample
d06f03	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d06f04	42,90%	0,00%	75,00%	Test Sample
d06f04	0,00%	7,10%	96,40%	Training Sample
d06f04	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d06f05	71,40%	33,30%	50,00%	Test Sample
d06f05	0,00%	10,00%	95,80%	Training Sample
d06f05	9,50%	5,30%	92,50%	10-fold Cross Validation-Resubstitution
d06f06	11,10%	0,00%	91,70%	Test Sample
d06f06	0,00%	6,20%	96,40%	Training Sample
d06f06	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d06f07	33,30%	28,60%	70,00%	Test Sample
d06f07	0,00%	8,30%	96,70%	Training Sample
d06f07	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d06f08	30,00%	25,00%	71,40%	Test Sample
d06f08	9,10%	6,70%	92,30%	Training Sample
d06f08	0,00%	10,50%	95,00%	10-fold Cross Validation-Resubstitution
d06f09	33,30%	50,00%	54,50%	Test Sample
d06f09	0,00%	0,00%	100,00%	Training Sample
d06f09	4,80%	10,50%	92,50%	10-fold Cross Validation-Resubstitution
d07f01	14,30%	0,00%	88,90%	Test Sample

c03	Type I	Type II	Overall Success	Evaluation Methodology
d07f01	0,00%	0,00%	100,00%	Training Sample
d07f01	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d07f02	0,00%	33,30%	92,30%	Test Sample
d07f02	0,00%	0,00%	100,00%	Training Sample
d07f02	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d07f03	66,70%	50,00%	40,00%	Test Sample
d07f03	0,00%	0,00%	100,00%	Training Sample
d07f03	4,80%	0,00%	97,50%	10-fold Cross Validation-Resubstitution
d07f04	42,90%	16,70%	69,20%	Test Sample
d07f04	7,10%	0,00%	96,30%	Training Sample
d07f04	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d07f05	60,00%	16,70%	63,60%	Test Sample
d07f05	0,00%	0,00%	100,00%	Training Sample
d07f05	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d07f06	40,00%	0,00%	81,80%	Test Sample
d07f06	0,00%	7,70%	96,60%	Training Sample
d07f06	0,00%	5,30%	97,50%	10-fold Cross Validation-Resubstitution
d07f07	25,00%	37,50%	68,80%	Test Sample
d07f07	6,70%	0,00%	95,80%	Training Sample
d07f07	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d07f08	42,90%	0,00%	70,00%	Test Sample
d07f08	7,10%	6,20%	93,30%	Training Sample
d07f08	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution
d07f09	46,70%	0,00%	54,50%	Test Sample
d07f09	8,30%	0,00%	96,60%	Training Sample
d07f09	4,80%	5,30%	95,00%	10-fold Cross Validation-Resubstitution

Appendix K. Historical Data about Closed Banks[7]

	Establish. Year	Historical Data
Adapazarı Emniyet Bankası T.A.Ş.	1919	"Emniyet Bankası Komandit Şirketi" was founded in 1919 and its name was changed to "Adapazarı Emniyet Bankası A.Ş." in 1928. The bank was liquidated upon the decision taken in the extraordinary general meeting in 30 September 1971.
Ak Uluslararası Bankası A.Ş.	1985	"Bnp-Ak Bankası A.Ş." was founded as a privately owned deposit bank in 1985 and then, 30% of its shares was sold to Dresdner Bank A.G. in 1989. Its name was changed to Bnp-Ak Dresdner Bank A.Ş. in 27 January 1989 and transferred to "Foreign Banks Founded in Turkey" group. The total 60% shares of BNP Paribas, Societe Jovacienne de Participations and Dresdner Bank A.G. was then sold to the remaining shareholder, Akbank T.A.Ş.(39,99) in 9 March 2005. The name of the bank was changed to "Ak Uluslararası Bankası A.Ş." in 30 March 2005 and the bank transferred to "privately owned deposit bank" group. Then, the shares of Ak Uluslararası Bankası A.Ş. was transferred to Akbank T.A.Ş., as of September 20, 2005, according to the Resolution Nr. 1695 of BRSB, dated September 9, 2005. The legal entity of "Ak Uluslararası Bankası A.Ş." from the İstanbul Trade Registry was repealed, as of September 19, 2005.
Akseki Ticaret Bankası T.A.Ş.	1927	"Akseki Ticaret Bankası T.A.Ş." was founded in 1927. The name of the bank and the fields of activity was changed in 25 December 1958 upon the decision taken in general meeting.
Akşehir Bankası T.A.Ş.	1916	"Akşehir Bankası T.A.Ş." was founded in 1916 for 50 years. The bank was liquidated upon the decision taken in general meeting, in 7 January 1966.

