MFDM: MRI FREE DECISION MODEL FOR DIAGNOSIS AND TREATMENT SELECTION IN PATIENTS WITH LOW BACK AND NECK PAIN

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MFDM: MRI FREE DECISION MODEL FOR DIAGNOSIS AND TREATMENT SELECTION IN PATIENTS WITH LOW BACK AND NECK PAIN

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ABSTRACT

MFDM: MRI FREE DECISION MODEL FOR DIAGNOSIS AND TREATMENT SELECTION IN PATIENTS WITH LOW BACK AND NECK PAIN

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Low back pain (LBP) and neck pain (NP) are public health problems affecting life quality worldwide. Our goal was to develop a machine learning model that can direct LBP and NP patients for the appropriate treatment without magnetic resonance imaging (MRI) findings, thus reducing the demand for MRI and its burden on the health system. Following features from the patient data are analyzed to evaluate the treatment outcomes; demographic information, clinical findings, preoperative evaluation of pain, movement restriction, and pain data duration. Support Vector Machine (SVM) models are built by analyzing ten different attributes from 1482 patient data to classify correct treatment: drug, Radiofrequency (RF)/ Intradiscal Electrothermal Therapy (IDET), or surgical intervention. The stepwise model proposed here classifies drug therapy patients with an 84% success ratio and can direct patients to surgery or RF/IDET with a 74.47% success ratio without MRI results. The proposed MRI Free Decision Model (MFDM) can be utilized in primary healthcare facilities to direct the patients to the appropriate treatment options without MRI, reducing the cost and load on the healthcare system while benefiting the patient by reducing the time to initiate the treatment. There are several guideline recommendations for treating LBP and NP used in various countries, and we expect the proposed MFDM will provide a backbone to form guidelines in Turkey, similar to other guides followed in the EU and USA.

Keywords: Pain Treatment Analysis, Neck and Low Back Pain, Binary SVM, Multi-Class Classification, Burden of MRI

ÖZ

BEL VE BOYUN AĞRISI YAŞAYAN HASTALARDA TEŞHİS VE TEDAVİ SEÇİMİ İÇİN MR GÖRÜNTÜSÜ OLMADAN KARAR MODELİ

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Bel ağrısı (LBP) ve boyun ağrısı (NP), yaşam kalitesini etkileyen dünya çapında yaygın bir sağlık sorunudur. Bu çalışmadaki amacımız, LBP ve NP hastalarını manyetik rezonans görüntüleme (MRG) bulguları olmadan uygun tedavi için yönlendirebilen bir makine öğrenme modeli geliştirerek MRG talebini ve bunun sağlık sistemi üzerindeki yükünü azaltmaktır. Tedavi sonuçlarını değerlendirmek için hasta verilerinden aşağıdaki özellikler analiz edilir; demografik bilgiler, klinik bulgular, ağrının ameliyat öncesi değerlendirilmesi, hareket kısıtlaması ve ağrı veri süresi. Destek Vektör Makinesi (SVM) modelleri, ilaç, RF/IDET veya cerrahi müdahale tedavilerini doğru sınıflandırmak için 1482 hasta verisinden on farklı özellik analiz edilerek oluşturulmuştur. Burada önerilen aşamalı model, ilaç tedavisi hastalarını %84 başarı oranıyla sınıflandırır ve hastaları MRG sonuçları olmadan %74.47 başarı oranıyla cerrahiye veya RF/IDET'e yönlendirebilir. Önerilen MRG İçermeyen Karar Modeli (MFDM), birinci basamak sağlık kuruluşlarında hastaları MRG'siz uygun tedavi seçeneklerine yönlendirmek, maliyet ve sağlık sistemi üzerindeki yükü azaltmak ve tedaviye başlama süresini kısaltarak hastaya fayda sağlamak için kullanılabilir. Çeşitli ülkelerde kullanılan LBP ve NP'yi tedavi etmek için birkaç kılavuz tavsiyesi vardır ve önerilen MFDM'nin AB ve ABD'de izlenen diğer kılavuzlara benzer şekilde Türkiye'de kılavuz oluşturmak için bir omurga oluşturmasını bekliyoruz.

Anahtar Sözcükler: Ağrı Tedavi Analizi, Boyun ve Bel Ağrısı, İkili SVM, Çok Sınıflı Sınıflandırma, MRI Yükü

To my lovely family

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LIST OF ABBREVIATIONS

DRG	Dorsal Root Ganglion
FTR	Physical Medicine and Rehabilitation
ICD 10	10th Revision of the International Statistical Classification of Diseases and Related Health Problems
IDET	Intradiscal Electro Thermal Therapy
LBP	Low Back Pain
MCs	Musculoskeletal conditions
MFDM	MRI Free Decision Model
MRI	Magnetic Resonance Imaging
NP	Neck Pain
NSAIDs	Non-Steroidal Anti-Inflammatory Drugs
RCTs	Randomized Controlled Trials
RF	Radiofrequency Therapy
SVM	Support Vector Machine
VAS	Visual Analogue Scale
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

1.1. Background

According to the 2017 global burden of diseases, injuries, and risk factors, the magnitude of the non-fatal disease burden has increased globally, with an increasing number of people suffering from various conditions. Despite minor improvements in age-standardized rates, the global non-fatal burden continues to rise. For nearly three decades, three causes (low back pain, headaches, and depressive disorders) have been the leading causes of non-fatal health loss. [1].

Musculoskeletal conditions (MCs) severely limit mobility and dexterity, resulting in early retirement and a reduction in accumulated wealth. MCs are frequently associated with depression and increase the risk of developing other chronic health problems[2]. MCs and injuries affect people of all ages and are not merely conditions of old age. Musculoskeletal pain affects between one in three and one in five persons, including children[3]. According to World Health Organization (WHO) statistics, MCs are the leading cause of disability, with low back pain (LBP) being the leading cause of disability worldwide. LBP affects physical and mental functioning and affects life quality for almost 80% of adults at some point in their lifespan [4], [5], [6].

The most common diseases in Turkey are low back and neck pain. As we have presented in our results in a regular pain clinic workflow, the doctor examines the patient's MRI and determines which treatment the patient will be directed to according to the bulging or exudation status (Figure 1) in the spine and pain level. Patients are directed to radiofrequency, intradiscal electrothermal therapy, surgery, or drug treatment. In RF treatment, electrodes apply the radiofrequency wave to the facet joint or dorsal root ganglion nerve points. IDET is the process of entering the disc with a catheter and burning the disc by giving heat. Through SURGERY, the discs are repaired with open surgery. Also, there are approved prescriptions for DRUG treatment. Although MRI has a high cost and requires time, doctors frequently request it as it aids in diagnosis.

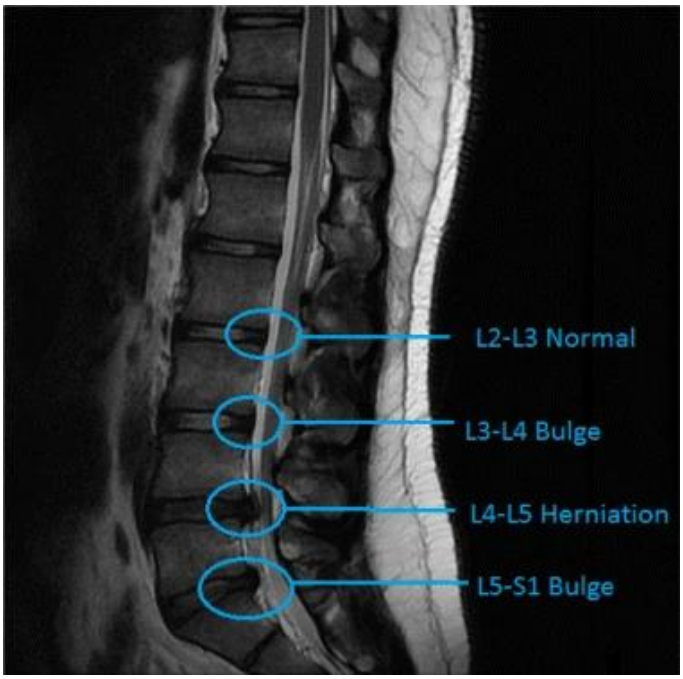

Figure 1. Mid-sagittal lumbar MRI [7]

In this study, we developed a decision support system to support the doctors' decision to order the appropriate treatment only based on the patient's clinical and demographic information without MRI findings for the low back and neck problems. We evaluated the proposed model's diagnostic power compared to the clinic workflow and demonstrated the potential savings from reduced MRI orders.

1.2. Motivation

Low back pain and neck pains are the most common diseases in Turkey and worldwide. Turkey has no commonly accepted guidelines for LBP and neck pain (NP) diagnosis. According to MRI results, patients are directed either to radiofrequency therapy, intradiscal electro thermal therapy, surgery, or drug therapy in the algology departments. MRI-based approach for the diagnosis and the therapy decision increases the cost and time lost, as it requires multiple visits to the doctor’s office, besides MRI fees.

We examined how patients with low back and neck pain can be directed to the right clinic with the patient's pre-data, avoiding MRI costs. So, we aimed to find answers to the following research questions.

- In primary health care facilities, can we direct the patients to the right clinic with the decision support system with only the patient's preliminary data without needing an MRI?

- Do the pre-evaluation criteria used in diagnosing low back and neck pain cause an unnecessary burden for the health system?

- How can we project the amount of potential savings for the healthcare system when the MRI is not required as the pre-evaluation criteria for diagnosing low back and neck pain?

1.3. Contributions of the Study

In this study, we focused on developing a decision support system that could guide the patients to the proper treatment method with no initial MRI tests for the low back and neck problems, which are the leading health problems.

'what was already known on the topic.'

- The study's first phase was conducted in 2017, where 493 lumbar facet syndrome patients were treated using radiofrequency from 2008-to 2013.
- Various decision support systems have been applied in the literature to determine whether the patient has low back or neck pain.
- There is no research on which treatment method the patient can be directed to based on preliminary data.

'what this study added to our knowledge.'

- This study proposes a new decision model (MFDM) to reduce MRI costs during diagnosing low back and neck pain, a global problem.
- We observed that unnecessary MRI costs were incurred, especially for patients who received medication that did not need MRI.
- MFDM aims to direct the patient to the correct clinic by evaluating the patient’s preliminary data at the primary healthcare facilities before any MRI testing.
- Policymakers and other healthcare stakeholders should consider that with the developed model, a general practitioner can direct patients with low back and neck pain to the right clinic while reducing unnecessary MRI testing and cost, which will positively affect the overall performance.

1.4. Organization of the Dissertation

The dissertation consists of six main chapters: Introduction, Background and Literature Review, Materials and Methods, Results, and Discussion and Conclusions. In the Introduction part, the reason why we started this study, our motivation to start, and the study's contributions are explained.

In the Background and Literature Review section, the definition, causes, and treatment methods of LBP and NP are mentioned, and the relevant areas within this scope are explained. In addition, studies related to these issues in the literature were examined.

The Materials and Methods section explains the scope and content of our data set, the data mining method used, and the pre-processing process applied to the data set before using

data mining methods are detailed. In addition, the analysis method used for possible cost savings is revealed.

In the Results section, the outputs and model cost analysis results obtained by data mining methods according to the workflow of the pain clinic from which we received the data are given.

Finally, in the Discussion section, the innovations that our results have added to the literature are discussed, the results are presented in the conclusion section, and future studies that can be done are indicated. All the details of Low Back and Neck pain and the proposed MRI Free Decision Model (MFDM) in this study are given in detail in the following chapters.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

This chapter briefly discusses the background and literature related to this study. The literature review is laid out in four main sections: (1) Low Back Pain and Neck Pain; (2) Causes of LBP and NP; (3) Treatment Methods for LBP and NP; and (4) Studies in LBP and NP with Decision Support Systems. The chapter is concluded with a summary of the background and literature review section.

2.1.Low Back Pain and Neck Pain

The human spine consists of 33 vertebrae stacked on top of each other. There are discs between each vertebra. Each disc has two parts, the soft inner part, nucleus pulpos, and the d rigid outer part, annulus fibros. With the weakening of the annulus fibros and the outward pressure of the nucleus pulpos, when the weakened outer part expands outward, this is called bulging and can press on the nerve roots, and pain is felt as a limitation of movement. The outer part is torn in the herniated exuded disc, and the soft structure spills out, leading to nerve compression in disc herniation.

Low back pain and neck pain are prevalent symptoms. It occurs in high-income, middle-income, and low-income countries and all age groups, from children to the elderly [8]. Low back pain is a symptom, not a disease, and can result from several different known or unknown abnormalities or diseases[8]. With or without leg pain, low back pain (LBP) is localized between the 12th rib and the inferior gluteal folds (Figure 2). Most cases are non-specific, but in 5-10% of cases, a specific cause is identified. Some degenerative conditions, metabolic bone disease, infective and neoplastic causes, inflammatory conditions, psychogenic pain, trauma, referred pain, and congenital disorders are specific causes of back pain. Back pain with no known underlying pathology is referred to as non-specific LBP [9]. Pain is a significant cause of morbidity, and the low back is one of the most common sites of symptoms. Low back pain (LBP) significantly impacts individuals and society [10]. Acute LBP appears suddenly after at least six months of no LBP and lasts for less than six weeks. Subacute LBP, on the other hand, appears suddenly after a minimum of 6 months without LBP and lasts between 6 weeks and three months. Chronic LBP is defined as lasting more than three months or occurring episodically within six months. [9].

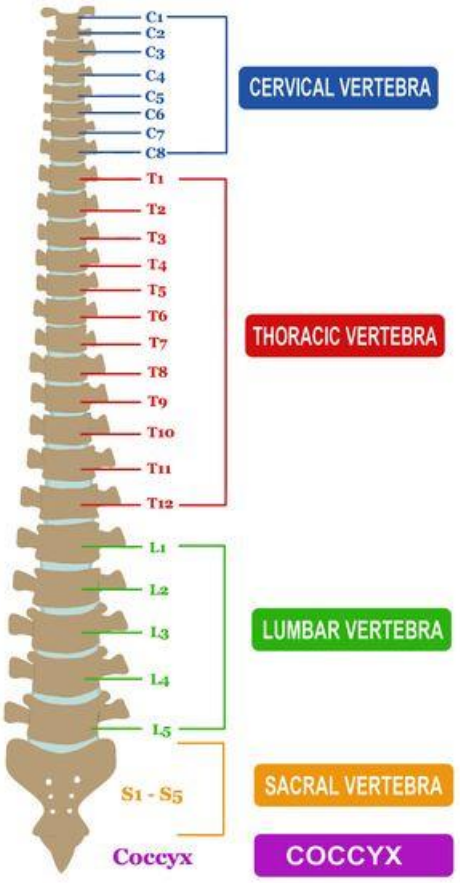

Figure 2. Anatomy of the spine; drawing shows a view of the spine, including the cervical spine (C1-C7), thoracic spine (T1-T12), lumbar spine (L1-L5), sacral spine (S1-S5), and the coccyx (tailbone)[11].

Neck pain is the second most common musculoskeletal disorder in population surveys and primary care, and it, like low back pain, imposes a significant health and economic burden and is a frequent source of disability [12]. Neck pain is generally defined as stiffness or pain felt dorsally in the cervical region between the occipital condyles and the C7 vertebral prominence (Figure 2). Neck pain, however, is often accompanied by pain in the occiput (a headache), the upper thoracic region, and the jaws. Clinically, it is recognized that even in subjects with no evidence of nerve root irritation or compression, neck pain may be associated with pain referred along with myotomal patterns to the anterior chest, arm, and dorsal spine regions.[12]. Based on the available evidence, various types of exercise can be strongly recommended for at-risk populations and patients suffering from acute and chronic non-specific neck pain. This condition can also be treated with low-level laser therapy, electromagnetic pulse treatment, transcutaneous electric nerve stimulation, or radiofrequency denervation to alleviate symptoms.[13].

2.2.Cause of LBP and NP

Almost all people suffering from low back and neck pain cannot pinpoint a specific nociceptive cause. Only a small percentage of people have a well-known pathological cause, such as a vertebral fracture, cancer, or infection. People with physically demanding jobs, physical and mental comorbidities, smokers, and obesity are more likely to report LBP and NP [8]. Because a specific cause of low back and neck pain is rarely identified, the majority of low back and neck pain is labeled as non-specific[8]. This section describes in detail the causes of LBP and NP, summarized as congenital injuries, degenerative problems, nerve and spinal cord problems, non-spine sources, and lifestyle factors. (Figure 3).