[7] All of the table is copied without any changes from: (TBB, 2011); BRSB: The Banking Regulation and Supervision Board, Treasury: The Under-secretariat of Treasury, Fund: Savings Deposit Insurance Fund

	Establish. Year	Historical Data
Anadolu Bankası T.A.Ş.	1962	"Anadolu Bankası A.Ş." was founded as a privately owned deposit bank formed by Türk Ekspres Bank, Buğday Bankası and the Treasury, in 1962. The statute was changed in 1985 and its name changed to "Anadolu Bankası T.A.Ş." and it was transferred to the "State-owned deposit Banks" group. It was merged with Emlak Kredi Bankası A.O. in 8 January 1988. During the privatization process of Etibank A.Ş. in 1997(which was divided into 3 parts Etibank A.Ş., Denizcilik Bankası T.A.Ş. and Anadolu Bankası T.A.Ş.), the privileges of trade name and banking license of Anadolu Bankası T.A.Ş. were transferred to Anadolubank A.Ş. *(please refer to Anadolubank A.Ş.)*
Ankara Halk Sandığı T.A.Ş.	1938	"Ankara Halk Sandığı T.A.Ş." was founded in 1938 and then, it became a branch of Türkiye Halk Bankası A.Ş. in 1964.
Atlas Yatırım Bankası A.Ş.	1999	"Süzer Yatırım Bankası A.Ş." was founded in 1999. Its name was changed to "Atlas Yatırım Bankası A.Ş." in 11 May 1999. The BRSB has decided to revoke the license of "Atlas Yatırım Bankası A.Ş." to perform banking operations with the Decree No. 378, which is published in the Official Gazette No.24458 dated 10 July 2001.
Bank Kapital Türk T.A.Ş.	1986	"'Bank Indosuez" was founded as a foreign bank in 1986 and its name was changed to "Bank Indosuez Türk A.Ş." in 31 December 1990 by changing its group to "Foreign Banks Having Branches in Turkey" to "Foreign Banks Founded in Turkey" group. The name was again changed to "Bank Indosuez Generale Euro Türk A.Ş. (Eurotürk Bank)" in 8 November 1993. Its name was changed to "Bank Kapital Türk A.Ş." in 22 June 1995, by transferring Ceylan Group. Bank Kapital Türk A.Ş. was transferred to Fund in 27 October 2000. Then, the banking license of Bank Kapital Türk A.Ş. was revoked and it was consolidated under the name of Sümerbank A.Ş. in 18 February 2001.
Bank of Credit and Commerce International	1982	"Bank of Credit and Commerce International Ltd." was licensed with 3 branches in İstanbul, İzmir and İçel by the Council of Ministers upon Decree Nr: 8/1967 dated 21 November 1980. The permission of "Bank of Credit and Commerce International Ltd." to accept deposits was revoked upon Decree Nr: 91/1992 dated 20 July 1991 of the Council of Ministers.
Banka Kommerçiale İtalyana	1919	"Banca Commerciale Italiana" was founded in 1919 and then liquidated upon the decision taken in the Board of Directors in 28 March 1977.
Birleşik Türk Körfez Bankası A.Ş.	1988	"Birleşik Türk Körfez Bankası A.Ş." was founded as a foreign bank in 7 July 1988. It was transferred to "Privately-owned Commercial Banks" group in 7 July 1995. Then, it was consolidated under the name of Osmanlı Bankası A.Ş. in 29 August 2001.

	Establish. Year	Historical Data
Birleşik Yatırım Bankası	1989	"Birleşik Yatırım Bankası A.Ş." was founded with the Decree of Council of Ministers, which was published in the Official Gazette Nr. 19972, dated 27 November 1988. The banking operations were started in 29 June 1989. The banking license of "Birleşik Yatırım Bankası A.Ş." was revoked with the Decree no. 99/13765, which is published in the Official Gazette Nr. 23914, dated 22 December 1999.
Bor Zürra ve Tüccar Bankası	1922	The license was revoked in 13 June 1961 and the bank was liquidated in 22 September 1961 by the decision of Board of Directors.
Credit Lyonnais S.A.	1987	"Credit Lyonnais S.A. İstanbul Branch" was transferred to Credit Agricole Indosuez Türk Bank A.Ş. together with all its rights, assets and liabilities as of 3 March 2004, and by cancellation of its Trade Registry in 18 March 2004.
Credit Suisse First Boston	1998	"Credit Suisse First Boston İstanbul Branch" was founded with Decree of Council of Ministers, which was published in the Official Gazette Nr. 23316, dated 17 April 1998. The liquidation process of "Credit Suisse First Boston İstanbul Branch" has started in accordance with the Resolution of BRSB Nr. 1127, dated 11 September 2003, which refer to paragraph 2 Article 18 of the Banks Act Nr. 4389.
Demirbank T.A.Ş.	1953	"Demirbank T.A.Ş." was founded in 1953 in order to finance the iron trade in Galata in İstanbul. It was transferred to Fund in accordance with the Resolution of BRSB Nr.123, which was published in Official Gazette Nr.24252(supplement), dated 6 December 2000. It was transferred to "HSBC Bank A.Ş." in accordance with the Resolution of BRSB Nr.547, dated 11 December 2001, which was published in Official Gazette Nr.24612, dated 13 December 2001 by losing its status of legal entity, all rights, assets and liabilities.
Denizcilik Bankası T.A.Ş.	1952	"Denizcilik Bankası" was founded as a state bank in 1938 in order to finance the maritime sector. Its name was changed to Denizcilik Bankası T.A.O. in 1952. The statute was changed in 1983 and its name changed to "Denizcilik Bankası T.A.Ş." It was merged with Emlak Kredi Bankası A.O. in accordance with the Decree of Council of Ministers, which was published in the Official Gazette Nr:21420(supplement), dated 20 November 1992. It was privatized and separated from Türkiye Emlak Bankası A.Ş. in 1997. Then, it was transferred to Zorlu Holding A.Ş. *(please refer to Denizbank A.Ş.)*
Doğubank	1952	"Doğubank" was liquidated in 2 January 1962 upon the Decree of the Council of Ministers published in Official Gazette with Nr:10975 dated 5 December 1961. The liquidation process would be made under the supervision of Türkiye İş Bankası A.Ş.