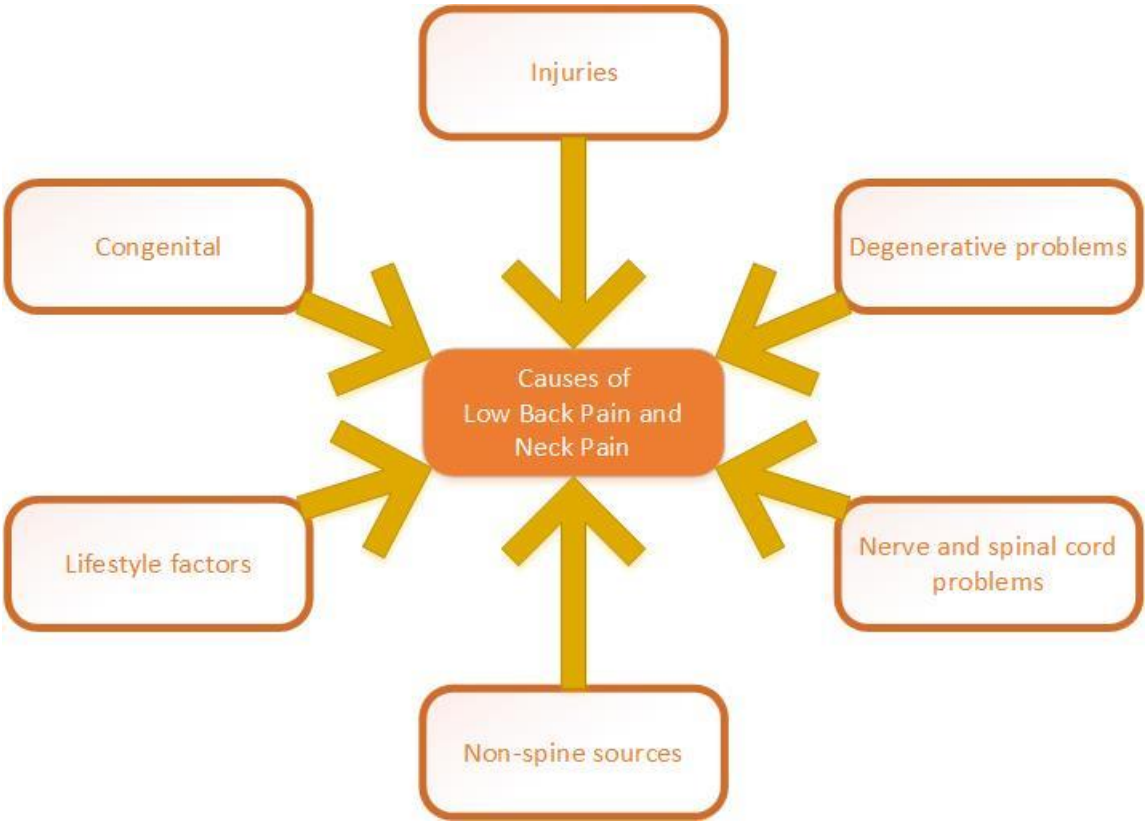

Figure 3. Causes of Low Back Pain and Neck Pain; are summarized as congenital injuries, degenerative problems, nerve and spinal cord problems, non-spine sources, and lifestyle factors.

2.2.1. Congenital

Back and neck pain can be caused by skeletal irregularities such as lordosis (an abnormally exaggerated arch in the waist), kyphosis (an excessive outward arc of the spine), scoliosis (a curvature of the spine), and other congenital spine anomalies. Furthermore, one of the congenital diseases that can cause low back and neck pain is spina bifida, which includes the incomplete development of the spinal cord and the protective cover and can cause

problems such as malformation, abnormal sensations, and even paralysis in the vertebrae.[14].

2.2.2. Injuries

One of the causes of low back pain may be excessive mechanical stress on the intervertebral disc[15]. Traumatic Injuries such as from playing sports, car accidents, or a fall can injure tendons, ligaments, or muscles, causing pain, compressing the spine, and causing discs to rupture or herniate. Also, sprains, strains, and spasms can cause low back and neck pain[14].

2.2.3. Degenerative problems

Spondylolysis can cause back pain in adolescents, but it is unknown if it causes back pain in adults; pain worsens with spine extension and activity. It is similar to lumbar strain in that disk pain frequently worsens with flexion activity or sitting, while facet pain frequently worsens with extension activity, standing, or walking[16]. Spondylosis is the general degeneration of the spine caused by normal wear and tear on the joints, discs, and bones of the spine as people age[14].

2.2.4. Nerve and spinal cord problems

Nerve and spinal cord problems that cause back and neck pain include spinal nerve compression, inflammation or injury, sciatica, spinal stenosis, Spondylolisthesis, herniated or ruptured discs, and osteoporosis[14], [17]. Disc herniation is the protrusion or extrusion of the disc tissue that causes pain by compressing or irritating neural tissues[18].

2.2.5. Non-spine sources

Psychological constructs such as anxiety, depression, catastrophizing (i.e., an irrational belief that something is far worse than it is), self-efficacy (i.e., belief in one's ability to influence events affecting one's life) are frequently studied separately. Even though the mechanisms are not fully understood, the presence of these factors in people with low back pain is associated with an increased risk of developing disability[8].

2.2.6. Lifestyle factors

Physical activity is frequently necessary for pain prevention and management. This simplistic view ignores the possibility that the relationship between activity level and LBP and NP is a U-shaped curve, implying that both inactivity and excessive activity (back-unhealthy activity) increases the risk of LBP and NP[19].

2.3.Treatment Methods for LBP and NP

Treatment methods for LBP and NP are summarized as non-pharmacological therapy, pharmacological therapy, interventional therapies, and surgery and are described in detail in this section (Figure 4).

Figure 4. Treatment Methods for LBP and NP; include non-pharmacological therapy, pharmacological therapy, interventional therapies, and surgery.

2.3.1. Non-pharmacological therapy

Physical treatments recommended, particularly for chronic low back pain (lasting more than 12 weeks), include a graded activity or exercise program that focuses on improving function and preventing disability from worsening. Because there is no evidence that one type of exercise is superior to another, guidelines recommend exercise programs that consider individual needs, preferences, and capabilities when determining the type of exercise[20]. Supportive treatments for chronic low back and neck pain include exercise therapy, spinal manipulation, cognitive behavioral therapy, massage, yoga, mindfulness-based stress reduction, acupuncture, and interdisciplinary rehabilitation.[20].

2.3.2. Pharmacological therapy

Acute low back pain should be treated orally with nonsteroidal anti-inflammatory drugs (NSAIDs) [21]. To control pain, some patients with acute low back pain, and more commonly those with sciatica, require oral opioids prescribed by a physician (opioids should be used only for a short period and under the supervision of a physician, as opioids can be addictive, aggravate depression, and have other side effects) [14], [21].

2.3.3. Interventional therapies

For low back pain treatment, various non-surgical interventional techniques are performed. Some examples include using various forms of thermal or radiofrequency energy within the spine, injecting medicines, irritants, or proteolytic enzymes into soft tissues outside or within the spine, and spinal cord stimulation [22]. Some non-surgical interventional procedures are given in Table 1.

Table 1. Interventional Therapies

Interventional Therapies	Definition
Intradiscal Electrothermal Therapy	Intradiscal electrothermal therapy (IDET) is a minimally invasive procedure used to treat chronic discogenic low back pain in patients who have undergone unsuccessful conservative treatment and may be good candidates for spinal fusion. It entails inserting a resistive copper coil into the annulus of the degenerative disc and circumnavigating it while heating the coil.[18].
Radiofrequency	Radiofrequency denervation attempts to deactivate the nerve by cauterizing it with an electric current[23].
Nucleoplasty	The basis of nucleoplasty is percutaneous intradiscal RFA. In June 2001, the U.S. Food and Drug Administration (FDA) authorized nucleoplasty to treat confined herniated discs. Using coblation and bipolar RF technology over a conductive liquid, such as saline, nucleoplasty is a non-thermal procedure that removes tissue with little thermal harm to nearby tissues.[18].

2.3.4. Surgery

Sciatica is low back pain caused by lumbar disc herniation, degenerative spinal disease, or spinal stenosis. Mechanical compression and inflammatory changes in nerve roots caused by nucleus pulposus tissue are important pathogenetic factors. Surgical treatment aims to decompress the nerve roots and remove the nucleus pulposus tissue[24].

Decompression surgery has been used for nearly 200 years to treat chronic low back pain. It involves the complete or partial removal of anatomic structures in the lumbar spine that are thought to be causing neural impingement. The two most common types of decompression surgery are discectomy and laminectomy, which are frequently performed together. Decompression surgery procedures include open, conventional, and microscopic

approaches. This procedure, widely available in the United States, is typically offered by orthopedic and neurologic spine surgeons[25]. Discectomy removes the bulk of the nucleus pulposus while leaving most of the annulus fibrosus intact. It can be done either openly or endoscopically[26].

The bony ring's posterior portion surrounding the spinal cord is removed during a laminectomy. Laminectomies are performed to treat spinal stenosis or to provide access to treatment. A decompressive laminectomy, while not a fusion procedure, is frequently performed in conjunction with a fusion to treat certain spinal disorders. Laminectomies are frequently performed in the lumbar, sacral, thoracic, and cervical spine regions[22].

2.4.Operational Model

2.4.1. Preprocessing

Data preprocessing can frequently significantly impact a supervised machine learning algorithm's generalization performance. Typically, the removed instances have excessively deviating instances with an excessive number of null feature values. Outliers are characteristics that deviate significantly from the norm. Another issue frequently addressed during the data preparation steps is missing data handling[27]. The quality of the data is critical to data mining. Missing values, noisy, incomplete, inconsistent, and outlier data are expected in raw data. As a result, these data must be processed before they can be mined. Preprocessing data is an essential step in improving data efficiency. Data preprocessing is a data mining step that deals with data preparation and transformation while attempting to make knowledge discovery more efficient. Cleaning, integration, transformation, and reduction are all aspects of preprocessing[28].

2.4.2. Data Types

It is crucial to analyze the collected data before using data mining algorithms. The collected data is generally mixed. Figure 5 shows the data types.

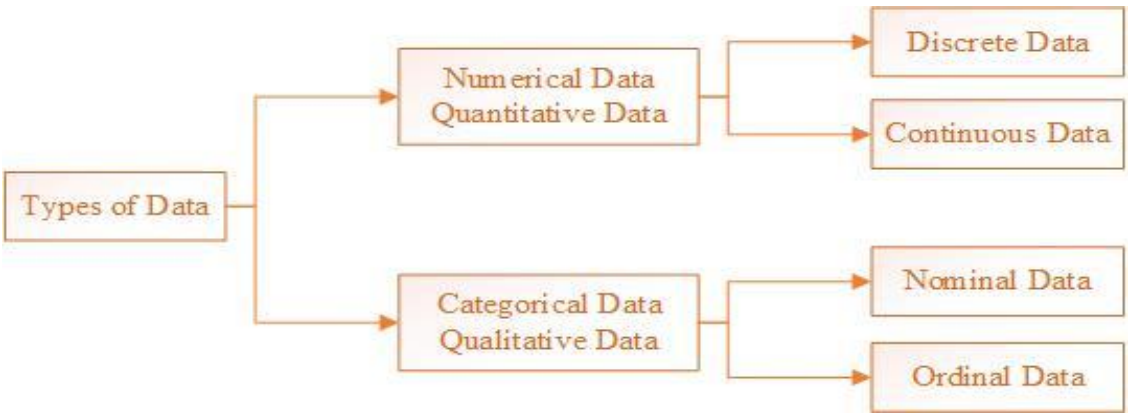

Figure 5. Types of Data: The Most Common Data Types in Statistics

2.4.2.1. Numerical Data

Quantitative data can be expressed numerically, allowing it to be counted and allowing statistical data analysis. These types of data are also referred to as numerical data. It provides answers to questions such as "how much," "how many," and "how frequently." The price of a phone, the amount of RAM in a computer, a person's height or weight, and so on are examples of quantitative data [29]. The numerical data is classified into two groups; discrete and continuous. Discrete data refers to the data values which can only attain certain specific values and cannot attain a range of values, so it should be represented using bar charts [30]. Continuous data has an infinite number of probable values that can be selected within a specific range and calculated based on its formula [31].

2.4.2.2. Categorical Data

Data that cannot be measured or counted numerically is referred to as qualitative or categorical data. These types of data are organized by category rather than by number. This is why it is also referred to as Categorical Data. These data can be audio, images, symbols, or text. Gender, whether male or female, is an example of qualitative data[29]. There are two types of categorical data, nominal and ordinal. Nominal data is a sub-category belonging to one of the types of qualitative information. Also known as the nominal scale, it labels the variables without providing the numerical value. Nominal data attributes cannot either be ordered or measured [30]. Ordinal data/variable is a type of data that follows a natural order. The significance of the nominal data is that the difference between the data values is not determined [31].

2.4.3. Normalization Methods

Many data normalization methods include min-max normalization, z-score normalization, and normalization by decimal scaling [32].

Min-Max normalization is a simple technique to fit the data in a pre-defined boundary with a pre-defined boundary [33]. The min-max normalization provides the lowest misclassification problem [34] and has better performance in speed, cross-validation accuracy, and the number of support vectors than other normalization methods [35].

As per the Min-Max normalization technique,

$$A' = \left(\frac{\mathrm{A} - \min value\ of\ A}{\max value\ of\ A - \min value\ of\ A}\right) * (D - C) + C \qquad (1)$$

Where,

A' contains Min-Max Normalized data one

The pre-defined boundary is [C, D]
A is the range of original data

Z-score normalization, the values of an attribute A are normalized according to their mean and standard deviation. A value a of A is normalized to a′ by computing[36]:

$$a' = \left(\frac{\mathrm{a} - \mathrm{mean(A)}}{std(A)}\right) \tag{2}$$

Where,

Mean(A) = sum of the all attribute values of A
Std(A) = Standart deviation of all values of A

This method is helpful in stationary environments when the actual minimum and maximum values of attribute A are unknown, but it cannot deal well with non-stationary time series since the mean and standard deviation of the time series vary over time.

Decimal scale normalization is based on the movement of the decimal point of the attribute value. The decimal point numbers are moved depending on the maximum absolute attribute values. The decimal Scale normalization formula is [34],

$$d' = \left(\frac{\mathrm{d}}{10^{m}}\right) \tag{3}$$

Where,
m is the smallest integer that max (| d ′ |)<1.

2.4.4. Binarization

Binarization is transforming data features of any entity into vectors of binary numbers to make classifier algorithms more efficient [37]. Using binary attributes to represent nominal and integer data is beneficial for classification accuracy [38]. "Logical analysis of data" (LAD) is a methodology developed in the late eighties, aimed at discovering hidden structural information in data sets; LAD was developed initially for analyzing binary data by using the theory of partially defined Boolean functions [29]. The methodology of LAD is extended to the case of numerical data by a process called binarization, consisting of the transformation of numerical (real-valued) data to binary (0,1) ones [29].

2.4.5. Unbalanced Data Problem

2.4.5.1.Oversampling

Random oversampling is the most basic oversampling technique for balancing the dataset's imbalance. It evens out the data by replicating minority class samples. This results in no information loss, but the dataset is prone to overfitting because the same information is copied [39].

2.4.5.2.Undersampling

Highly imbalanced data, which occurs in many real-world applications, often makes machine-based processing difficult or even impossible. The over- and under-sampling methods help to tackle this issue. However, they often have serious shortcomings[40].

Undersampling is a technique for balancing uneven datasets by retaining all data in the minority class while decreasing the size of the majority class. It is one of several techniques available to data scientists for extracting more accurate information from initially imbalanced datasets. Despite its drawbacks, such as the risk of losing potentially important information, it remains an ordinary and necessary skill for data scientists [41].

2.4.5.3. Synthetic Data Generation (SMOTE)

Synthetic Data Generation is an oversampling method that oversamples the minority class by creating "synthetic" examples rather than oversampling with replacement. Each minority class sample is over-sampled by introducing synthetic examples along the line segments connecting any/all of the k minority class nearest neighbors. Neighbors from the k nearest neighbors are chosen randomly depending on the amount of over-sampling required[42].

Many learning algorithms struggle with unbalanced classification problems. The uneven proportion of cases for each class of problem characterizes these problems. SMOTE is a well-known algorithm for dealing with this issue. The general idea behind this method is to generate new examples of the minority class by using the cases' nearest neighbors[42]. Furthermore, most class examples are under-sampled, resulting in a more balanced dataset.

2.4.6. SVM

In 1963, Vladimir Vapnik and Alexey Chervonenkis developed a new classification. Invented by Vapanik, the tool SVM was initially unsuccessful. After being unused for almost 27 years, it became a famous tool for data in 1990, with Vapnik redefining its method[43]**.**

A support vector machine (SVM) is an algorithm. SVMs are one of the supervised learning methods generally used in classification problems. Draws a line to separate points

placed on a plane and aims the line to be at the maximum distance for the points of both classes. It is a complex but suitable algorithm for small and medium datasets.

It works based on the structure of statistical theory, so it performs well for data that is not generally visible. It has been used in many real applications, such as classification problems. However, it still has some issues when working with real-world unbalanced data[44].

2.4.6.1. SVM Working Principle

Support Vector Machines are developed within the framework of Statistical Learning Theory.

The supervised learning problem in statistical learning theory (SLT) is formulated as follows. Given a set of training data {(x1,y1)...(xl,yl)} in Rn × R sampled according to an unknown probability distribution, P(x,y) and a loss function V(y,f) (x)) measures the error made when f(x) is "guessed" for a given x, rather than the actual y value. The problem consists of finding a function f that minimizes the expectation of error in new data, that is, a function f that minimizes the expected error [45].

Since P(x,y) is unknown, some induction principles must be used to extract a function that minimizes the expected error from the available training examples.

A significant consequence of the theory is that it specifies conditions where two errors are close together and provides probabilistic limits on the distance between empirical and expected errors. These limits are given in terms of a measure of the complexity of the hypothesis space H: the more "complex" H is, the greater the distance between empirical and expected errors in probability.

An essential question in SLT is measuring the "complexity" of hypothesis space. Quantities that measure this "complexity" of a hypothesis space are discussed, and suggestions are made on how to measure these quantities experimentally.

The first quantity discussed is standard in SLT and is called the VC dimension of a set of functions. This is a combinatorial quantity characterizing the capacity of the set of functions to break up a set of points and is valid regardless of the probability distribution of the P(x,y) data.

In the P(x,y) distribution, the distance between the empirical and expected error is also considered. Taking P(x,y) into account is to limit it to using a "complexity" amount. The presented limits are tighter than the previous one but require knowledge of the amount of complexity associated with the distribution. This theorem discusses the basic theoretical framework under which learning machines such as SVM are developed and proposes possible research directions that could lead to the improvement of theory and, therefore, possible improvement of SVM.

From the theoretical framework outlined, here is how SVM is formed. Support Vector machines realize the ideas outlined above. To understand why two things need to be pointed out:

Hypothesis spaces used by SVM and loss functions that are used.

SVM believes they find an "optimal" hyperplane to solve the learning problem.

The SVM finds a hyperplane in a different space x from the input data in its most general formulations. It is a hyperplane induced by a K kernel in a feature space. Through the K kernel, the hypothesis space is defined as a series of "hyperplanes" in the feature space induced by K. This can also be seen as a set of functions in the Reproduce Kernel Hilbert Space (RKHS) defined by K.

To summarize, the hypothesis space used by SVM is a subset of the set of hyperplanes defined in space - an RKHS.

In the framework of SLT discussed above, the constant A is used to describe the structure of hypothesis spaces (the larger A, the more complex the hypothesis space). The purpose of SVM is to find the solution with the "optimal" RKHS norm, that is, to find the optimal A [45].

2.4.6.2. Types of SVM

2.4.6.2.1. Linear

Linear SVM is used for data that can be separated linearly, which are datasets that can be divided into two using a single straight line. Such data points are called linearly separable data, and a Linear SVM classifier can be used to define the groups.

The way the SVM algorithm works can be understood through the following example. There is a dataset with two labels (green and blue), and the dataset has two properties, x1 and x2 (Figure 6). We are looking for a classifier that can classify the green or blue coordinate pair (x1, x2).

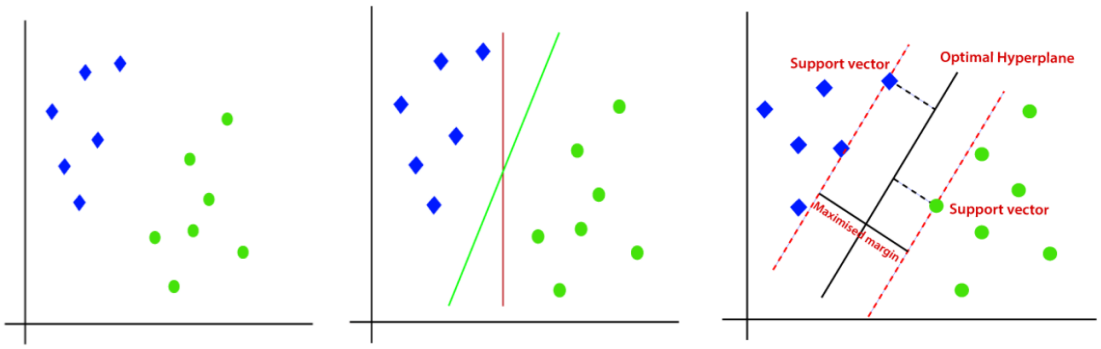

Figure 6. Separation of a 2-label dataset with SVM algorithm[46]

Since it is a 2-dimensional space, these two classes can be separated by a straight line. However, there may be multiple lines that can separate these classes.

The SVM algorithm helps to find the best line or decision boundary, and this best boundary or region is called the hyperplane. The SVM algorithm tries to find the closest point of the lines from both classes. These points are called support vectors. The distance between the vectors and the hyperplane is called the margin, which is maximized during SVM classification. The hyperplane with the maximum margin is called the optimal hyperplane [47].

2.4.6.2.2. Non-Linear

If the data is in a linearly flat environment, it can be separated using a straight line. When a straight line cannot be used to classify a dataset, such data points are called nonlinear data (Figure 7). A single straight line is insufficient to cluster data in a nonlinear distribution, but non-linear SVM classifiers can be used. The structure known as the kernel trick is used by non-linear SVM, which sets the data points to a higher dimension where they can be separated using planes or other mathematical functions.

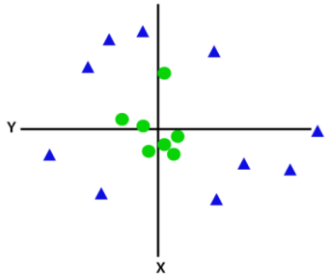

Figure 7. Nonlinear 2-label dataset distribution[48]

In this case, one more dimension must be added to separate the data points. Two dimensions x and y were used for linear data, but a third z dimension is needed for nonlinear data (Figure 8).

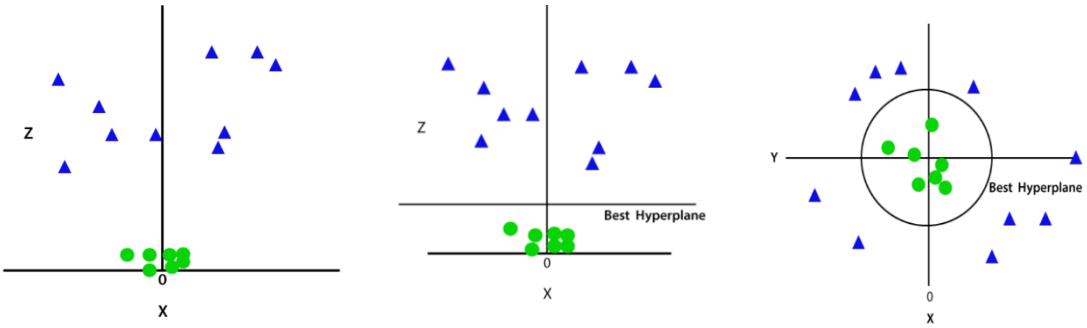

Figure 8. Separation of a nonlinear 2-label dataset with SVM algorithm[48]

SVM will classify the datasets as in the picture, which looks like a plane parallel to the x-axis in 3D Space. The plane can also be represented as circular if transformed with z=1 in 2d space [46].

2.4.6.3. SVM in Machine Learning

As mentioned above, SVMs depend on supervised learning algorithms. The purpose of using SVM is to classify unseen data correctly. SVMs have applications in various fields.

Some common applications of SVM are:

- Face detection – SVM classifies parts of the image as face and non-face and creates a square border around the face.
- Text and hypertext classification – SVMs are used in Text and hypertext classification for both inductive and transformative models. Training data is used to classify documents into different categories. It is categorized according to the created model and compared with the threshold value.
- Classification of images – Using SVMs provides better search accuracy for image classification. It provides better accuracy compared to traditional query-based search techniques.
- Bioinformatics – It is used in protein classification and cancer classification studies. SVM is used to classify genes based on genes and to define other biological problems.
- Handwriting recognition – SVMs are used to recognize commonly used handwritten characters.

2.4.6.4. Multi-Class SVM

Classification problems with more than two classes are called multiclass classification problems. The 'K' Binary classifier is typically solved by generating SVM and k-classes. The K-class classification problem is to design a considered decision function. The support vector network is a new learning machine for binary classification. Since the input vectors cannot be linearly separated to transform the space of high-dimensional functions, it gives more generations due to the unique properties of the decision boundary, which increases the machine learning capability.

New SVM algorithm TSVM derived for multi classes—the main aim of Twin SVM is to detect two intersecting planes for each class. Every class is divided into a pair of small-size quadratic programming sub-problems. The basic idea is "splitting and combining "; this approach directly uses a binary support vector classifier. Multi-class classification can be solved in two ways that are "one verses rest" and "one verse one" [43].

2.4.7. Accuracy Paradox

The accuracy paradox is the perplexing discovery that accuracy is not a good metric for predictive models when classifying in predictive analytics. A simple model may be accurate but too crude to be useful. [49].

The following terms are fundamental to understanding the utility of clinical tests: When evaluating a clinical test, the terms sensitivity and specificity are used. They are independent of the population of interest subjected to the test. The terms positive predictive value (PPV) and negative predictive value (NPV) are used when considering the value of a test to a clinician and are dependent on the prevalence of the disease in the population of interest[50].

True positive (TP): the patient has the disease, and the test is positive.
False-positive (FP): the patient does not have the disease, but the test is positive.
True negative (TN): the patient does not have the disease, and the test is negative
False-negative (FN): the patient has the disease, but the test is negative.

2.4.7.1.Specificity and Sensitivity

Measures of accuracy include sensitivity and specificity. Sensitivity is the probability of a positive test result among those having the target condition[51].

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

A test with 100% sensitivity correctly identifies all patients with the disease. A test with 80% sensitivity detects 80% of patients with the disease (true positives), but 20% with the disease go undetected (false negatives). High sensitivity is sought when the test identifies a severe but treatable disease[50].

Specificity,

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

A test with 100% specificity correctly identifies all patients without the disease. A test with 80% specificity correctly reports 80% of patients without the disease as test negative (true negatives), but 20% of patients without the disease are incorrectly identified as test positive (false positives)[50]

2.5.Studies in LBP and NP with Decision Support Systems

Decision support systems and machine learning algorithms using the patient's preliminary data have been reported in the current studies in the literature. Decision support systems studies for different diseases use the SVM algorithm. The diagnosis of different diseases such as Parkinson's, heart disease, melanoma recognition, and breast cancer has been tried to be developed by researchers with the SVM algorithm.

Gilmore et al. reported the utility of support vector machine (SVM) technology in melanoma diagnosis, using an archive of 199 digital dermoscopic images of excised atypical melanocytic lesions for dermatology. They propose to reduce the underdiagnosis. In line with the utility of decision support systems in clinical practice, dermatologists' assessment and the SVM diagnosis are incorporated into the clinical decision-making process [52]. Bhatia et al. present a decision support system for heart disease classification based on support vector machines (SVM) and an integer-coded genetic algorithm (GA). A simple Support Vector Machine (SSVM) algorithm has been used to determine the support vectors in a fast, iterative manner [53]. Farhadian et al. aimed to design a support vector machine (SVM) based decision-making support system to diagnose various periodontal diseases. Data were collected from 300 patients referring to the Periodontics department of Hamadan University of Medical Sciences, west of Iran. Among these patients, 160 were Gingivitis, 60 were localized periodontitis, and 80 were generalized periodontitis. In the designed classification model, 11 variables, such as age, sex, smoking, gingival index, plaque index, and so on used as input and output variables to show the individual's status as a periodontal disease [54]. Irenaeus et al. present a tumor detection algorithm from mammograms using an SVM classifier [55].

There is a lack of research and literature on which patient group benefits from the treatment by investigating only patients' pre-diagnostic data, which is one of this study's novelties. Primary care physicians cannot direct patients to the appropriate treatment choice as they are not certified to interpret MRI findings. Therefore, the patients can be prescribed ineffective treatment or referred to inappropriate clinics. Moreover, for the patients who can benefit from drug therapies, MRI would be unnecessary and increase the cost of diagnosis, leading to a significant burden for the healthcare management system.

Many studies with data mining algorithms diagnose various diseases, such as melanoma, heart attack, or cancer, but few studies have previously provided decision support systems for low back or neck pain. Lin et al. developed an online knowledge base verification tool that performs system validation with a modified Turing test that clinicians and patients can use with basic medical knowledge[56]. Clinical efficacy assessment is performed with five clinicians and 180 real-world cases collected from geographically dispersed clinics. In classifying lower back pain, machine learning algorithms such as KNN, Logistic Regression, Naive Bayes, Random Forest, Decision Tree, and CART were used [57]. Sandag G. et al. classified lower back pain as normal or abnormal based on twelve Range of Motion attributes using the K-Nearest Neighbor algorithm. Gaonkar A. et al. aimed to determine primary care practitioners' research priorities who manage low back

pain daily and classify patients using collected physical spine data of 381 patients with twelve parameters [58].

2.6.Summary of Background and Literature Review

Low back and neck pain is a widespread health problem worldwide. Neck pain is caused by structural defects in the vertebrae between C1-C7 in the spine for various reasons, and disorders in the L1-L5 vertebrae cause low back pain. The disorders that develop in these regions affect the relevant area and other body parts. Neck pain can spread to the shoulder, arms, hands, and fingers, while low back pain can spread to the leg.

Low back and neck pain can be caused by congenital structural defects and various reasons such as injury, old age, sprains, heavy lifting, and lifestyle. After the pre-evaluation various treatment methods such as Non-pharmacological therapy, Pharmacological therapy, Interventional therapies, or surgery can be determined.

The clinical data may vary due to the collection of the medical history of patients with low back and neck pain in combination who were referred to various treatment methods. So, as the first step, the data undergoes a preprocessing process and is prepared for data mining applications with normalization and binarization processes. Later, machine learning can be applied by solving the imbalance problems between data groups, if there are any. The results are evaluated according to the specificity and sensitivity values, considering the concept of the accuracy paradox.

In the literature, there are decision support studies about the preliminary data of the patient. These studies generally work with the patient's preliminary data and classify the patient as normal or abnormal. However, studies that direct the patient to the right treatment option with the preliminary data of the patient are very few. There is even no such study for low back and neck disease.

To fill in the gap in the literature here, we investigated whether the patient with low back and neck pain that will benefit from drug treatment can be detected at the primary care facilities without the need for the MRI findings. Our contribution to the literature here is to conduct a comprehensive study with the highest number of patients that can guide the patient to the appropriate treatment method beyond just classifying the patient as normal or abnormal. In addition, it reveals the possible cost savings of the developed model for the health system.

CHAPTER 3

MATERIALS AND METHODS

3.1.Data Sets

The data from patients diagnosed with low back pain (LBP) or neck pain (NP) used in this study was acquired from Sivas Cumhuriyet University, Faculty of Medicine, Pain Department. The study's first phase in 2017 aimed to evaluate the effectiveness of the new procedure, Radiofrequency (RF), by reviewing the medical records of 493 lumbar facet syndrome patients treated using Radiofrequency between 2008 and 2013 [59]. In addition to the data collected specifically for this study, in the second phase of the study, data from 301 RF, 309 IDET patients, 31 surgery, and 27 patients directed to drug treatment is acquired from the center. Various studies were carried out with the 1161 data, but since the imbalance between the groups is high and the number of surgery and drug-treatment groups is very few and inadequate, a practical result could not be obtained. Therefore, the third data collection process was carried out. In the third phase, it was attempted to collect as much data as possible for the study from patients undergoing surgery and medication. The data of 74 patients who received RF treatment, 79 patients who received IDET treatment and 84 patients who were referred for surgical treatment, and 84 patients who received drug treatment were added to the whole data set, and a total of 1482 patients data were obtained (Table 2).

Table 2. The Number of Patient Data

	RF	IDET	SURGERY	DRUG	TOTAL
The number of patient data	868	388	115	111	1482

Demographic information as age, sex, height, weight, and attributes for pre-operation as pain severity which was provided by the Visual Analogue Scale (VAS), limitation of movement, duration of pain, previous treatments, the spread of pain, other diseases of patients, and MRI results were collected and used by the clinicians to decide to the diagnosis and treatment groups (Table 3). However, we only used ten pre-diagnostic data attributes, except for the MRI findings.

Table 3. Features used in the study

#	Feature	Description	Type
1	Age	Age of patient	Numerical (Discrete)
2	Gender	Gender of patient	Categorical (Nominal)
3	Height	Height of patient	Numerical (Discrete)
4	Weight	Weight of patient	Numerical (Discrete)
5	Duration of Pain	The knowledge of how many months the patient's pain continues	Numerical (Discrete)
6	Pain Severity	VAS (Visual Analogue Scale)	Categorical (Ordinal)
7	Previous Treatments	Treatments That the Patient Had Previously	Categorical (Nominal)
8	Limitation of Movement	Evaluation of the patient's limitation of movement between 1 and 5 after the examination	Categorical (Ordinal)
9	Spread of Pain	Where pain spreads throughout the body	Categorical (Nominal)
10	Other Diseases	Whether the patient has any other illnesses	Categorical (Nominal)
11	Method	Treatment Method	Categorical (Nominal)

Turkey's Ministry of Health (MOH) data for the number of diagnoses, treatments, and MRI orders between 1 January-31 December 2018 is requested (Appendix A). Also, the reimbursement cost announced by the Social Security Institution of Turkey calculated the burden.

10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD 10) and Medical Enforcement Declaration (MED) codes [60] is given in Tables 4 and 5 for the analysis of the data requested from the Ministry of Health. MED is a legislative communique that enables the implementation of the state's health-related social policies, guides, prices, regulates, and includes all other implementation details. Since ICD 10 and MED codes are not in our area of expertise, we could extract the codes of the procedures performed in line with the information we received from the doctors in the Pain Clinic. Details of ICD 10 and MED codes can be viewed in Appendix B.

Table 4. 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD 10) Codes

	ICD 10 Code
Regarding neck discomfort	M54.2
Regarding back discomfort	M54.3 M54.4 M54.5

Table 5. Medical Enforcement Declaration (MED) codes

	Radiofrequency (RF)	IDET	Surgery	Low Back MRI	Neck MRI
MED Code	550.970 550.980 551.000 551.010 551.030 551.070 551.80	551.040 551.050 551.060	615.880 615.890 615.900 615.910 615.920 615.930 615.940 615.950 615.960	804.320	804.210 804.450

3.2.Preprocessing of the Data Set

Preprocessing of the patient data is completed before developing the data models. The irrelevant and redundant information or noisy and unreliable data is removed before the data mining process. Following the cleaning process, Min-Max normalization is performed for the numerical data. There are a few normalization methods, such as Min-Max normalization, Z-score normalization, and Decimal scaling normalization [33]. Min-Max normalization (Feature Scaling) is used for 1482 patients' numerical data to reduce the data to a scale between 0 and 1.