	Establish. Year	Historical Data
Efesbank Ltd. Şti.	1932	"Efesbank Ltd. Şti." was founded as a local bank in 1932. The statute was changed in 1962 and it was liquidated in 1 October 1972.
Ege Giyim Sanayicileri Bankası A.Ş.	1995	"Ege Giyim Sanayicileri Yatırım Bank A.Ş." was founded in 1995 as a non-depository bank and its name was changed to "Ege Giyim Sanayicileri Bankası A.Ş." in 1 December 1996 by transferring to "Privately-owned Deposit Banks" group. It was transferred to the Fund in 10 July 2001 and it was consolidated under the name Bayındırbank A.Ş. in the same year, 26 December 2001. The transfer and merge was completed as of 18 January 2008, as of this date the banking license and the permission to accept deposits was revoked.
Egebank A.Ş.	1928	"Egebank A.Ş." was transferred to the Fund in 22 December 1999. Then, the banking license of Egebank A.Ş. was revoked and it was consolidated under the name of "Sümerbank A.Ş." in 18 February 2001.
Eskişehir Bankası T.A.Ş.	1927	"Eskişehir Bankası T.A.Ş." was founded as a local bank in 15 September 1927 and made banking operations with one branch until 1955. The bank spread out its operations and transferred to Zeytinoğlu group in 1977. It was transferred to Fund in accordance with the Decree of Council of Ministers Nr:99/13765, dated 21 December 1999, which was published in the Official Gazette with Nr:23914(supplement), dated 22 December 1999. It was merged under the name of "Etibank A.Ş." in 2 July 2001, in accordance with the Resolution of BRSB with Nr.346, dated 15 June 2001.
Esnaf Kredi Bankası	1957	The license of "Esnaf Kredi Bankası to accept deposits was revoked upon the Decree of the Council of Ministers published in the Official Gazette with Nr:10533 dated 23 June 1969. The liquidation process was made under the supervision of Türkiye İş Bankası A.Ş. (the Decree was published in the Official Gazette with Nr:10713 dated 21 January 1961.

	Establish. Year	Historical Data
Etibank A.Ş.	1935	"Etibank" was founded as a state bank in 1935 and played o great role in constracting power stations, producing electricity, bringing out underground resources, marketing etc. It started its banking activities in 1955. The banking division was seperated from the main group in accordance with the Decree of Council of Ministers with Nr.93/4611(Official Gazette with Nr.21636, dated 13 July 1993), by changing its name to Etibank Bankacılık A.O. It was privatized in 2 March 1998 and sold to Medya İpek Holding A.Ş. Its name again was changed to Etibank A.Ş. It was tansferred Medya Sabah Holding A.Ş. in 2000. It was transferred to Fund (Official Gazette Nr.24213(supplement1), dated 27 October 2000). Eskişehir Bankası T.A.Ş. and Interbank A.Ş. were merged into Etibank A.Ş. in 2 July 2001, (Resolution of BRSB with Nr.346, dated 15 June 2001; Official Gazette Nr.24439, dated 21 June 2001). The banking license of "Etibank A.Ş." was revoked decided to be liquidated in 28 December 2001(Resolution of BRSB with Nr.554, dated 13 December 2001; Official Gazette Nr.24613, dated 14 December 2001). Then, the liquidation process was revoked and it was transferred to Bayındırbank A.Ş., with its assets and liabilities, in 5 April 2002.
Fiba Bank A.Ş.	1985	"Chemical Mitsui Bank A.Ş." was founded in 1985 as a foreign bank. Its name was changed to "Türk Mitsui Bank A.Ş." in 1 December 1989 when the 51% shares are sold to Mitsui Bank Limited. Its name again changed to "Türk Sakura Bank A.Ş." in 1 Nisan 1992. It was transferred to the "Privately-owned Commercial Banks" group after it was sold to Fiba Holding in 23 November 1999. The name of the bank was changed to Fiba Bank A.Ş. in 13 April 2000. Fiba Bank A.Ş." was taken over by the Finans Bank A.Ş. with its assets, liabilities and deposits, with the Resolution Nr.1023 of BRSB. Its legal entity was ended in 9 April 2003.
Fortis Bank A.Ş.	1964	"Amerikan-Türk Dış Ticaret Bankası A.Ş." was founded as a private bank in 9 April 1964 and its name was changed to "Türk Dış Ticaret Bankası A.Ş." in 1970. Then, 89.34 percent paid-in capital of Türk Dış Ticaret Bankası A.Ş was transferred to Fortis Bank NV-SA, as of 4 July 2005 and the bank was transferred from "Privately-owned Commercial Banks" group to "Foreign Banks Founded in Turkey" group. Then its name was changed to "Fortis Bank A.Ş." in 24 November 2005. Fortis Bank A.Ş. was taken over by Türk Ekonomi Bankası A.Ş. together with all assets and liabilities in 25 January 2011. Its legal entity was ended in 14 February 2011.

	Establish. Year	Historical Data
Hisarbank A.Ş.	1910	"Terakki Servet Osmaniyesi" was founded as local bank in 1910 and the name of the bank was changed to "Afyon Terakki Servet Bankası T.A.Ş." in 1926. The statute was changed in 1975 and the name was again changed to "Hisarbank" in 28 June 1979. Lastly, it was transferred to Türkiye Cumhuriyeti Ziraat Bankası in accordance with the Decree of Council of Ministers, which was published in the Official Gazette with Nr.18231, dated 24 November 1983.
ING Bank N.V.	1997	ING Bank N.V. İstanbul Branch was founded in 1997 as a foreign bank having branch in Turkey. It was registered to the Turkish Trade Registry in 11 April 1997, Nr. 4259. The BRSB decided to revoke the license of "ING Bank N.V. İstanbul Branch" upon request to perform banking operations and to accept deposits according to Banks Act Article 18/2 with the Decree No.1037 dated 1 May 2003. It was started to be liquidated in 30 June 2003.
İktisat Bankası T.A.Ş.	1927	"Denizli İktisat Bankası" was founded as a local bank in 1927. The statute was changed and it was transferred to the privately owned deposit banks group in 1971. Its name was changed to "İktisat Bankası T.A.Ş." in 1980 by moving its head office to İstanbul. "İktisat Bankası A.Ş." was transferred to the Fund with the Resolution Nr.198 of BRSB, dated 14 March 2001, which was published in the Official Gazette Nr.24343(supplement), dated 15 March 2001. The banking license of Egebank A.Ş. was revoked with the Resolution Nr.527 of BRSB, dated 28 November 2001, which was published in the Official Gazette Nr.24599, dated 30 November 2001. It was started to be liquidated in 7 December 2001. Then, the liquidation process was revoked and it was transferred to Bayındırbank A.Ş., with its assets and liabilities, in 5 April 2002.
İnterbank A.Ş.	1888	"Selanik Bankası T.A.Ş." was founded as a foreign bank in 1888 in Selanik and the head office was moved to İstanbul in 1912. Its name was changed to "Uluslararası Endüstri ve Ticaret Bankası" in 1969. The statute was changed and it was transferred to the privately owned deposit banks group in 1978. When the %71.94 shares was moved to Çukurova Group and its name was again changed to "Interbank A.Ş." in 1990, by announcing in Turkish Trade Registry with Nr. 2663, dated 30 November 1990. Then, the shares are Çukurova Group to Nergis Holding in 1996. Interbank A.Ş. was transferred to Fund 7 January 1999 and it was merged under the name of "Etibank A.Ş." with the Resolution Nr.346 of BRSB, dated 15 June 2001, which was published in the Official Gazette Nr.24439, dated 21 June 2001 and it was closed in 2 July 2001.

	Establish. Year	Historical Data
İstanbul Bankası T.A.Ş.	1953	" İstanbul Bankası T.A.Ş." was founded in 1953. It was transferred to Türkiye Cumhuriyeti Ziraat Bankası with its all assets and liabilities, with the Decree Nr.18231 of Council of Ministers, which was published in the Official Gazette Nr. 18231, dated 24 November 1983.
İstanbul Emniyet Sandığı	1868	"İstanbul Emniyet Sandığı" was founded in 1868. It was bound to T.C. Ziraat Bankası in 1907 and then it was taken in the name of T.C. Ziraat Bankası in 1 January 1984.
İstanbul Halk Sandığı T.A.Ş.	1936	"İstanbul Halk Sandığı T.A.Ş." was founded in 1936 and then it became a branch of Türkiye Halk Bankası A.Ş. in 1964.
İşçi Kredi Bankası T.A.Ş.	1954	"İşçi Kredi Bankası T.A.Ş." was founded as a local bank in 1957 in Kayseri. The statute was changed and it was transferred to privately owned deposit banks group in 1964. The management and the control of the bank was transferred to the main shareholder (ie.Türkiye İş Bankası A.Ş.) with the Order Nr. 5238/217/6-63673 of Ministry of Finance in 16 September 1983. The banking license of "İşçi Kredi Bankası T.A.Ş." was revoked with the Decree Nr.8/723 of Council of Ministers in 25 October 1983.
İzmir Halk Sandığı T.A.Ş.	1957	"İzmir Halk Sandığı T.A.Ş." was founded in 1957 and then, it became a branch of Türkiye Halk Bankası A.Ş. in 1964.
Kentbank A.Ş.	1992	"Türkiye Konut Endüstri ve Ticaret Bankası A.Ş." was founded in 2 March 1992 and its name was changed to "Kentbank A.Ş." when the shares were transferred to Süzer Holding in 6 April 1994. Kentbank A.Ş. was transferred to Fund with the Resolution Nr.382 of BRSB, which was published in the Official Gazette Nr.24458, dated 10 July 2001. The banking license of Kentbank A.Ş. was revoked with the Resolution Nr.552 of BRSB, which was published in the Official Gazette Nr.24613, dated 14 December 2001 and it was started to be liquidated in 28 December 2001. Then, the liquidation process was revoked and it was transferred to Bayındırbank A.Ş., with its all assets and liabilities, in 5 April 2002.
Kıbrıs Kredi Bankası Ltd.	1989	"Kıbrıs Kredi Bankası Ltd." was founded in 1989 as a foreign bank having branches in Turkey. The BRSB decided to revoke the license of "Kıbrıs Kredi Bankası Ltd." to perform banking operations and to accept deposits according to Banks Act Article 14/3 upon the Decree Nr.59, which was published in the Official Gazette Nr.24184, dated 28 September 2000.