Following the min-max normalization, the binarization is done during the preprocessing of the data[61]. The binarization is applied for non-numeric categorical data: gender, pain spread, and other diseases. The overall workflow is represented in Figure 9.

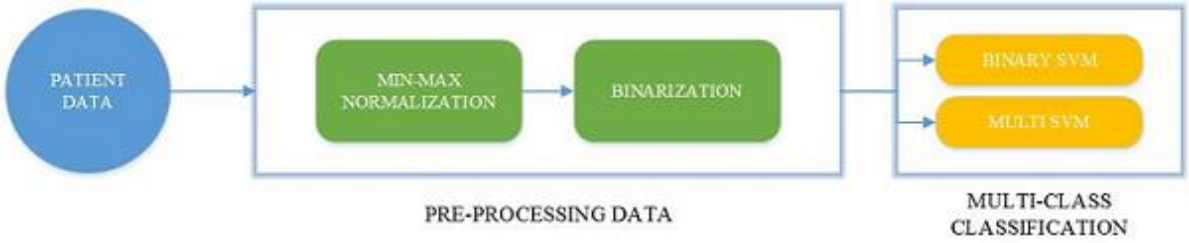

Figure 9. Model Development Workflow: MFDM is represented by preprocessing processes for patient data and algorithms used for multiclass classification.

3.3. Multi-Class Classification

For multi-class classification, binary Support Vector Machine (SVM) one versus all algorithm and Weston-Watkins multi-class SVM supervised learning methods are used. Balanced classes were built using each treatment method's equal amount of data for one versus all or multi-class SVM to train the model.

Trials have been made in undersampling, oversampling, and SMOTE algorithms to make the classes balanced. Various studies have been carried out according to the oversampling and undersampling methods before data augmentation, but it has been observed that either the determining data for undersampling is lost or there are overfit problems for oversampling. To give an example, we have 794 data for Radiofrequency (Class 1), 309 for Intradiscal therapy (Class 2), 31 data for surgery (Class 3), and 27 data for drug therapy (Class 4). So, the classes are unbalanced. We add copies of instances from the under-represented classes and get balanced data for RF 794, IDET 767, surgery 754, and drug 798. We used the SVM algorithm with 10-fold cross-validation and got 84% accuracy (Table 6).

Table 6. Oversampling for unbalanced treatment classes

		Actual Values			
		Class 1	Class 2	Class 3	Class 4
Model Prediction	Class 1	564	181	0	30
	Class 2	163	560	0	0
	Class 3	43	21	754	30
	Class 4	24	5	0	738
	Sensitivity (Recall)	71.03%	73.01%	100%	92.48%

When oversampling is done for each class, although the model's accuracy is high as 84%, it is interpreted that minority classes (Class 3, Class 4) are overfitted.

Another trial study was conducted on the importance of specificity and sensitivity values and the term accuracy paradox. Even if the model's accuracy is high, if the sensitivity is low, it can be interpreted that the model cannot make decent predictions. To give an example, we have 794 data for Radiofrequency (Class 1), 309 for Intradiscal electrothermal therapy (Class 2), 31 data for surgery (Class 3), and 27 data for drug therapy (Class 4). We used the SVM algorithm with 10-fold cross-validation and got 79.41% accuracy. For the robustness of the model, accuracy alone is not enough. We should examine accuracy with specificity and sensitivity.

Table 7. Confusion Matrix Sensitivity Values

		Actual Values			
		Class 1	Class 2	Class 3	Class 4
Model Prediction	Class 1	789	192	21	17
	Class 2	5	117	2	2
	Class 3	0	0	8	0
	Class 4	0	0	0	8
	Sensitivity(Recall)	99.37%	37.86%	25.80%	29.63%

As can be interpreted from Table 7, although the overall accuracy of the model was about 80%, the model was able to predict class 1, class 2, and class 3 below 40%.

After evaluating the accuracy paradox and class balancing studies, a testable number of data was collected for each class, and the study continued.

Although SVMs are initially designed as binary classifiers, approaches that address a multi-class problem as a single “all-together” optimization problem exist but are computationally have higher complexity than solving several binary problems [62], [63].

In this study, both one-versus-all and all-together optimizations were used for SVM since 1482 data with ten attributes were analyzed, and its size was not very large.

3.4.Used Technologies

The ‘e1071’ library of R is used for statistical data mining analysis, and the ‘kernlab' library is used for kernel functions. The SVM method performs “one versus all“and “multi-class” classification problems with tenfold cross-validations. The model performances and total accuracy is calculated during tenfold cross-validation. The problem with residual evaluations is that they do not indicate how well the learner will do when asked to make new predictions for novel data. One way to overcome this problem

is to divide the data into training and testing sets. In each validation step, considering the amount of data for each model's classes, a balanced training set was created by taking an equal amount of data from each class used. Data that was not used in the training set is reserved for the testing set. So, the reserved data is used to test the learned model's performance on "new" data [35].

To elaborate, we used the SVM method using the libsvm library of R's 1071 package. We used version 3.4.2 of R, widely used in machine learning, which we chose as the programming language.

With the libsvm library, we also implemented the SVM method quickly and easily, and we could use the methods automatically. First, we saved the edited data in .csv format and read all the data with the read.csv method. Then, we randomly collected as much data as we wanted from the data groups that we separated according to their categories with the sampling method and recorded the data we did not collect to use as a test. Then, with the SVM method, we created a model by creating the part with no MRI data as data and the part with MRI as a result of the data we randomly pulled.

While creating the SVM Model, C-Classification was used for the type, radial basis function was used for the kernel, cross-validation was run ten times, and the results were averaged. Other values are set as default values. Then, the data that were not used while creating the model were tested with the predict method with the model created, and the data predicted by the model and the actual data were summarized as a confusion matrix with the table method. The results were interpreted according to both the model's success and specificity and sensitivity values.

The results obtained according to the one versus all method and the multi-class SVM method were interpreted, and an appropriate MFDM was created.

3.5. Ethics Clearance

Permission for the study was obtained from the Practical Ethics Research Board at METU on 05/12/2016 (see Appendix C: Approval Letter of the Practical Ethics Research Board and Appendix D: Example of Participant Consent).

3.6. Analysis of the Savings from MRI Reimbursement Cost

The Ministry of Health statistics about patients with LBP and NP in 2018 (Appendix A) examined to calculate the potential savings from MRI. As explained in the model cost analysis section, assuming that MRI results will be required during the surgical interventions rather than drug treatment, the potential savings from MRI were calculated only for patients treated with medication.

Since the patients directed to the drug treatment in the proposed model can be correctly predicted with 84% accuracy, the savings from MRI examinations are calculated as:

$$S = \left(\frac{\mathrm{M} * \mathrm{C}}{100}\right) * P \tag{6}$$

Where,

S is one year savings from MRI
M is the number of medication patient in one year for LBP and NP
C is the cost of an MRI for one patient
P is the percent success rate of the model

CHAPTER 4

RESULTS

This study explored how to direct low back pain (LBP) and neck pain (NP) patients to the appropriate treatment and clinic with the patient's clinical data without MRI findings. The MRI Free Decision Model (MFDM) is proposed for diagnosis and treatment decisions without MRI examination. Additionally, the health system's burden due to the unnecessary MRI examination for the patients referred to drug treatment is calculated based on the Ministry of Health data.

4.1. The workflow in Pain Clinic and the Proposed Model

In a pain clinic, according to MRI results, patients are directed either to radiofrequency treatment, intradiscal electrothermal therapy, surgery, or drug treatment, as depicted in Figure 10. Doctors direct patients to appropriate treatment in the pain clinic by examining their MRIs. If bulging is not detected in the patient's MRI and if the pain is low, the patient is directed to drug treatment, but the patient is directed to RF treatment if the pain is high. If bulging is detected on MRI and there is no exudation at the disc, the patient is directed to IDET treatment, but the patient is directed to an open surgical operation if there is an exudation.

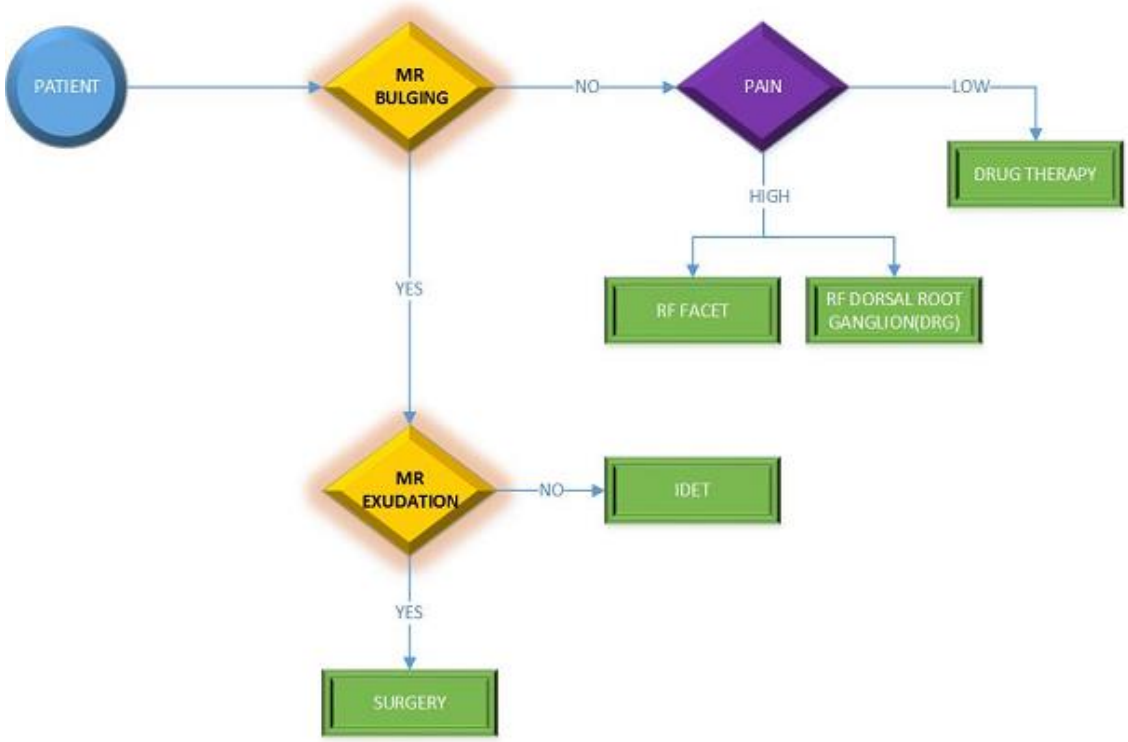

Figure 10. Observed Pain management workflow based on patients' radiological and clinical findings: Turkey has no commonly used guideline for low back pain (LBP) and neck pain (NP) diagnosis and initial treatment decision. The workflow represents pain management protocols used in the Cumhuriyet University Pain Clinic between 2014-2018.

4.2. SVM Modeling

We have applied the binary and multi-SVM methods to our data, categorized as multi-class, to determine which treatment method the patient can benefit from, regardless of the MRI results, by examining the patients' pre-diagnostic data results were compared.

All data were configured and preprocessed for data mining. For the cleaned and structured data, SVM methodologies were tested to find the best algorithm for the decision support system.

All classifications have performed tenfold cross-validation to ensure the results' insensitivity to the random train/test division [64]. Data is separated into ten groups in each fold, nine as training data and one as test data. The classical approach to solving k-class pattern recognition problems considers the problem a collection of binary classification problems. In the one-versus-all method, one constructs k classifiers for each class [63]. Support vector machines (SVMs) were initially designed for binary classification. How to effectively extend it for multi-class classification is still an ongoing

research issue [65]. A more natural way to solve k-class problems is to construct a piecewise linear separation of the k classes in a single optimization. Against this background, we analyze the patients' multi-category data with the one-versus-all Binary SVM method and k-SVM. Each treatment method is considered an individual class, and one versus all binary SVM methods is applied (see Table 8).

Table 8. The Model I - One versus All Binary SVM Model for RF and IDET

Class 1	**Class 0**	**Model Success Ratio**	**Test Success Ratio**	**Confusion Matrix of Test Set**	**Sensitivity** $\frac{TP}{TP+FN}$	**Specificity** $\frac{TN}{TN+FP}$
RF	IDET SURGERY DRUG	78%	73%	Actual Values Model 0 1 Prediction 0 144 69 1 170 499	87.8%	45.8%
IDET	RF SURGERY DRUG	76%	58%	Actual Values Model 0 1 Prediction 0 446 23 1 348 65	73.8%	56.2%
SURGERY	IDET RF DRUG	70%	75%	Actual Values Model 0 1 Prediction 0 947 3 1 321 12	80%	74.6%
DRUG	IDET SURGERY RF	80%	84%	Actual Values Model 0 1 Prediction 0 1074 1 1 198 10	90.9%	84.4%

The sample size of the four treatment groups was not balanced. The size of surgery and drug therapy groups was around 100, while the RF therapy group was 868, presenting a class imbalance problem for concept-learning [66]. Therefore, the number of data is balanced for Class 1 and Class 0. The model success ratio was calculated with tenfold cross-validation. Testing is performed with the remaining data not used during the model training to calculate the success ratios (Table 8).

The model I consists of 4 sub-models: RF, IDET, surgery, and drug, where a test success ratio of 84% with approximately 90% sensitivity and 84% specificity [67] is obtained for the drug model. However, the specificity values for the RF and IDET models were low. The specificity of the RF and IDET models is seen as approximately 50% in Model I. Considering that classes have similar properties, it has been investigated whether these classes can be combined or not.

Next, we have selected 300 RF and IDET data to examine if we can distinguish these treatment groups from each other. The confusion matrix in Table 9 shows that these classes cannot be distinguished from each other with the patient's pre-diagnostic data.

Table 9. Distinguishing RF and IDET Patient Data from Each Other

Class 1	Class 0	Model Success Ratio	Test Success Ratio	Confusion Matrix of Test Set	Sensitivity $\frac{TP}{TP+FN}$	Specificity $\frac{TN}{TN+FP}$
RF	IDET	68%	59.7%	Actual Values Model 0 1 Prediction 0 70 246 1 18 322	56.6%	79.5%

Based on our analysis and input from the interviews with doctors in the pain clinic, RF and IDET were considered a single class, so a second model was created (see Table 10). In the second model, three sub-models are built where RF and IDET are considered a single class. As in Model I, the patient's pre-diagnostic data is evaluated separately in these models, whether the patient is referred to medication, RF/IDET, or surgery.

Table 10. The Model II - One versus All Binary SVM Model where RF and IDET combined in a single class

Class 1	Class 0	Model Success Ratio	Test Success Ratio	Confusion Matrix of Test Set	Sensitivity $\frac{TP}{TP+FN}$	Specificity $\frac{TN}{TN+FP}$
DRUG	RF/IDET SURGERY	82.5%	85.4%	Actual Values Model 0 1 Prediction 0 1105 7 1 186 24	77.41%	85.6%
RF/IDET	DRUG SURGERY	82.75%	81%	Actual Values Model 0 1 Prediction 0 19 198 1 7 858	81.25%	73.07%
SURGERY	RF/IDET DRUG	72.5%	80.34%	Actual Values Model 0 1 Prediction 0 1022 7 1 245 8	53%	80.6%

Binary SVM is used to build the drug, RF/IDET, and surgery sub-models. For the drug sub-model, 80 samples from the drug group and 40 samples from each RF/IDET and surgery group are selected randomly to build the balanced sets. For RF/IDET sub-model, 200 samples from RF/IDET and 100 samples of each drug and surgery are selected randomly from the whole set. For the surgery sub-model, 100 samples from the surgery

group and 50 samples from each RF/IDET and drug group are selected. All sub-models have been created with balanced sets.

In the third model, using the Weston-Watkins [63] multi-class SVM method, patient groups, including three treatment methods, were examined in a single model. The results of the three models are compared. The model that best classifies the patients referred to drugs with the patient's pre-diagnostic data is the first model with an 84% test success ratio by examining the models' sensitivity and specificity.

Table 11. The Model III - Multi SVM

Class	Test Success Ratio	Confusion Matrix of Test Set				Sensitivity $\frac{TP}{TP+FN}$	Specificity $\frac{TN}{TN+FP}$
DRUG	74.47%	Actual Values				61.29%	90.50%
RF/IDET		Model Prediction	RF/IDET	SURGERY	DRUG	75.08%	80.30%
		RF/IDET	883	9	4		
		SURGERY	181	23	8		
SURGERY		DRUG	112	3	19	65.71%	84.34%

The previous models showed that RF / IDET patient groups could not be distinguished with high accuracy based on the patient's pre-diagnostic data (see Table 8,9). To find the best RF/IDET and surgery classification model, Model II, and Model III are compared. Although the test success ratio of Model II is higher than the Model III for both IDET and surgery data, the Model III can be interpreted as the most successful, as the specificity values of Model II are lower for both groups and are more likely to lead to false interventional processing. Therefore, we can state that Model III classified patients who will benefit from RF/IDET or surgery with fewer errors.