	Establish. Year	Historical Data
Koçbank A.Ş.	1981	"American Express I.B.C." was founded as a foreign bank in 1981.It was transferred "Privately-owned deposit banks" group when the 51% of its shares were owned by Koç Group in 1986 by changing its name to Koç Amerikan Bank A.Ş. Then, Koç Group acquired 100% shares of the bank and its name was changed to Koçbank A.Ş. in 1993. Exclusive negotiations between Koç Financial Services (KFS – the 50/50 joint venture between Unicredit and Koç Group, which owned Koçbank and other financial subsidiaries) and the Çukurova Group was started in January 2005. An agreement was signed in May 2005 for the acquisition of 57.4 percent share in Yapı ve Kredi Bankası A.Ş. (held by the Çukurova Group and Fund). Losing its status of legal entity, all rights, assets and liabilities of Koçbank A.Ş. were transferred to Yapı ve Kredi Bankası A.Ş by the resolution Nr: 1990 of the BRSB, dated 28 September 2006.
Lüleburgaz Birlik Ticaret Bankası	1929	"Lüleburgaz Birlik Ticaret Bankası" was founded as a local bank in 1929 and decided to be liquidated in 28 June 1964. Its operations was ceased in 1 September 1964.
Maden Kredi Bankası A.Ş.	1957	"Maden Kredi Bankası A.Ş." was founded as a local bank in 4 October 1957. The statute of the bank was changed in 1962 and it transferred to "privately-owned commercial banks" group. Then, it was liquidated in 12 April 1972.
Marmara Bankası A.Ş.	1987	"Netbank A.Ş." was founded in 1987 and its name was changed to "Marmara Bankası A.Ş." in 1991. The banking license of "Marmara Bankası A.Ş." was revoked with the Decree Nr. 94/5483 of Council of Ministers, which was published in the Official Gazette Nr. 21914, dated 24 April 1994 and it was liquidated by Türkiye İş Bankası A.Ş.
Milli Aydın Bankası T.A.Ş. (Tarişbank)	1913	"Milli Aydın Bankası T.A.Ş.(Tarişbank)" was founded as a local bank in İzmir in 1913 and started its operations in 1914. The banking operations was temporarily ceased during the world war, then it started again in 1925. It was transferred to Fund with the Resolution Nr.381 of BRSB, dated 9 July 2001, which was published in the Official Gazette Nr.24458, dated 10 July 2001. Then, the Council of State was stopped this decision within the same year. It was transferred to Denizbank A.Ş., with the Resolution Nr.929 of BRSB, dated 19 December 2002, which was published in the Official Gazette Nr.24970, dated 21 December 2002, with its assets and liabilities, Its legal entity was ending by announcing in İzmir Trade Registry in 27 December 2002.

	Establish. Year	Historical Data
Morgan Guaranty Trust Co.	1999	"Morgan Guaranty Trust Company" was founded as a foreign bank having branches in Turkey in 1999. The holding companies The Chase Manhattan Bank and Morgan Guaranty Trust Company of New York located in the USA have merged with The Chase Manhattan Corporation and J.P. Morgan & Co Incorporated as of 31 December 2000. As a result of this merge, "Morgan Guaranty Trust Company" have merged with "The Chase Manhattan Bank" in 10 November 2001. The title of this bank was changed to "JPMorgan Chase Bank" in 21 December 2001 *(please refer to JPMorgan Chase Bank N.A.).*
Niğde Bankası	1948	"Niğde Bankası" was liquidated in 7 May 1960 upon the decision taken by the Board of Directors. The banking license and the permission to accept deposits was revoked upon the Decree Nr: 5/371 of Council of Ministers, dated 23 September 1960.
Okan Yatırım Bankası A.Ş.	1998	"Okan Yatırım Bankası A.Ş." was founded as a development and investment bank in 1998. The BRSB decided to revoke the license of Okan Yatırım Bankası A.Ş. to perform banking operations with the Resolution of BRSB Nr.380 dated 9 July 2001, which was published in the Official Gazette Nr. 24458, dated 10 July 2001.
Ortadoğu İktisat Bankası T.A.Ş.	1929	"Elazığ İktisat Bankası" was founded as a local bank in 1929. The statute of the bank was changed in 1974. The head office was moved to İstanbul and its name was changed to "Ortadoğu İktisat Bankası T.A.Ş." in 29 July 1980. Then, it was transferred to TC Ziraat Bankası A.Ş. for liquidation according to the Decree of Council of Ministers which was published in the Official Gazette Nr.18231, dated 24 November 1983.
Osmanlı Bankası A.Ş.	1863	"Bank-ı Osmanii Şahane (Ottoman Bank)" was founded in 1863 and its name was changed to "Osmanlı Bankası A.Ş." in 1923. Birleşik Türk Körfez Bankası A.Ş. was merged to Osmanlı Bankası A.Ş. with the Resolution of BRSB Nr.450 dated 27 August 2001, which was published in the Official Gazette Nr. 24508, dated 29 August 2001. Osmanlı Bankası A.Ş. was transferred to Türkiye Garanti Bankası A.Ş. upon the Resolution Nr. 548 of The BRSB in 11 December 2001, which is published in the Official Gazette no.24612 dated 13 December 2001, by losing its status of legal entity, all rights, assets and liabilities.

	Establish. Year	Historical Data
Pamukbank T.A.Ş.	1955	"Pamukbank T.A.Ş." was founded as a privately owned deposit bank in 1955. It was transferred to Fund with the Resolution of BRSB Nr.742 dated 18 June 2002, which was published in the Official Gazette Nr. 24790, dated 19 June 2002. Then, Pamukbank T.A.Ş. was transferred to "Türkiye Halk Bankası A.Ş." together with all assets, liabilities and off-balance sheet commitments, with the Resolution of BRSB Nr.1415 dated 9 November 2004, which was published in the Official Gazette Nr. 25639, dated 10 November 2004. The transfer was realized in 12 November 2004 and all the branches of Pamukbank T.A.Ş. are started to operate as the branches of Türkiye Halk Bankası A.Ş. in 17 November 2004.
Park Yatırım Bankası A.Ş.	1992	Park Yatırım Bankası A.Ş." was founded as a development and investment bank in 1992.The BRSB decided to revoke the license of "Park Yatırım Bankası A.Ş." to perform banking operations according to Banks Act Article 14/3 and 20/2, upon the Resolution Nr.122 of BRSB, which was published in the Official Gazette Nr.24252(supplementary), dated 6 December 2000.
Rabobank Nederland	1998	"Rabobank Nederland" was founded as a foreign bank in 1998. The BRSB has decided to revoke the license of "Rabobank Nederland İstanbul Branch to perform banking operations and to accept deposits according to Banks Act Article 18/2 with the Resolution Nr. 678, dated 2 April 2002, which was published in the Official Gazette Nr. 24715, dated 3 April 2002.
Raybank	1956	"Raybank" was decided to be liquidated by the directions of the Ministry of Finance, published in the Official Gazette, Nr.11747, dated 7 July 1964. The liquidation was made under the control and supervision of Türkiye Emlak Kredi Bankası.
Sağlık Bankası A.Ş.	1928	"Şarkikaraağaç Bankası" was founded in 1928 and the name was changed to "Sağlık Bankası A.Ş." in 1962. The bank was liquidated in 24 March 1975.
Sınai Yatırım Bankası A.Ş.	1963	"Sınai Yatırım ve Bankası A.O." was founded as an investment bank in 13 March 1963. Its name was changed to "Sınai Yatırım Bankası A.Ş." in 18 June 1997. Sınai Yatırım Bankası A.Ş. was transferred to Türkiye Sınai Kalkınma Bankası A.Ş. with the Resolution Nr.659 of BRSB, dated 27 March 2002, which was published in the Official Gazette Nr.24710, dated 29 March 2002, losing its status of legal entity, all rights, assets and liabilities.

	Establish. Year	Historical Data
Sümerbank A.Ş.	1933	Sümerbank Holding A.Ş. was founded in 1933 and the banking department of "Sümerbank Holding A.Ş." was separated from the holding and started its operations as "Sümerbank A.O." in 1993. "Sümerbank A.O." was privatized in 24 October 1995, sold to Garipoğlu Group and its name was changed as "Sümerbank A.Ş.". It was transferred to Fund with the Decree Nr.99/13765 of Counsil of Ministers, which was published in the Official Gazetee Nr.23914(supplement) in 22 December 1999. Egebank A.Ş., Bank Kapital Türk A.Ş., Yurt Ticaret ve Kredi Bankası A.Ş., Türkiye Tütüncüler Bankası Yaşarbank A.Ş. and Ulusal Bank A.Ş. were merged to Sümerbank A.Ş. in 2001. Then, the shares of Sümerbank A.Ş. was decided to be sold to Oyak in 9 August 2001 and the bank transferred again to "privately-owned deposit banks" group. Then, Sümerbank A.Ş. was transferred to Oyak Bank A.Ş. in 11 January 2002, losing its status of legal entity, all rights, assets and liabilities.
Tekfen Yatırım ve Finansman Bankası A.Ş.	1989	"Tekfen Yatırım ve Finansman Bankası A.Ş." was founded as a development and investment bank in 1989. It was transferred to Bank Ekspres A.Ş. upon the Resolution Nr. 489 of BRSB, dated 18 October 2001, losing its status of legal entity.
The American Express Bank Co.	1955	"The American Express Bank Co." was founded as a foreign in 1955 and the bank and it was liquidated in 1961.
Toprakbank A.Ş.	1992	"Toprakbank A.Ş." was founded as a privately owned deposit bank in 1948 and it was transferred to Fund with the Resolution Nr. 538 of BRSB, which was published in the Official Gazette Nr.24600, dated 1 December 2001. Then, it was decided to be transferred to Bayındırbank A.Ş. with the Resolution Nr. 826 of BRSB, which was published in the Official Gazette Nr.24889, dated 27 September 2002. Toprakbank A.Ş. was merged with Bayındırbank A.Ş. in 30 September 2002 and the banking license of Toprakbank A.Ş. was revoked at the same date.
Tutum Bankası T.A.O.	1948	"Tutum Bankası T.A.O." was decided to be liquidated with the Decree No. 6/1782 of Council of Ministers in 20 May 1963. It was declared in Official Gazette Nr. 11445 that the liquidation process would be made under the supervision of Türkiye Emlak Bankası A.Ş. in 4 July 1963.