So, we propose a stepwise approach as the final model for MRI-free diagnosis of LBP and NP patients. The pre-diagnostic data of the patient are first examined in the first model to understand whether the patient will benefit from drug treatment or not, and according to this model, the patients who are not classified for the drug treatment are examined in Model III to decide whether RF / IDET or surgical treatments would benefit.

4.3. Model Cost Analysis

MRI costs are a massive burden on the healthcare system. Reducing unnecessary MRI examinations can decrease costs and benefit the states and the public. To present the potential savings, we have requested the yearly statistics for low back(waist) and neck problems from the Ministry of Health (Appendix A) to analyze the MRI burden cost. The patient data with the number of patients admitted to the hospital with low back and neck problems, the number of patients with MRI, and the number of patients referred to RF, IDET, and surgical operations are collected. In 2018, 13,796,441 patients were admitted to the hospital with LBP and NP symptoms, and 1,825,348 MRIs were ordered for these patients (see Table 12).

Table 12. Data obtained from the Ministry of Health for the year 2018

The number of patients admitted to the healthcare facility	**LBP**	**NP**
The number of admitted	11,679,716	2,116,725
The number of MRI	1,379,896	445,452
The number of RF procedures	632	63
The number of IDET procedures	5	0
The number of open surgery operations	10,754	1273

According to the public health services price list published on 28.01.2019 [1], the reimbursement cost per MRI scan for the neck, vertebra, lumbar and cervical regions was 93 TL. The MR's cost for low back and neck pain in 2018 is calculated as 1,825,348 * 93 = 169,757,364 TL. The total number of patients admitted to hospitals with LBP referred to RF, IDET, and surgical operations are 11,391 (632 + 5 + 10.754). The number of patients admitted to hospitals with neck problems and referred to RF, IDET, and surgical operations are 1336 (63 + 1273). The number of patients administered to hospitals with low back and neck problems referred to RF, IDET, and surgical operations is 12,727 (11,391 + 1336). Based on MOH statistics in 2018, the number of patients who underwent MRI but were referred only to medication was 1,812,621 (1,825,348-12,727).

Unnecessary MR cost for the patients who have had an MRI but benefit from medication without any need for surgical interventions can be calculated as 1,812,621 * 93 = 168,573,753 TL. The proposed MFDM can classify the patients who will benefit from drug treatment with an 84% success rate with the patient's pre-diagnostic data

[1] The price list can be examined in detail by downloading the document from https://tig.saglik.gov.tr/TR,67390/kamu-saglik-hizmetleri-fiyat-tarifesi-guncellenmistir.html

(168,573,753) * 0.84 = 141,601,952.52TL savings would have been achieved in Turkey only for 2018.

CHAPTER 5

DISCUSSION

The magnitude of the non-fatal disease burden has expanded globally [1], where musculoskeletal problems, such as low back and neck pain, are the leading health problems worldwide. Musculoskeletal pain, the leading cause of disability worldwide, is most commonly managed in primary care. People suffering from musculoskeletal pain in different body regions have similar symptoms and prognoses and may respond to similar treatments [68]. Many treatment options exist for musculoskeletal pain, most of which are delivered in primary care by first-contact clinicians such as general practitioners, physiotherapists, chiropractors, and osteopaths. Non-pharmacological treatments (such as self-management advice and education, exercise therapy, manual therapy, and psychosocial interventions), complementary therapies (such as acupuncture), and pharmacological interventions (such as analgesics, nonsteroidal anti-inflammatory drugs (NSAIDs), and corticosteroid injections) are examples. Surgical interventions (such as arthroscopic debridement, total knee replacements, and laminectomies) may be considered for those with refractory symptoms. However, recommendations regarding the effectiveness of various treatment options used across a range of common musculoskeletal pain presentations are ambiguous for the overarching goal of reducing pain and improving function [68].

According to a study conducted in 195 countries between 1990 and 2017, NP is a severe public health problem in the general population, with the highest burden in Norway, Finland, and Denmark [69]. According to Safari et al., the age-standardized rates for point prevalence of neck pain per 100000 population in 2017 were 3551.1 (95 percent uncertainty interval 3139.5 to 3977.9), and the incidence of neck pain per 100000 population was 806.6 (713.7 to 912.5), and for years lived with disability from neck pain per 100000 population was 352.0 (245.6 to 493.3). Between 1990 and 2017, these estimates did not change significantly. In 2017, females had a higher global point prevalence of neck pain than males, though this was not statistically significant at the 0.05 level. Prevalence increased with age until 70-74 years, and then it began to decline. In 2017, the three countries with the highest age-standardized point prevalence estimates were Norway (6151.2 (95 percent confidence interval 5382.3 to 6959.8), Finland (5750.3 (5058.4 to 6518.3), and Denmark (5316 (4674 to 6030.1). From 1990 to 2017, the United Kingdom (14.6 percent (10.6 percent to 18.8 percent)), Sweden (10.4 percent (6.0 percent to 15.4 percent)), and Kuwait (2.6 percent (2.0 percent to 3.2 percent) had the highest increases in age-standardized point prevalence estimates. In general, positive associations were found between age-standardized years lived with disability for neck pain and sociodemographic index at the global level and across all Global Burden of Disease regions, implying that the burden is higher at higher sociodemographic indices[69]. From 1990 to 2016, the Global Burden of Disease Study (GBD) results were used to report

trends in state-level disease burden, injuries, and risk factors. When the Burden of Diseases, Injuries, and Risk Factors Among US States is examined, LBP ranks third [70].

Musculoskeletal disorders will become more prevalent as the US population ages. More Americans are experiencing neck and back pain, and the number of falls is increasing. Musculoskeletal disorders come with a high medical cost. Preventive measures to reduce the burden of these risk factors are needed at all stages of life [70]. Studies show that both LBP and NP significantly burden the world's health care systems, mainly through unnecessary surgical operations. Back and neck pain, osteoarthritis, rheumatoid arthritis, and fractures are among the most disabling musculoskeletal conditions that endanger healthy aging by limiting physical and mental capacities and functional ability. Although the prevalence of primary musculoskeletal conditions rises with age, they are not limited to the elderly. Regional pain disorders, low back and neck pain, musculoskeletal injury sequelae, and inflammatory arthritides are common in children, adolescents, and middle-aged people during their formative and peak income-earning years, establishing trajectories of intrinsic capacity decline in later years [71]. The World Health Organization and its Member States can help reduce the global disability burden by incorporating musculoskeletal health into noncommunicable disease system reform initiatives and healthy aging policy agendas [71].

Turkey Statistical Institute (TURKSTAT) 's Turkey Health Survey in 2016 reports that the most common diseases are low back and neck pain in Turkey. 27.1% of the patients had low back problems, while 18.1% had neck problems in the last 12 months (Table 13) [72]. LBP is the leading cause of activity limitation and work absence worldwide, imposing a massive economic burden on individuals, families, communities, industries, and governments. Several European studies have been conducted to assess the socioeconomic impact of low back pain. Low back pain was identified as the most common cause of disability in young adults in the United Kingdom, with more than 100 million work days lost each year. According to a survey conducted in Sweden, low back pain increased the number of work days lost from seven million in 1980 to four times that number (28 million) by 1987; however, the authors state that social compensation systems may account for some of this increase. LBP is estimated to cost the United States 149 million work days annually. The condition is expensive, with total annual costs estimated to be between $100 and $200 billion, two-thirds of which are due to lower wages and productivity [73].

Table 13. Percentage of Major Diseases Seen in 15 and Over Aged Individuals in the Past 12 Months by Sex, (%), 2016

Disease/Health Problem	*Male*	*Female*	*Total*
Low Back Disorders (Lumbago, Back Hernia, Other Back Defections)	21,4	32,8	27,1
Neck Disorders (Neck Pain, Neck Hernia, Other Neck Defections)	11,5	24,6	18,1
High Blood Pressure (Hypertension)	11,1	20,5	15,8
Allergy (Such as Rhinitis, Eye Inflammation, Dermatitis, Food Allergy or Other) (Allergic Asthma Excluded)	7,5	13,9	10,8
Diabetes	7,1	10,9	9,1
Asthma (Allergic Asthma Included)	5,2	10,3	7,8
Arthrosis	4,9	10,5	7,7
Chronic Obstructive Pulmonary Disease(Chronic Bronchitis, Emphysema)	5,7	8,8	7,3
Depression	4,9	9,4	7,2
Coronary Heart Disease (Angina Pectoris, Chest Pain, Spasm)	5,9	7,1	6,5
Kidney Problems	5,2	7,5	6,4
Urinary Incontinence, Problems in Controlling the Bladder	3,9	7,8	5,9
Alzheimer	5,1	6,1	5,6
Myocardial Infarction (Heart Attack)	2,1	2,0	2,1
Cirrhosis of the Liver, Liver Dysfunction	1,1	1,8	1,5
Stroke (Cerebral Hemorrhage, Cerebral Thrombosis)	1,0	0,8	0,9

Few studies have previously provided decision support systems for low back or neck pain. However, according to the number of cases, ours is the most comprehensive study. Lin et al. developed an online knowledge base verification tool that performs system validation with a modified Turing test that clinicians and patients can use with basic medical knowledge [56]. Clinical efficacy assessment is performed with five clinicians and 180 real-world cases collected from geographically dispersed clinics. In classifying lower back pain, machine learning algorithms such as KNN, Logistic Regression, Naive Bayes, Random Forest, Decision Tree, and CART were used [57]. Sandag G. et al. classified lower back pain as normal or abnormal based on twelve Range of Motion attributes using the K-Nearest Neighbor algorithm. Gaonkar A. et al. aimed to determine primary care practitioners' research priorities who manage low back pain daily and classify patients using collected physical spine data of 381 patients with twelve parameters [58].

There is a lack of research and literature on which patient group benefits from the treatment by investigating only patients' pre-diagnostic data, which is one of this study's novelties. Primary care physicians cannot direct patients to the appropriate treatment choice as they are not certified to interpret MRI findings. Therefore, the patients can be prescribed ineffective treatment or referred to inappropriate clinics. Moreover, for the patients who can benefit from drug therapies, MRI would be unnecessary and increase the cost of diagnosis, leading to a significant burden for the healthcare management system.

An accurate and cost-effective diagnosis of such patients is essential since musculoskeletal problems are at the forefront of health problems in Turkey and the world. The number of people who visit the hospital, especially with low back and neck pain, is increasing. So, the MRI method used in diagnosing low back and neck pain significantly burdens the health system when used excessively.

Decision support systems and various machine learning algorithms using the patient's preliminary data have been reported in the current studies in the literature (40,41,42). The proposed model aims to analyze the preliminary data of patients with low back and neck pain to direct them to the proper treatment method. Our study's key innovation was to direct the patients to the right treatment option with only their pre-diagnostic data without examining their MRI findings. We examined whether the patient could be directed to the appropriate treatment through a model developed based on pre-diagnose data from algology departments. The proposed decision support model builds for non-specialist physicians based on the patient's clinical and demographic data without MRI reducing medical expenses, constituting a significant burden on the healthcare system. The results of the model predictions are compared with the specialist's clinical decision based on MRI results. Our analysis shows that the burden of MRI costs on the health system can be reduced since the need for MRI will be eliminated for patients who would be directed to drug therapy.

In order to direct the patient with low back and neck pain to the proper treatment method and reduce the burden of unnecessary MRI costs on the health system, we collected patient data according to the workflow in the algology clinic. When we evaluated the treatment options in Sivas Cumhuriyet University Pain Clinic, where we also collected patient data, we saw that the treatments performed in the algology clinic were collected under four main headings. Patients who come to the pain clinic are referred to the radiofrequency, IDET, drug therapy, or surgery polyclinic according to the doctor's diagnosis after the MRI findings and examination.

In the initial data collection phase, we collected data on 1161 patients, referred to 794 Radiofrequency, 309 IDET treatments, 27 drug treatments, and 31 surgical operations. However, as we have seen during our studies and the literature, there was a class imbalance problem among these four classes. There are different approaches and solutions for the class imbalance problem in the literature, but there is no suitable general approach [74]. Balanced distributions can be obtained by under-sampling the majority class, over-sampling the minority class, and combining both and other advanced sampling ways [75].

One way to deal with the class imbalance problem with re-sampling methods is re-sampling the small class at random until it contains as many examples as the other class, or down-sizing methods that consist of eliminating, at random, elements of the over-sized class until it matches the size of the other class [76].

To solve the imbalance problem for the initial dataset of 1161 participants, random oversampling, random under-sampling, and SMOTE algorithms were tried. However, since the number of patients directed to surgery or drug therapy in our data set was low, minority classes became overfit when they over-sampled those classes. When random under-sampling was applied to RF and IDET classes with more data, a significant result could not be obtained because too much data was extracted. We decided to collect new patient data on real-world domains.

Therefore, in the second data collection phase, we collect as much data as possible for the classes with insufficient data, that is, for the patients referred to surgery and drug therapy, to create more meaningful, balanced classes. The data of 74 patients who received RF treatment, 79 patients who received IDET treatment and 84 patients who were referred for surgical treatment, and 84 patients who received drug treatment were added to the whole data set, and a total of 1482 patients data were obtained.

In the literature, decision support systems studies for different diseases use the SVM algorithm. The diagnosis of different diseases such as Parkinson's, heart disease, melanoma recognition, and breast cancer has been tried to be developed by researchers with the SVM algorithm.

Gilmore et al. reported the utility of support vector machine (SVM) technology in melanoma diagnosis, using an archive of 199 digital dermoscopic images of excised atypical melanocytic lesions for dermatology. They propose to reduce the underdiagnosis.

In line with the utility of decision support systems in clinical practice, dermatologists' assessment and the SVM diagnosis are incorporated into the clinical decision-making process [52]. Bhatia et al. present a decision support system for heart disease classification based on support vector machines (SVM) and an integer-coded genetic algorithm (GA). A simple Support Vector Machine (SSVM) algorithm has been used to determine the support vectors in a fast, iterative manner [53]. Farhadian et al. aimed to design a support vector machine (SVM) based decision-making support system to diagnose various periodontal diseases. Data were collected from 300 patients referring to the Periodontics department of Hamadan University of Medical Sciences, west of Iran. Among these patients, 160 were Gingivitis, 60 were localized periodontitis, and 80 were generalized periodontitis. In the designed classification model, 11 variables, such as age, sex, smoking, gingival index, plaque index, and so on used as input and output variables to show the individual's status as a periodontal disease [54]. Irenaeus et al. present a tumor detection algorithm from mammograms using an SVM classifier [55]. Considering all the examples in the literature for disease diagnosis, we decided to work with the SVM algorithm, which gives fast and precise results and is generally preferred.

The first model used one versus all binary SVM algorithms for RF, IDET, surgery, and drug classes (Table 8) and consisted of 4 sub-models. A binary SVM study was performed with 11 pre-attribute as RF and other treatment options in the first sub-model, IDET and others in the second sub-model, surgery and others in the third sub-model, and drug and others in the fourth sub-model. While creating the model in the first sub-model, in order to establish balanced classes, 300 patient data were randomly selected from the RF data set, and 100 patient data were randomly selected from each IDET, surgery, and drug classes, 300 by 300 balanced classes were created, and a model was established with the one versus all binary algorithm. This model, which had a 78% model success, showed an accuracy rate of 73% when 882 data not used while creating the model were tested. It is seen that the model correctly predicts patients with RF with 87.8%, but it can predict patients referred to IDET, surgery, or drug treatment with only 45.8% success. In the IDET vs. others model, the 2nd sub-model was created using the same method; the model correctly predicted the non-IDET classes with 56.2% accuracy. The specificities of these two sub-models are low, and when interviewed with the doctors in the pain clinic, it is seen that the RF and IDET classes can be taken as a single class since the patient data are the same. In Table 9, balanced clusters were created by taking 300 random samples for each RF and IDET class. So, when we examine the confusion matrix of the test set, it is seen that while it correctly predicted 322 RF patients, 56.6% of the 568 RF data not used in the model mispredicted 246. Therefore, in other models, RF and IDET classes were combined.

Model I, Model II, and Model III were compared to find the model that best guides drug treatment (Tables 8,10,11). The aim was to find the best model to direct the patient to drug therapy with only the patient's preliminary data, without needing an MRI when the patient first comes to the clinic. The success ratios for the test set are acceptably high in the three models, but Model I best captures the patient referred to drug therapy with 90.9% sensitivity.

Model II and Model III, in which these classes are considered together, were compared to find the model best directed to RF and IDET treatment (Table 10-11). Here, it is essential to find the model that best predicts the patient referred to RF and IDET treatment while taking the model that guides the least wrong treatment method. A model that finds the RF/IDET treatment option for the patient to be cured by drug therapy is not desired. Therefore, Model III with a higher specificity value was preferred.

Models, I, II, and III were compared to find the model that best guides surgical treatment. Model II was eliminated because the sensitivity value of Model II, the percentage of correctly estimating the patient who should be referred for surgical treatment, was 53%. When Models I and III are compared, it is an undesirable situation for a patient who should be treated with RF/IDET or drug therapy but is mistakenly directed to surgery. Although the test success ratio and sensitivity are higher than Model I, Model III is the model that best captures the patient who is referred to surgical treatment with minor error since its specificity value is higher (84.34%).