	Establish. Year	Historical Data
Türk Ticaret Bankası A.Ş.	1913	"Adapazarı İslam Ticaret Bankası" was founded as a local bank in 1913. The name was changed to "Türk Ticaret Bankası A.Ş." in 1937. Its head office was moved to İstanbul in 1952. It was transferred to Fund in 27 June 1997. The banking license of Türk Ticaret Bankası A.Ş. was decided to be revoked and the bank was decided to be liquidated starting from 1 July 2001, with the Resolution Nr. 346 of BRSB, which was published in the Official Gazette Nr.24439, dated 21 June 200. Then, Türk Ticaret Bankası Employees` Pension and Mutual Aid Fund opened suits to the Council of State to stop the process several times. Lastly, Türk Ticaret Bankası A.Ş. made an extraordinary General Meeting and decided to liquidate the bank in 9 August 2002.
Türkiye Bağcılar Bankası A.Ş.	1917	"Manisa Bağcılar Bankası" was founded as a local bank in 1917 and the name of the bank was changed to "Türkiye Bağcılar Bankası A.Ş." in 1950. The banking license was revoked in 26 January 1984.
Türkiye Birleşik Tasarruf ve Kredi Bankası A.Ş.	1957	"Türkiye Muallimler, Memurlar ve Subaylar Bankası" (Tümsubank) was founded in 1967 and it was merged with "Türkiye Eski Muharipler Bankası" (Muhabank) in 1959, by changing its name to "Türkiye Birleşik Tasarruf ve Kredi Bankası A.Ş.". The liquidation process of the bank was made under the supervision of Türkiye Emlak Kredi Bankası in 28 March 1961.
Türkiye Cumhuriyeti Turizm Bankası A.Ş.	1962	"Türkiye Cumhuriyeti Turizm Bankası A.Ş." was founded as a state bank in 1962 and the statute was changed and the bank was transferred to "state owned development and investment banks" group in 1986. Then, the bank was merged with Türkiye Kalkınma Bankası A.Ş. in 1989, with its all assets and liabilities.
Türkiye Emlak Bankası A.Ş.	1926	"Emlak ve Eytam Bankası" was founded in 1926 and its name was changed to "Türkiye Emlak Kredi Bankası T.A.O." in 1 September 1946. It was merged with Anadolu Bankası T.A.Ş. in 8 January 1988 and its name again changed to "Türkiye Emlak Bankası A.Ş.". A new restructuring process was started by Act Nr 4603 in 2000 and it was transferred to Türkiye Cumhuriyet Ziraat Bankası A.Ş., together with all assets and liabilities, as of 6 July 2001. Consequently, as of 9 July 2001, the Head Office as well as all the branches of Türkiye Emlak Bankası A.Ş. continued their banking activities within and under the name of T.C. Ziraat Bankası A.Ş. Then, 96 branches of Türkiye Emlak Bankası A.Ş., together with balance-sheets and staff, was transferred to Türkiye Halk Bankası A.Ş. as of November 12, 2001.

	Establish. Year	**Historical Data**
Türkiye Eski Muharipler Bankası (Muhabank)	1949	"Türkiye Eski Muharipler Bankası (Muhabank)" was founded in 1949 and it was merged with "Türkiye Muallimler, Memurlar ve Subaylar Bankası (Tümsubank)" in 1959 *(please refer to Tümsubank)*.
Türkiye İmar Bankası T.A.Ş.	1928	"Turkiye İmar Bankasi T.A.Ş." was founded as a privately owned deposit bank in 1928. The license of "Turkiye İmar Bankasi T.A.Ş." to perform banking activities and accept deposits was revoked upon the Resolution Nr.1085 of BRSB, dated 3 July 2003, pursuant to Article 14/3 of the Banks' Act Nr. 4389, due to the fact that the Bank could not timely fulfill its obligations, that it did not take the required measures, and that continuation of its banking activities would have posed a danger to depositors' rights as well as the safety and soundness of the financial system. The Court decided the bank to bankruptcy in 8 June 2005
Türkiye İthalat ve İhracat Bankası A.Ş. (Impexbank)	1984	"Türkiye İthalat ve İhracat Bankası A.Ş. (Impexbank)" was decided to be liquidated with the Decree Nr. 94/5485 of Council of Ministers, which was published in the Official Gazette, Nr.21914, dated 24 April 1994. The liquidation process was made under the supervision of Türkiye Emlak Bankası A.Ş.
Türkiye Kredi Bankası A.Ş.	1948	"Türkiye Kredi Bankası" was liquidated by Türkiye İş Bankası A.Ş. in 1966.
Türkiye Maden Bankası A.Ş.	1968	"Türkiye Maden Bankası A.Ş." was not operated after it was founded and then it was decided to be liquidated in the General Meeting in 6 March 1974. This decision was published in the Turkish Trade Registry Nr.5142, dated 8 May 1974. The liquidation is made under the supervision of Türkiye İş Bankası A.Ş..
Türkiye Öğretmenler Bankası T.A.Ş. (Töbank)	1958	"Türkiye Öğretmenler Bankası T.A.Ş." was founded in 1958 in Ankara. The head office was moved to İstanbul in 1985. Then, it was merged with Türkiye Halk Bankası A.Ş. With the Decree of Council of Ministers which was published in Official Gazette Nr. 21235, dated 22 May 1992.
Türkiye Turizm Yatırım ve Dış Ticaret Bankası A.Ş. (TYT Bank)	1988	"Türkiye Turizm Yatırım ve Dış Ticaret Bankası A.Ş.(TYT Bank)" was founded as a development and investment bank in 1988. The license of the bank to perform banking activities and accept deposits was revoked and the bank decided to be liquidated upon the Decree No. 94/5483 of Council of Ministers, which was published in the Official Gazette, Nr. 21902, dated 11 April 1994. The bank was liquidated under the supervision of Türkiye İş Bankası A.Ş.