In general, in the literature, all classification algorithms accept the entire feature set as input to model the classifier. However, in the proposed stepwise approach, it considers part of a set of attributes and accepts as input a block of a partition in each of the steps in this stepwise SVM classification model. The three models' comparison shows that the proposed stepwise MFDM (Figure 11), which includes model I followed by model III, performs best when the specificity and sensitivity values are examined. The model I classifies whether patients should be directed to drug treatment or not with the highest actual positive ratio. It predicts patients who should not be directed to drug treatment with 84.4% specificity. Model II was established to classify the RF and IDET classes with one versus all binary SVM algorithms, and model III was established with Weston-Watkins multi-class algorithm to classify between RF and IDET classes and surgical treatment groups. According to the results, model III outperformed the one versus all approaches when the success ratio, sensitivity, and specificity values were examined.

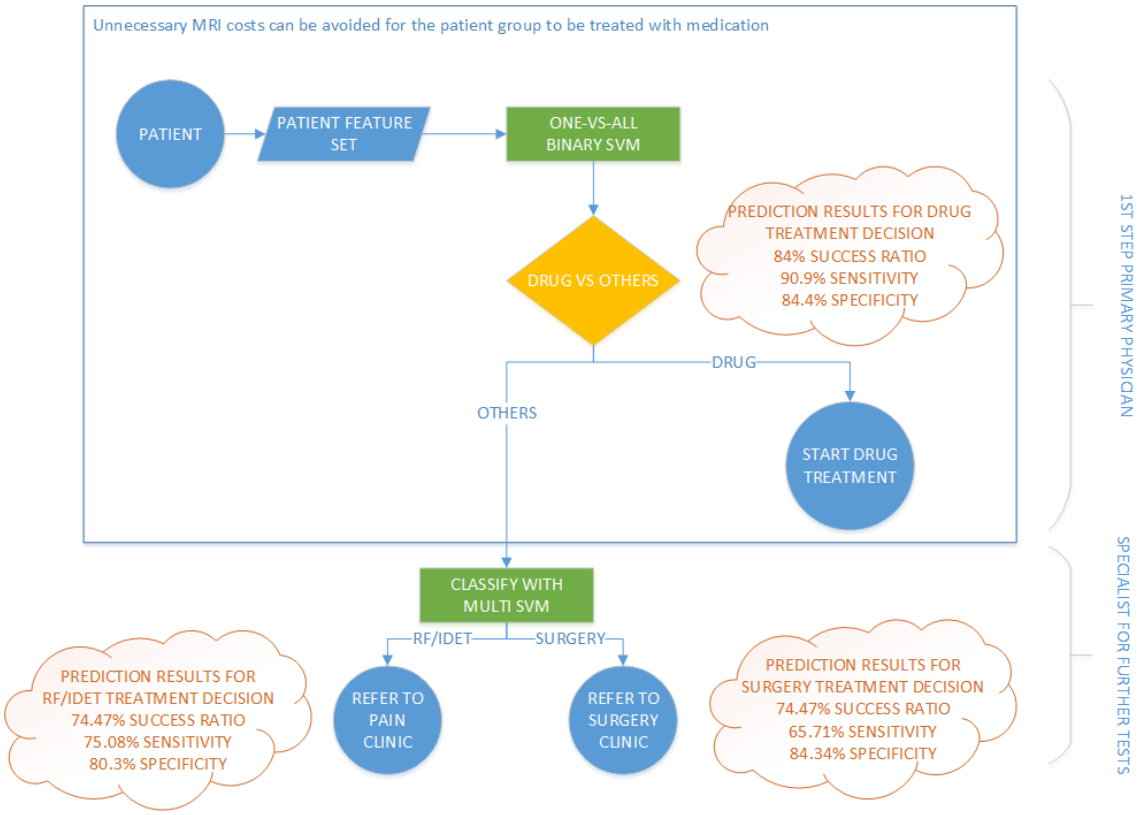

Figure 11. MRI Free Decision Model (MFDM): Workflow represents the proposed stepwise model to direct the patients to the appropriate treatment options without MRI. A workflow study can support creating a guideline in Turkey, just like the guidelines recommended for patients with low back and neck pain problems in Europe and America.

Based on the performance of the proposed stepwise model called MFDM, the amount of savings to be achieved in MRI, which is a considerable burden for hospitals, patients, and governments, was examined for Turkey. The cost analysis section explains how much the MFDM can save on MRI costs. According to the statistics in 2018 in Table 12 received with a petition from the Ministry of Health, approximately 142 million TL can be saved based on the 2020 public health services price list only. Since the Ministry of Health of Turkey's budget was approximately 37,9 billion TL in 2018 [77], it is predicted that the state will save 0.37% in the yearly health budget with the proposed MFDM in one year.

This 0.37% savings in the MOH budget only includes the reimbursement costs, as the actual MRI fees billed to patients in private and public hospitals were not used in this calculation. As the price of MRI scans in Turkey varies between private and public medical centers, we have based our analysis only on the reimbursement cost. Also, MRI scan prices are relatively higher in Europe and the United States compared to Turkey. According to statistics in 2017 (Figure 12), the average MRI scan price in America is 1430 dollars, while the average MRI cost in Europe varies between 100 and 500 dollars [78].

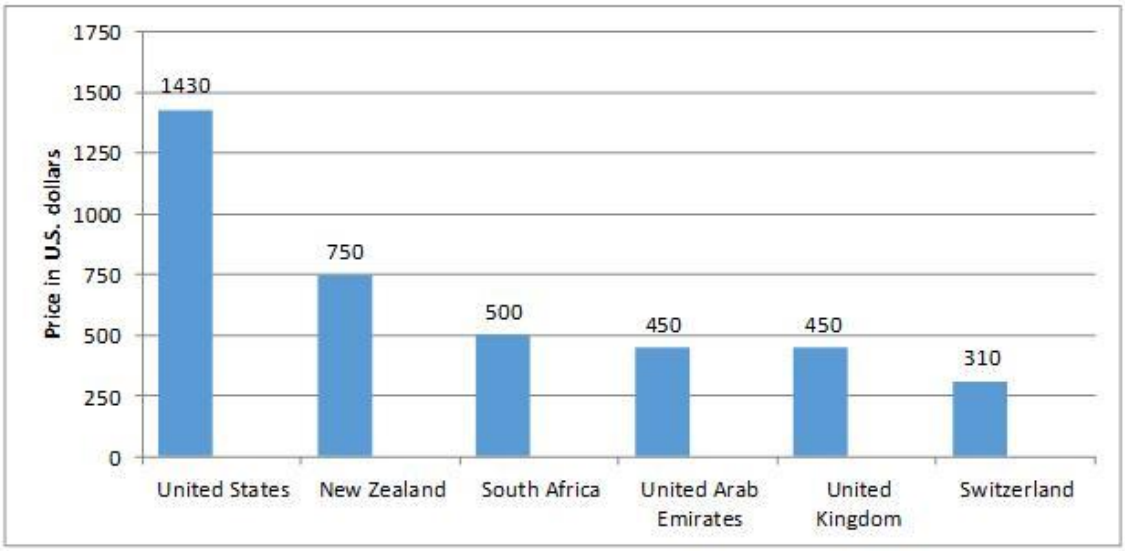

Figure 12. Average Prices of an MRI in Selected Countries in 2017

The burden caused by the operation of the MRI scanner should be mentioned within the healthcare system. According to a study of MRI costs from 1989-1996, acquiring and operating an MRI scanner at Walsgrave Hospital NHS Trust was covered under five main headings. These are (1) Capital costs, (2) Maintenance and service costs, (3) Personnel costs, (4) Consumable costs, and (5) General expenses [79]. So, there are hidden costs such as personnel, maintenance/repair, and consumables during its use. Also, MRI scanners have a certain period of use. After this period, the MRI device must be replaced, which is an additional expense. Our calculations do not include the savings that can be achieved from all these costs. Here we have only presented the potential savings achieved within one year using the developed stepwise model. If the cost of MRI scans, such as personal salary and other overhead, is considered, the savings will be much higher.

Besides, the fact that patients with claustrophobia cannot be diagnosed correctly with MRI reveals the importance of the decision support system developed in this study. Patients are subjected to severe and unnatural space and movement restrictions in the magnetic resonance imaging environment, which can last up to and beyond one hour. Significant motion artifacts that degrade image quality and reduce diagnostic utility are frequently caused by claustrophobia and increasing anxiety. Furthermore, 3-5 percent of patients drop out of their studies due to these stresses, necessitating the need for repeat studies, which consumes scarce and expensive resources. The negative experience may also cause the patient to refuse a repeat MRI, effectively excluding him or her from the non-invasive diagnostic accuracy of this imaging modality [80].

When the international guidelines for low back and neck pain are examined, it is seen that the American College of Physicians and the American Pain Society have various guideline recommendations for low back pain[81]. Our work can also be considered to prepare such a guideline in Turkey.

Since it was studied with actual patient data and the data were collected by our efforts, not from a previously collected data set, the number is few but comparable to similar studies in the literature. However, it is thought that a much better model will be established with more data. This study/model can be further developed with a system that constantly feeds itself regarding the number of patients.

CHAPTER 6

CONCLUSION

This thesis is a two-stage study that examines the preliminary data and clinical information of patients with low back and neck pain and their orientation to the proper treatment method without the need for MRI, and the costs and possible savings of the study results on the health system.

In the first stage, 1482 patient data collected with the questions in Appendix E were separated and categorized according to data types. The collected numerical and categorical data are ready for data mining using normalization and binarization methods. In the literature, it is possible to come across studies examining whether the patient is normal or abnormal by establishing a decision support system with the preliminary data of the patient. Also, the diagnosis of different diseases such as Parkinson's, heart disease, melanoma recognition, and breast cancer has been tried to be developed by researchers with the data mining algorithm.

This study developed a stepwise model that can refer neck and low back pain patients to appropriate treatment based on their clinical findings without MRI. The stepwise model named MRI free decision model (MFDM) classifies drug therapy patients with an 84% success ratio and can direct patients to surgery or RF / IDET with a 74.47% success ratio with no need for prior MRI testing. Through the application of MFDM, primary care doctors (family physicians), who are not algology specialists or surgeons, can diagnose neck and low back pain and determine which treatment protocol would suit the patient. MFDM will allow only considering the medical history and clinical symptoms of patients to direct them to the appropriate clinic at the first-level medical services, leading to a faster referral, shortening the time to see a specialist, and lowering the overall costs.

Additionally, MFDM can be seen as a solution for patients who cannot enter the MR environment. The magnetic imaging environment is a closed and unnatural environment that may make the patient uneasy and restricts movement. In particular, it becomes impossible to diagnose patients with claustrophobia accurately with MRI. The patient, who is restless and has increased anxiety, moves during the imaging process, and therefore either the procedure cannot be performed, or even if it is done, the imaging cannot be adequately provided due to the patient's movements, and the procedure costs increase for such patients as MRI can be repeated multiple times. The importance of MFDM, which was developed to reduce these costs, is seen more clearly. Moreover, those with a metallic vascular clip inside the head, a pacemaker, an automatic rhythm regulating heart device (automatic defibrillator and a biostimulator), those with some continuous drug delivery and implanted device (infusion device), those with an internal hearing aid, and those with metallic foreign bodies are eligible for MRI. Directing the patient to the proper treatment

method without MRI reveals the importance of MFDM with only the patient's preliminary data.

Secondly, the MRI device is very costly when the general expenses such as purchase (capital expenses), maintenance and service, technical personnel and doctor using the device, consumable expenses, and other electricity costs are evaluated. Moreover, the average MRI scan price in America is 1430 dollars, while the average MRI cost in Europe varies between 100 and 500 dollars.

From a management perspective, our findings show that based on patient's pre-diagnostic data, unnecessary MRI costs can be avoided for the patient group to be treated with medication with this stepwise model since there is no particular guideline for MRI in Turkey and the MRI image is requested for each patient as soon as the patient comes to the clinic. In concise terms, the potential savings through utilization of the MFDM in the first-level healthcare providers have been presented in this study. As described in the model cost analysis section, at least 0.37% of the MOH budget can be saved.

According to the public health services reimbursement cost per MRI scan for the neck, vertebra, lumbar and cervical regions and when the patients with low back and neck pain were examined (Appendix F) by the Ministry of Health, approximately 142 million TL can be saved based on the 2020 public health services price list only. Since the Ministry of Health of Turkey's budget was approximately 37,9 billion TL in 2018, it is predicted that the state will save 0.37% only in the yearly health budget with the proposed MFDM in one year.

Considering all these, it is evident that using the health care management model will increase the efficiency of the health system operation.

6.1. Limitation and Future Work

In this section, some limitations are listed, and future studies are suggested:

First, there are difficulties in collecting patient data in the pain clinic. Since the data collection period during the thesis study was limited, only the data of the patients who came to the clinic in that period could be obtained.

Algology is a very new science. Algology minor specialization was given for the first time in our country in 2011. Algology units are just being established, so in this respect, it is both an innovative study and the collection of patients in this department is very limited since algology units have just been established in Turkey.

Since it was studied with actual patient data and the data were collected by our efforts, not from a previously collected data set, the number is few, but the number is good enough among similar studies in the literature. However, it is thought that a much better model

will be established with more data. This study/model can be further developed with a system that constantly feeds itself regarding the number of patients.

TP and TN values were evaluated while making model cost analyses. FP and FN values can also be included in the calculations.

While cost analysis is performed for patients referred to drug therapy, a detailed examination can be made in subsequent studies for patients who need to receive treatment other than drug therapy but are referred to drug therapy according to the model. The fact that the model offers drug therapy to patients who need to be referred to surgery, IDET or RF (FP and FN values) does not pose a vital problem for patients. Delays or excess drug treatment cost calculations can be made in detail in future studies.

In addition, only the patient profile in the algology department of a particular hospital was studied. More precise results can be obtained by expanding the study with datasets across the country or worldwide.

REFERENCES

[1] S. L. James, D. Abate, K. Hassen, S. M. Abay, and C. Abbafati, "Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017," *Lancet*, vol. 392, no. 10159, pp. 1789–1858, 2018, doi: 10.1016/S0140-6736(18)32279-7.

[2] W. H. Organization, "Musculoskeletal conditions," 2019. https://www.who.int/news-room/fact-sheets/detail/musculoskeletal-conditions (accessed Nov. 12, 2020).

[3] "Care for low back pain: can health systems deliver?," 2020. https://www.who.int/bulletin/volumes/97/6/18-226050.pdf (accessed Jan. 08, 2020).

[4] National Institutes of Neurological Disorders and Stroke, "Low Back Pain Fact Sheet | National Institute of Neurological Disorders and Stroke," 2020. https://www.ninds.nih.gov/Disorders/Patient-Caregiver-Education/Fact-Sheets/Low-Back-Pain-Fact-Sheet (accessed Dec. 18, 2019).

[5] A. B. Bernstein, D. M. Makuc, and L. T. Bilheimer, "Health, United States, 2006 With chartbook on trends in the health of Americans," 2006.

[6] S. J. Kamper *et al.*, "Multidisciplinary biopsychosocial rehabilitation for chronic low back pain: Cochrane systematic review and meta-analysis," *BMJ*, vol. 350, Feb. 2015, doi: 10.1136/bmj.h444.

[7] A. Beulah, T. S. Sharmila, and V. K. Pramod, "Disc bulge diagnostic model in axial lumbar MR images using Intervertebral disc Descriptor (IdD)," *Multimed. Tools Appl.*, vol. 77, no. 20, pp. 27215–27230, Oct. 2018, doi: 10.1007/S11042-018-5914-8/TABLES/8.

[8] J. Hartvigsen *et al.*, "What low back pain is and why we need to pay attention," *The Lancet*, vol. 391, no. 10137. Lancet Publishing Group, pp. 2356–2367, Jun. 01, 2018. doi: 10.1016/S0140-6736(18)30480-X.

[9] M. Krismer and M. van Tulder, "Low back pain (non-specific)," *Best Practice and Research: Clinical Rheumatology*, vol. 21, no. 1. Baillière Tindall, pp. 77–91, Feb. 01, 2007. doi: 10.1016/j.berh.2006.08.004.

[10] A. F. Mannion, F. Balagué, F. Pellisé, and C. Cedraschi, "Pain measurement in patients with low back pain," *Nature Clinical Practice Rheumatology*, vol. 3, no. 11. Nature Publishing Group, pp. 610–618, Nov. 2007. doi: 10.1038/ncprheum0646.

[11] "Intervertebral disc disease: MedlinePlus Genetics." https://medlineplus.gov/genetics/condition/intervertebral-disc-disease/#resources (accessed Apr. 14, 2021).

[12] R. Ferrari and A. S. Russell, "Neck pain," *Best Practice and Research: Clinical Rheumatology*, vol. 17, no. 1. Bailliere Tindall Ltd, pp. 57–70, Feb. 01, 2003. doi: 10.1016/S1521-6942(02)00097-9.

[13] I. Jensen and K. Harms-Ringdahl, "Neck pain," *Best Practice and Research: Clinical Rheumatology*, vol. 21, no. 1. Baillière Tindall, pp. 93–108, Feb. 01, 2007. doi: 10.1016/j.berh.2006.10.003.

[14] "Low Back Pain Fact Sheet | National Institute of Neurological Disorders and Stroke." https://www.ninds.nih.gov/Disorders/Patient-Caregiver-Education/Fact-Sheets/Low-Back-Pain-Fact-Sheet#3102_6 (accessed Apr. 07, 2021).

[15] N. Yoganandan *et al.*, "Microtrauma in the Lumbar Spine: A Cause of Low Back Pain," *Neurosurgery*, vol. 23, no. 2, pp. 162–168, Aug. 1988, doi: 10.1227/00006123-198808000-00006.

[16] A. T. Patel and A. A. Ogle, "Diagnosis and Management of Acute Low Back Pain," *Am. Fam. Physician*, vol. 61, no. 6, pp. 1779–1786, Mar. 2000.

[17] M. Szpalski and R. Gunzburg, "Lumbar spinal stenosis in the elderly: An overview," *European Spine Journal*, vol. 12, no. SUPPL. 2. Springer, pp. S170–S175, Oct. 09, 2003. doi: 10.1007/s00586-003-0612-1.

[18] E. Veizi and S. Hayek, "Interventional Therapies for Chronic Low Back Pain," *Neuromodulation Technol. Neural Interface*, vol. 17, no. S2, pp. 31–45, Oct. 2014, doi: 10.1111/ner.12250.

[19] H. Heneweer, L. Vanhees, and H. S. J. Picavet, "Physical activity and low back pain: A U-shaped relation?," *Pain*, vol. 143, no. 1–2, pp. 21–25, May 2009, doi: 10.1016/j.pain.2008.12.033.

[20] N. E. Foster *et al.*, "Prevention and treatment of low back pain: evidence, challenges, and promising directions," *The Lancet*, vol. 391, no. 10137. Lancet Publishing Group, pp. 2368–2383, Jun. 09, 2018. doi: 10.1016/S0140-6736(18)30489-6.

[21] S. Kinkade, "Evaluation and Treatment of Acute Low Back Pain," Apr. 2007. Accessed: Mar. 09, 2021. [Online]. Available: www.aafp.org/afp.

[22] M. J. Aminoff and R. B. Daroff, *Encyclopedia of the Neurological Sciences*. 2014. Accessed: Apr. 09, 2021. [Online]. Available: https://www.sciencedirect.com/referencework/9780123851581/encyclopedia-of-

the-neurological-sciences

[23] L. Niemisto, E. A. Kalso, A. Malmivaara, S. Seitsalo, and H. Hurri, “Radiofrequency denervation for neck and back pain,” *Cochrane Database Syst. Rev.*, no. 1, Jan. 2003, doi: 10.1002/14651858.cd004058.

[24] “[Surgical treatment of low back pain]. - Abstract - Europe PMC.” https://europepmc.org/article/med/10380594 (accessed Apr. 08, 2021).

[25] S. Dagenais and S. Haldeman, *Evidence-Based Management of Low Back Pain*. Elsevier Inc., 2012. doi: 10.1016/C2009-0-41799-9.

[26] P. Ducheyne, *Comprehensive Biomaterials II*. 2017. Accessed: Apr. 09, 2021. [Online]. Available: https://www.sciencedirect.com/referencework/9780081006924/comprehensive-biomaterials-ii

[27] S. Kotsiantis, D. Kanellopoulos, and P. Pintelas, “Data Preprocessing for Supervised Leaning,” *Int. J. Comput. Sci.*, vol. 1, pp. 111–117, 2006.

[28] S. Alasadi, “Review of Data Preprocessing Techniques in Data Mining,” 2017, Accessed: Mar. 18, 2022. [Online]. Available: https://www.researchgate.net/publication/320161439

[29] E. Boros, P. L. Hammer, T. Ibaraki, and A. Kogan, “Logical analysis of numerical data,” *Math. Program. Ser. B*, vol. 79, no. 1–3, pp. 163–190, Oct. 1997, doi: 10.1007/BF02614316.

[30] “Explain different types of data in statistics - GeeksforGeeks.” https://www.geeksforgeeks.org/explain-different-types-of-data-in-statistics/ (accessed Mar. 23, 2022).

[31] “Types of Data in Statistics (4 Types - Nominal, Ordinal, Discrete, Continuous).” https://byjus.com/maths/types-of-data-in-statistics/ (accessed Mar. 23, 2022).

[32] L. Al Shalabi and Z. Shaaban, “Normalization as a Preprocessing Engine for Data Mining and the Approach of Preference Matrix,” *Proc. Int. Conf. Dependability Comput. Syst. DepCoS-RELCOMEX 2006*, pp. 207–214, 2006, doi: 10.1109/DEPCOS-RELCOMEX.2006.38.

[33] S. G. K. Patro and K. K. Sahu, “Normalization: A Preprocessing Stage,” Mar. 19, 2015. http://arxiv.org/abs/1503.06462 (accessed Dec. 19, 2019).

[34] C. Saranya and G. Manikandan, “A Study on Normalization Techniques for Privacy Preserving Data Mining,” *Int. J. Eng. Technol.*, vol. 5, pp. 2701–2704, 2013.

[35] W. Li and Z. Liu, “A method of SVM with normalization in intrusion detection,” *Procedia Environ. Sci.*, vol. 11, no. PART A, pp. 256–262, 2011, doi: 10.1016/j.proenv.2011.12.040.

[36] E. Ogasawara, L. C. Martinez, D. De Oliveira, G. Zimbrão, G. L. Pappa, and M. Mattoso, “Adaptive Normalization: A novel data normalization approach for non-stationary time series,” *Proc. Int. Jt. Conf. Neural Networks*, 2010, doi: 10.1109/IJCNN.2010.5596746.

[37] “Binarization Definition | DeepAI.” https://deepai.org/machine-learning-glossary-and-terms/binarization (accessed Mar. 23, 2022).

[38] Y. Masmoudi, M. Turkay, and H. Chabchoub, “A binarization strategy for modelling mixed data in multigroup classification,” *2013 Int. Conf. Adv. Logist. Transp. ICALT 2013*, pp. 347–353, 2013, doi: 10.1109/ICADLT.2013.6568483.

[39] “7 Over Sampling techniques to handle Imbalanced Data | by Satyam Kumar | Towards Data Science.” https://towardsdatascience.com/7-over-sampling-techniques-to-handle-imbalanced-data-ec51c8db349f (accessed Aug. 17, 2021).

[40] M. Bach, A. Werner, and M. Palt, “The Proposal of Undersampling Method for Learning from Imbalanced Datasets,” *Procedia Comput. Sci.*, vol. 159, pp. 125–134, Jan. 2019, doi: 10.1016/J.PROCS.2019.09.167.

[41] “What Is Undersampling? .” https://www.mastersindatascience.org/learning/statistics-data-science/undersampling/ (accessed Nov. 15, 2021).

[42] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “SMOTE: Synthetic Minority Over-sampling Technique,” *J. Artif. Intell. Res.*, vol. 16, pp. 321–357, Jun. 2002, doi: 10.1613/JAIR.953.

[43] Z. Zhang *et al.*, “Multi-class classification for large datasets with optimized SVM by non-linear kernel function,” *J. Phys. Conf. Ser.*, vol. 2089, no. 1, p. 012015, Nov. 2021, doi: 10.1088/1742-6596/2089/1/012015.

[44] B. Li, J. Hu, and K. Hirasawa, “Support Vector Machine Classifier with WHM Offset for Unbalanced Data,” *J. Adv. Comput. Intell. Intell. Informatics*, vol. 12, no. 1, pp. 94–101, Jan. 2008, doi: 10.20965/JACIII.2008.P0094.

[45] T. Evgeniou and M. Pontil, “Support Vector Machines: Theory and Applications,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 2049 LNAI, pp. 249–257, 2001, doi: 10.1007/3-540-44673-7_12.

[46] J. A. K. Suykens, “Support vector machines: A nonlinear modelling and control

perspective," *Eur. J. Control*, vol. 7, no. 2–3, pp. 311–327, 2001, doi: 10.3166/EJC.7.311-327.

[47] G. M. Foody and A. Mathur, "A relative evaluation of multiclass image classification by support vector machines," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 6, pp. 1335–1343, Jun. 2004, doi: 10.1109/TGRS.2004.827257.

[48] "Support Vector Machine (SVM) Algorithm - Javatpoint." https://www.javatpoint.com/machine-learning-support-vector-machine-algorithm (accessed Apr. 15, 2022).

[49] "Accuracy paradox - Wikipedia." https://en.wikipedia.org/wiki/Accuracy_paradox (accessed Jun. 04, 2021).

[50] A. G. Lalkhen and A. McCluskey, "Clinical tests: sensitivity and specificity," *Contin. Educ. Anaesth. Crit. Care Pain*, vol. 8, no. 6, pp. 221–223, Dec. 2008, doi: 10.1093/BJACEACCP/MKN041.

[51] K. J. Van Stralen, V. S. Stel, J. B. Reitsma, F. W. Dekker, C. Zoccali, and K. J. Jager, "Diagnostic methods I: sensitivity, specificity, and other measures of accuracy," *Kidney Int.*, vol. 75, no. 12, pp. 1257–1263, Jun. 2009, doi: 10.1038/KI.2009.92.

[52] S. Gilmore, R. Hofmann-Wellenhof, and H. P. Soyer, "A support vector machine for decision support in melanoma recognition," *Exp. Dermatol.*, vol. 19, no. 9, pp. 830–835, Sep. 2010, doi: 10.1111/J.1600-0625.2010.01112.X.

[53] S. Bhatia, P. Prakash, and G. Pillai, "SVM Based Decision Support System for Heart Disease Classification with Integer-Coded Genetic Algorithm to Select Critical Features," 2009.

[54] M. Farhadian, P. Shokouhi, and P. Torkzaban, "A decision support system based on support vector machine for diagnosis of periodontal disease," *BMC Res. Notes*, vol. 13, no. 1, Jul. 2020, doi: 10.1186/S13104-020-05180-5.

[55] Y. Ireaneus, A. Rejani, and S. T. Selvi, "EARLY DETECTION OF BREAST CANCER USING SVM CLASSIFIER TECHNIQUE," *Int. J. Comput. Sci. Eng.*, vol. 1, no. 3, pp. 127–130, 2009.

[56] L. Lin, P. J. H. Hu, and O. R. Liu Sheng, "A decision support system for lower back pain diagnosis: Uncertainty management and clinical evaluations," *Decis. Support Syst.*, vol. 42, no. 2, pp. 1152–1169, Nov. 2006, doi: 10.1016/j.dss.2005.10.007.

[57] G. A. Sandag, N. E. Tedry, and S. Lolong, "Classification of Lower Back Pain Using K-Nearest Neighbor Algorithm," in *2018 6th International Conference on*

Cyber and IT Service Management, CITSM, 2018, pp. 1–5. doi: 10.1109/CITSM.2018.8674361.

[58] A. P. Gaonkar, R. Kulkarni, R. D. Caytiles, and N. C. S. . Iyengar, "Classification of Lower Back Pain Disorder Using Multiple Machine Learning Techniques and Identifying Degree of Importance of Each Parameter," *Int. J. Adv. Sci. Technol.*, vol. 105, pp. 11–24, 2017, doi: 10.14257/ijast.2017.105.02.

[59] C. Mimaroglu *et al.*, "The evaluation of radiofrequency facet nerve denervation in the patients with lumbar facet syndrome: Experience with 493 patients," *Anaesth. Pain Intensive Care*, vol. 21, pp. 438–441, 2017.

[60] "Başbakanlık Mevzuatı Geliştirme ve Yayın Genel Müdürlüğü," 2010. https://www.resmigazete.gov.tr/eskiler/2010/03/20100325M1-1.htm (accessed Nov. 23, 2020).

[61] R. Chamchong and C. C. Fung, "Optimal selection of binarization techniques for the processing of ancient palm leaf manuscripts," in *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, 2010, pp. 3796–3800. doi: 10.1109/ICSMC.2010.5642008.

[62] G. Madzarov, D. Gjorgjevikj, and I. Chorbev, "A Multi-class SVM Classifier Utilizing Binary Decision Tree," *Informatica*, vol. 33, no. 2, pp. 225–233, 2009.

[63] J. Weston and C. Watkins, "Support Vector Machines for Multi-Class Pattern Recognition," *Proc. 7th Eur. Symp. Artif. Neural Networks*, 1999.

[64] J. Cai, L. Hu, Z. Liu, K. Zhou, and H. Zhang, "An Embedded Feature Selection and Multi-Class Classification Method for Detection of the Progression from Mild Cognitive Impairment to Alzheimer's Disease," *J. Med. Imaging Heal. Informatics*, vol. 10, no. 2, pp. 370–379, Feb. 2020, doi: 10.1166/jmihi.2020.2888.

[65] C. W. Hsu and C. J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Networks*, vol. 13, no. 2, pp. 415–425, Mar. 2002, doi: 10.1109/72.991427.

[66] A. Estabrooks, T. Jo, and N. Japkowicz, "A Multiple Resampling Method for Learning from Imbalanced Data Sets," *Comput. Intell.*, vol. 20, no. 1, pp. 18–36, Feb. 2004, doi: 10.1111/j.0824-7935.2004.t01-1-00228.x.

[67] R. Parikh, A. Mathai, S. Parikh, G. C. Sekhar, and R. Thomas, "Understanding and using sensitivity, specificity and predictive values," *Indian J. Ophthalmol.*, vol. 56, no. 1, pp. 45–50, 2008, doi: 10.4103/0301-4738.37595.

[68] O. O. Babatunde, J. L. Jordan, D. A. Van Der Windt, J. C. Hill, N. E. Foster, and J. Protheroe, "Effective treatment options for musculoskeletal pain in primary care:

A systematic overview of current evidence," *PLoS ONE*, vol. 12, no. 6. Public Library of Science, Jun. 01, 2017. doi: 10.1371/journal.pone.0178621.

[69] S. Safiri *et al.*, "Global, regional, and national burden of neck pain in the general population, 1990-2017: systematic analysis of the Global Burden of Disease Study 2017," *BMJ*, vol. 368, p. m791, 2020, doi: 10.1136/bmj.m791.

[70] A. Mokdad *et al.*, "The state of US health, 1990-2016: Burden of diseases, injuries, and risk factors among US states," *JAMA - J. Am. Med. Assoc.*, vol. 319, p. 1444, 2018, doi: 10.1001/jama.2018.0158.

[71] A. Briggs *et al.*, "Reducing the global burden of musculoskeletal conditions," *Bull. World Health Organ.*, vol. 96, pp. 366–368, 2018, doi: 10.2471/BLT.17.204891.

[72] The Ministry of Health of Turkey, "Health Statistics Yearbook," 2017. Accessed: Dec. 17, 2019. [Online]. Available: https://dosyasb.saglik.gov.tr/Eklenti/30148,ingilizcesiydijiv1pdf.pdf?0

[73] B. Duthey, "Priority Medicines for Europe and the World 'A Public Health Approach to Innovation' Update on the 2004 Background Paper," in *World Health Organization Background Paper 6.24 Low Back Pain*, 2013, pp. 1–122. [Online]. Available: https://www.who.int/medicines/areas/priority_medicines/BP6_24LBP.pdf

[74] S. M. Abd Elrahman and A. Abraham, "A Review of Class Imbalance Problem," *J. Netw. Innov. Comput.*, vol. 1, pp. 332–340, 2013, Accessed: Feb. 01, 2022. [Online]. Available: www.mirlabs.net/jnic/index.html

[75] X. Guo, Y. Yin, C. Dong, G. Yang, and G. Zhou, "On the class imbalance problem," *Proc. - 4th Int. Conf. Nat. Comput. ICNC 2008*, vol. 4, pp. 192–201, 2008, doi: 10.1109/ICNC.2008.871.

[76] N. Japkowicz, "The Class Imbalance Problem: Signiicance and Strategies".

[77] "T.C. Sağlık Bakanlığı," 2018. https://www.saglik.gov.tr/TR,50291/saglik-bakanligi-2019-butcesi-tbmmde-kabul-edildi.html (accessed Feb. 18, 2021).

[78] C. Stewart, "Average price MRI in selected countries 2017 | Statista," 2020. https://www.statista.com/statistics/312020/price-of-mri-diagnostics-by-country/ (accessed Nov. 13, 2020).

[79] J. Fletcher, M. D. Clark, F. A. Sutton, R. Wellings, and K. Garas, "The cost of MRI: Changes in costs 1989-1996," *Br. J. Radiol.*, vol. 72, no. MAY, pp. 432–437, 1999, doi: 10.1259/BJR.72.857.10505004.

[80] K. J. Kieran and J. A. Brunbergz, "Adult claustrophobia, anxiety and sedation in

MRI," *Magn. Reson. Imaging*, 1997, doi: 10.1016/S0730-725X(96)00351-7.

[81] R. Chou *et al.*, "Diagnosis and treatment of low back pain: a joint clinical practice guideline from the American College of Physicians and the American Pain Society," *Ann. Intern. Med.*, vol. 147, no. 7, pp. 478–491, Oct. 2007, doi: 10.7326/0003-4819-147-7-200710020-00006.

APPENDICES

APPENDIX A

APPLICATION FOR THE DATA REQUESTED FROM THE MINISTRY OF HEALTH

03.06.2020

SAĞLIK BAKANLIĞINA

ODTÜ, Enformatik Enstitüsü, Sağlık Bilişimi Anabilim Dalı, Tıp Bilişimi Doktora programında yürütmekte olduğum "BOYUN VE BEL AĞRISI BULUNAN HASTALARDA RADYOFREKANS UYGULAMASI ÖNCESİ VE SONRASINDAKİ BULGULARIN İLİŞKİLENDİRİLMESİ" başlıklı doktora tezimde kullanılmak üzere aşağıdaki verilerin tarafıma verilmesi için gereğinin yapılmasını arz ederim.

1. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında bel rahatsızlığı ile hastanelere başvuran hasta sayısı
2. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında boyun rahatsızlığı ile hastanelere başvuran hasta sayısı
3. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında bel rahatsızlığı ile hastanelere başvurup MR çekilen hasta sayısı
4. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında boyun rahatsızlığı ile hastanelere başvurup MR çekilen hasta sayısı
5. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında bel rahatsızlığı ile hastanelere başvurup Radyofrekans (RF), İntradiskal Elektrotermal Terapi (İDET) ve Cerrahi operasyona yönlendirilen hasta sayısı
6. Türkiye'de 2018 (01.01.2018-31.12.2018) yılında boyun rahatsızlığı ile hastanelere başvurup Radyofrekans (RF), İntradiskal Elektrotermal Terapi (İDET) ve Cerrahi operasyona yönlendirilen hasta sayısı

Saygılarımla,

Beste Mimaroğlu Altınay

Ek:

1-Öğrenci Belgesi (4 Sayfa)

2-Çalışma Belgesi (1 Sayfa)

APPENDIX B

ICD10 and MED codes required for the data requested from the Ministry of Health

1. **ICD10 codes for low back problem**

ICD10 Code	ICD10 Description
M54.3	Sciatica
M54.4	Lumbago with sciatica
M54.5	Low back pain

2. **ICD10 code for neck problem**

ICD10 Code	ICD10 Description
M54.2	Low back pain

3. **MED codes for Radiofrequency Thermocoagulation (RFT)**

550.970 Annuloplasty RFT (waist-neck)

550.980 Facet Joint (single) RFT (waist-neck)

551.000 Nucleoplasty RFT (waist-neck)

551.010 Paravertebral lumbar RFT (waist)

551.030 Percutaneous facet nerve (single) denervation RFT (waist-neck)

551.070 Sacroiliac joint (single) RFT (lumbar)

551.80 Cervical / Thoracic / Lumbar DRG-RFT (each) (waist-neck)

4. **MED codes for IDET**

551.040 Percutaneous intradiscal RFT, RFT application into the disc- IDET (waist)

551.050 PIRFT intradiscal (waist)

551.060 RFT Neurotomy (waist)

5. **MED codes for surgery**

615.880 Lumbar discectomy single level (waist)

615.890 Lumbar discectomy single level bilateral (waist)

615.900 Lumbar laminectomy and disc, bilateral disc (waist)

615.910 Lumbar laminectomy and disc, unilateral disc (waist)

615.920 Lumbar microsurgery discectomy single level (waist)

615.930 Lumbar microsurgery with discectomy single level bilateral (waist)

615.940 Cervical discectomy with microsurgery with anterior approach single space (neck)

615.950 Cervical discectomy microsurgery with anterior approach, single space and intervertebral graft-cage application (neck)

615.960 Cervical laminectomy and disc evacuation (neck)

6. **MED code for waist MRI**

804.320 MR, vertebra, lomber

7. **MED codes for neck MRI**

804.210 MR, neck

804.450 MR, Vertebra, cervical

APPENDIX C

APPROVAL LETTER OF THE PRACTICAL ETHICS RESEARCH BOARD

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

ORTA DOĞU TEKNİK ÜNİVERSİTESİ
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05 ARALIK 2016

Konu: Değerlendirme Sonucu

Gönderilen: Doç.Dr. Yeşim Aydın SON,
Enformatik Enstitüsü

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın, Doç.Dr. Yeşim Aydın SON;

Danışmanlığını yaptığınız doktora öğrencisi Beste Mimaroğlu ALTINAY'ın "Boyun ve Bel Ağrısı Bulunan Hastalarda Radyofrekans Uygulaması Öncesi ve Sonrasındaki Bulguların İlişkilendirilmesi" başlıklı araştırması İnsan Araştırmaları Kurulu tarafından uygun görülerek gerekli onay **2016-FEN-068** protokol numarası ile **01.12.2016-01.12.2017** tarihleri arasında geçerli olmak üzere verilmiştir.

Bilgilerinize saygılarımla sunarım.

Prof. Dr. Canan SÜMER
İnsan Araştırmaları Etik Kurulu Başkanı

Prof. Dr. Mehmet UTKU
İAEK Üyesi

Prof. Dr. Ayhan SOL
İAEK Üyesi

Prof. Dr. Ayhan Gürbüz DEMİR
İAEK Üyesi

Doç.Dr. Yaşar KONDAKÇI
İAEK Üyesi

Yrd .Doç .Dr. Pınar KAYGAN
İAEK Üyesi

Yrd. Doç. Dr. Emre SELÇUK
İAEK Üyesi

APPENDIX D

EXAMPLE OF PARTICIPANT CONSENT

Araştırmaya Gönüllü Katılım Formu

Bu araştırma, ODTÜ Tıp Bilişimi Bölümü doktora öğrencisi Beste Mimaroğlu ALTINAY ve tez danışmanı ODTÜ Tıp Bilişimi Bölümü Öğretim Üyesi Doç. Dr. Yeşim Aydın SON tarafından yürütülen bir çalışmadır. Bu form sizi araştırma koşulları hakkında bilgilendirmek için hazırlanmıştır.

Çalışmanın Amacı Nedir? Araştırmanın amacı, bel ve boyun ağrısı ile ağrı kliniğine gelen hastaların hangi tedavi yöntemine yönlendirileceğinin modelleme başarısının ölçülmesidir.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz? Araştırmaya katılmayı kabul ederseniz, kliniğinize bel ya da boyun ağrısı ile gelen hastalar ile ilgili veri paylaşımı ve MR görüntüsü yorumlamanız istenecektir.

Sizden Topladığımız Bilgileri Nasıl Kullanacağız? Araştırmaya katılımınız tamamen gönüllülük temelinde olmalıdır. Ankette, sizden kimlik veya kurum belirleyici hiçbir bilgi istenmemektedir. Cevaplarınız tamamıyla gizli tutulacak, sadece araştırmacılar tarafından değerlendirilecektir. Katılımcılardan elde edilecek bilgiler toplu halde değerlendirilecek ve bilimsel yayımlarda kullanılacaktır. Sağladığınız veriler gönüllü katılım formlarında toplanan kimlik bilgileri ile eşleştirilmeyecektir.

Katılımınızla ilgili bilmeniz gerekenler: Katılımınız ile sizlere risk oluşturabilecek herhangi bir veri gizlemesi ya da ifşası yapılmayacaktır. Katılım sırasında herhangi bir nedenden ötürü kendinizi rahatsız hissederseniz cevaplama işini yarıda bırakıp çıkmakta serbestsiniz. Böyle bir durumda çalışmayı uygulayan kişiye, çalışmadan çıkmak istediğinizi söylemek yeterli olacaktır. Çalışma sonunda, bu araştırmayla ilgili sorularınız cevaplanacaktır.

Araştırmayla ilgili daha fazla bilgi almak isterseniz: Bu çalışmaya katıldığınız için şimdiden teşekkür ederiz. Araştırma hakkında daha fazla bilgi almak için ODTÜ Tıp Bilişimi Bölümü öğretim üyelerinden, tez danışmanım Doç. Dr. Yeşim Aydın Son (E-posta: yesim@metu.edu.tr) ile iletişim kurabilirsiniz.

Yukarıdaki bilgileri okudum ve bu çalışmaya tamamen gönüllü olarak katılıyorum.
(Formu doldurup imzaladıktan sonra uygulayıcıya geri veriniz).

İsim Soyad Tarih İmza

[redacted]

APPENDIX E

Middle East Technical University

To be submitted to the Human Research Ethics Committee (IAEK)

Interview Questions Prepared by Beste Mimaroğlu Altınay

QUESTIONS:

1. What is the patient's weight?
2. What is the patient's height?
3. Patient's Age?
4. Gender of the patient?
5. What is the patient's BMI?
6. How many years did the patient have a hernia?
7. What is the Cause of Hernia?
    a. FORCING- HEAVY LIFTING
    b. OPERATION
    c. TRAUMA
    d. STANDING
    e. INACTIVITY
    f. UNKNOWN
8. How many years has the patient had pain? (the duration of the pain will be coded in months)
9. How many points does the patient rate his/her pain between 0-10? (0-10 VAS VALUE)
10. What treatments has the patient received before?
    a. NONE,
    b. FTR,
    c. SURGICAL,
    d. RF,
    e. FTR+RF,
    f. FTR+SURGERY,
    g. ID
11. Which part of the patient has a hernia?
    a. WAIST
    b. CERVICAL
    c. WAIST+CERVICAL
12. What is the number of hernia, if known?
13. Is there any deformity, curvature or humpback in the body?
    a. There is
    b. no

14. What is the degree of limitation of movement of the patient before coming to the clinic? (between 1 and 5)

1. Very Severe Restriction of Movement
2. Severe Restriction of Movement
3. Moderate Mobility Restriction
4. Few Restrictions of Movement
5. No Movement Restrictions

15. Is there any loss of feeling in the arms/legs?

a. There is
b. no

16. How far does the pain spread to the arms/legs?

a. WAIST
b. HIP
c. LEG
d. KNEE
e. HEEL
f. NECK
g. SHOULDER
h. forearm
i. HAND
j. NONE

17. Is there any loss of strength in the arms/legs?

a. There is
b. no

18. Do you have drop feet, urinary/fecal incontinence?

a. There is
b. no

19. Is There Any Additional Disease?

a. There is
b. no

20. According to the MRI results, which treatment method should the patient be directed to?

a. Medication
b. Radiofrequency Therapy
c. Intradiscal Electrothermal Therapy
d. Surgical

APPENDIX F

The number of patients who applied to the health institution with low back problem in 2018	11.679.716
The number of patients who applied to the health institution with neck problem in 2018	2.116.725
Number of patients who applied to a health institution with low back problem and underwent MRI in 2018	1.379.896
Number of patients who applied to a health institution with neck problem and underwent MRI in 2018	445,452
Number of patients who applied to health institutions with low back problem and underwent RF procedure in 2018	632
Number of patients who applied to health institutions with low back problem and underwent IDET in 2018	5
Number of patients who applied to health institutions with low back problem and underwent surgical operation in 2018	10,754
Number of patients who applied to health institutions with neck problem and underwent RF procedure in 2018	63
Number of patients who applied to health institutions with neck problem and underwent surgical operation in 2018	1273

CIRRICULUM VITAE

PERSONAL INFORMATION

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Nationality	: Turkish (TC)
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EDUCATION

Degree	Institution	Year of Graduation
MS	Gazi University, Human Resources Management	2010
BS	Başkent University, Computer Engineering	2006

WORK EXPERIENCE

Year	Place	Enrollment
2016-Present	Social Sciences University of Ankara	IT Manager
2013-2016	Social Sciences University of Ankara	Engineer
2011-2013	Sivas Cumhuriyet University	Research Assistant
2011	Objekt Yazılım ve Bilgisayar Hizmetleri, Teknopark/ Bilkent-Ankara	Computer Engineer
2006-2009	Çözüm Bilgisayar Ltd. Şti., Teknokent/ ODTÜ-Ankara	R&D Specialist

FOREIGN LANGUAGES

Advanced English

COMMITTEE MEMBERSHIPS

- Organization committee member at HIBIT2012 (Health Informatics and Bioinformatics Technologies).
- Organization committee member at SSUA (Social Sciences University of Ankara) IDEC2021 (International Distance Education Congress)

PUBLICATIONS

Papers presented at international scientific meetings and published in the proceedings:

1. C.Mimaroglu, **B.Mimaroglu Altinay**, C.Duger, A.C.Isbir, F.Bulut, S.Gursoy, K.Kaygusuz, I.Ozdemir Kol, WIP 2014 konferansı dahilinde , "", bildiri kitapçığındaki "The Evaluation of Radiofrequency therapy in the patients with cervical radicular pain: Our Experiences", 51 pp.,Maastricht, Hollanda, Mayıs, 2014
2. C.Mimaroglu, **B.Mimaroglu Altinay**, C.Duger, A.C.Isbir, S.Gursoy, I.Ozdemir Kol, K.Kaygusuz, WIP 2014 konferansı dahilinde , "WIP 2014", bildiri kitapçığındaki "Our Experience with intraarticular ozone therapy in the patients with gonarthrosis", 50 pp.,Maastricht, Hollanda, Mayıs, 2014
3. C.Mimaroglu, **B.Mimaroglu Altinay**, C.Duger, A.C.Isbir, I.Ozdemir Kol, K.Kaygusuz, S.Gursoy, WIP 2014 konferansı dahilinde , "WIP 2014", bildiri kitapçığındaki "Intradiscal Electrothermal Therapy (IDET) in the patients with lumbar disc herniation: Our experience of 206 patients", 55 pp.,Maastricht, Hollanda, Mayıs, 2014
4. C.Mimaroglu, **B.Mimaroglu Altinay**, C.Duger, A.C.Isbir, S.Gursoy, K.Kaygusuz, I.Ozdemir , WIP 2014 konferansı dahilinde , "WIP 2014", bildiri kitapçığındaki "The Evaluation of radiofrequency facet nerve denervation in the patients with lumbar facet syndrome: Experience with 493 patients", 54 pp.,Maastricht, Hollanda, Mayıs, 2014
5. C. Mimaroglu, **B. Mimaroglu Altinay**, C. Duger, A.C. Isbir, S. Gursoy, K. Kaygusuz, I. Ozdemir Kol, Our Six year experience of radiofrequency therapy in the patients with lumbar facet syndrome, EFIC 2015, Viyana, Avusturya
6. C. Mimaroglu, **B. Mimaroglu Altinay**, C. Duger, A.C. Isbir, S. Gursoy, I. Ozdemir Kol, K. Kaygusuz, Our Experience with intraarticular ozone injection therapy in the patients with gonarthrosis, EFIC 2015, Viyana, Avusturya
7. C. Mimaroglu, **B. Mimaroglu Altinay**, C. Duger, A.C. Isbir, I. Ozdemir Kol, K. Kaygusuz, S. Gursoy, Intradiscal Electrothermal therapy(IDET) in the patients with lumbar disc herniation, EFIC 2015, Viyana, Avusturya
8. C. Mimaroglu, **B. Mimaroglu Altinay**, C. Duger, A.C. Isbir, F. Bulut, S. Gursoy, K. Kaygusuz, I. Ozdemir Kol, The Evaluation of radiofrequency therapy in the patients with cervical radicular pain: Our experiences, EFIC 2015, Viyana, Avusturya
9. C.Mimaroglu, **B.Mimaroglu Altinay**, C.Duger, K.Kaygusuz, I.Ozdemir Kol, A.C.Isbir, S.Gursoy, Our Epiduroscopic adhesiolysis therapy experiences with 30 patients, EFIC 2015, Viyana, Avusturya

10. C. Mimaroglu, **B. Mimaroglu Altinay**, C. Duger, S. Gursoy, A.C. Isbir, I. Ozdemir Kol, K. Kaygusuz, Our experience with intraarticular platelet rich plasma injection therapy in the patients with gonarthrosis, EFIC 2015, Viyana, Avusturya

Papers presented at national scientific meetings and published in proceedings:

1. C. Mimaroğlu, **B. Mimaroğlu Altınay**, C. Düger, A.C İsbir, S. Gürsoy, K. Kaygusuz, İ. Özdemir Kol, "The Evaluation Of Radiofrequency Facet Nerve Denervation In The Patients With Lumbar Facet Syndrome: Experience With 493 Patients", TARK 2014, Ankara
2. C. Mimaroğlu, **B. Mimaroğlu Altınay**, C. Düger, A.C İsbir, S.Gürsoy, İ.Özdemir Kol, K.Kaygusuz, "Our Experience With Intraarticular Ozone Injection Therapy In The Patients With Gonarthrosis", TARK 2014, Ankara
3. C. Mimaroğlu, **B. Mimaroğlu Altınay**, C. Düger, A.C İsbir, İ. Özdemir Kol, Kenan Kaygusuz, Sinan Gürsoy, "Intradiscal Electrothermal Therapy (IDET) In The Patients With Lumbar Disc Herniation: Our Experience Of 206 Patients" , TARK 2014, Ankara
4. C. Mimaroğlu, **B.Mimaroğlu Altınay**, C. Düger, A.C İsbir, F. Bulut, S. Gürsoy, K. Kaygusuz, İ. Özdemir Kol, "Servikal radiküler ağrılı hastalarda radyofrekans tedavi deneyimlerimiz", TARK 2014, Ankara
5. C. Mimaroğlu, **B. Mimaroğlu Altınay**, C.Düger, A.C İsbir, S. Gürsoy, K. Kaygusuz, İ.Özdemir Kol, "Lomber faset sendromlu 493 hastada radyofrekans faset sinir denervasyonu tedavi deneyimimiz", TARK 2014, Ankara
6. **B. Mimaroğlu Altınay**, Y. Aydın Son, "Development of a Clinic Decision Support Model for Directing Patients with Neck and Lower Back Pain to Appropriate Treatment Option", TurkMIA 2017, Antalya

Poster:

1. **B. Mimaroğlu Altınay**, Y. Aydın Son, "A Data Mining Approach for Directing the Patient to Appropriate Treatment Method in Pain Clinic and Finding the Possible Effects of Treatment in Radiofrequency Patients", Middle East Technical University, Graduate School of Informatics, Open Research Day 2018, Ankara