	Establish. Year	Historical Data
Türkiye Tütüncüler Bankası Yaşarbank A.Ş.	1924	"Akhisar Tütüncüler Bankası" was founded as a local bank in Akhisar in 26 August 1924. Its name was changed to "Türkiye Tütüncüler Bankası A.Ş." in 1954. Its head office first moved to İzmir in 1955, then to İstanbul in 1989. Then, The bank was acquired from Yaşar Group and its name again changed to "Türkiye Tütüncüler Bankası Yaşarbank A.Ş." in 26 December 1996. The bank was transferred to Fund with the Decree Nr.99/13765 of Council of Ministers, dated 21 December 1999, which was published in the Official Gazette Nr.23914 (supplement), dated 22 December 1999. Then, the banking license of Türkiye Tütüncüler Bankası Yaşarbank A.Ş. was revoked with the Resolution Nr.178 of BRSB, which was published in the Official Gazette Nr.24322, dated 18 February 2001. It was consolidated under the name of "Sümerbank A.Ş." in 18 February 2001.
Ulusal Bank T.A.Ş.	1985	"Saudi American Bank" was founded as a foreign bank in 1985. The bank was acquired from Ephesus Group and its name was changed to "Ulusal Bank T.A.Ş." in 6 February 1997. By then, it was transferred from "Foreign banks having branches in Turkey" group to "Foreign banks founded in Turkey" group. The bank was transferred to Fund in with the Resolution Nr.189 of BRSB, which was published in the Official Gazette Nr.24332, dated 28 February 2001. The banking license of Ulusal Bank T.A.Ş. was revoked and it was consolidated under the name of "Sümerbank A.Ş." with the Resolution Nr.290 of BRSB, which was published in the Official Gazette Nr.24407, dated 20 May 2001.
Unicredit Banca di Roma S.p.A.	1911	"Banco di Roma" was founded in 1911 and its name was changed to "Banca di Roma S.P.A." in 1992. The main shareholder of the bank- Capitalia S.P.A- merged with Unicredit Group worldwide in 2007. As a result of this, Banca di Roma-İstanbul Branch Office transferred its commercial banking activities to Yapı ve Kredi Bankası A.Ş. in 8 December 2007. Then, its name of "Banca di Roma S.P.A." was changed to "Unicredit Banca di Roma S.p.A." in 26 March 2008. The banking license was revoked and liquidation process was started according to the Resuliton Nr.2893 of BRSB dated 13 November 2008.

	Establish. Year	Historical Data
Yurt Ticaret ve Kredi Bankası A.Ş. (Yurtbank)	1993	"Eurocredit Türk Fransız Ticaret Bankası A.Ş." was founded as a foreign bank in 7 September 1993. Then, it was transferred to privately owned deposit banks group after its name was changed to "Yurt Ticaret ve Kredi Bankası A.Ş." in 6 October 1994. The bank was transferred to Fund with the Decree Nr.99/13765 of Council of Ministers, dated 21 December 1999, which was published in the Official Gazette Nr.23914(supplement), dated 22 December 1999. The banking license of Yurt Ticaret ve Kredi Bankası A.Ş. was revoked and it was consolidated under the name of "Sümerbank A.Ş." upon the Resolution Nr.178 of BRSB, which was published in the Official Gazette Nr.24322, dated 18 February 2001.

TEZ FOTOKOPİ İZİN FORMU

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YAZARIN

Soyadı : BOYRAZ
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Bölümü : İktisat

TEZİN ADI (İngilizce) : An Empirical Study on Early Warning Systems for Banking Sector

TEZİN TÜRÜ : Yüksek Lisans ☒ Doktora ☐

1. Tezimin tamamı dünya çapında erişime açılsın ve kaynak gösterilmek şartıyla tezimin bir kısmı veya tamamının fotokopisi alınsın. ☐
2. Tezimin tamamı yalnızca Orta Doğu Teknik Üniversitesi kullanıcılarının erişimine açılsın. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.) ☐
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Yazarın imzası .... Tarih ....