PREDICTING RISK OF MORTALITY IN PATIENTS UNDERGOING CARDIOVASCULAR SURGERY

A THESIS

SUBMITTED TO THE DEPARTMENT OF COMPUTER ENGINEERING

AND THE INSTITUTE OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

MASTER OF SCIENCE

By

Ayşen Tunca

September, 2008

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Prof. Dr. Halil Altay Güvenir(Advisor)

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Assoc. Prof. Dr. Rüçhan Akar

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Assist. Prof. Dr. Çiğdem Gündüz Demir

Approved for the Institute of Engineering and Science:

Prof. Dr. Mehmet B. Baray
Director of the Institute

ABSTRACT

PREDICTING RISK OF MORTALITY IN PATIENTS UNDERGOING CARDIOVASCULAR SURGERY

Ayşen Tunca
M.S. in Computer Engineering
Supervisor: Prof. Dr. Halil Altay Güvenir
September, 2008

It is very important to inform the patients and their relatives about the risk of mortality before a cardiovascular operation. For this respect, a model called EuroSCORE (The European System for Cardiac Operative Risk Evaluation) has been developed by European cardiovascular surgeons. This system gives the risk of mortality during or 30 days after the operation, based on the values of some parameters measured before the operation. The model used by EuroSCORE has been developed by statistical data gathered from large number of operations performed in Europe.

Even though due to the surgical techniques that have been developed recently and the risk of mortality has been reduced in a large extent, predicting that risk as accurately as possible is still primary concern for the patients and their relatives in cardiovascular operations. The risk of operation also essentially tells the surgeon how a patient with similar comorbidity would be expected to fare based on a standard care. The risk of patient is also important for the health insurance companies, both public or private. In the context of this project, a model that can be used for mortality is developed.

In this research project, a database system for storing data about cardiovascular operations performed in Turkish hospitals, a web application for gathering data, and a machine learning system on this database to learn a risk model, similar to EuroSCORE, are developed. This thesis proposes a risk estimation system for predicting the risk of mortality in patients undergoing cardiovascular operations by maximizing the Area under the Receiver Operating Characteristic (ROC) Curve (AUC).

When the genetic characteristics and life styles of Turkish patients are taken

into consideration, it is highly probable that the mortality risks of Turkish patients may be different than European patients. This thesis also intends to investigate this issue.

Keywords: Machine learning, ROC, AUC, risk estimation, cardiovascular operation, data mining.

ÖZET

KALP VE DAMAR CERRAHİSİNDE ÖLÜM RİSKİ TAHMİNİ

Ayşen Tunca
Bilgisayar Mühendisliği, Yüksek Lisans
Tez Yöneticisi: Prof. Dr. Halil Altay Güvenir
Eylül, 2008

Kalp damar cerrahisi kapsamında yapılan ameliyatlarda ölüm riskinin belirlenip hasta ve hasta yakınlarına ameliyat öncesinden bildirilmesi büyük önem arz etmektedir. Bu amaçla Avrupalı araştırmacılar tarafından EuroSCORE (The European System for Cardiac Operative Risk Evaluation) adında bir sistem geliştirilmiştir. Bu sistem ameliyat öncesi ölçülen bazı parametreleri kullanarak ameliyat sırasında veya ameliyattan sonraki ilk 30 gün içerisinde hastanın ölüm (mortality) riskini vermektedir. Bu model Avrupa'da yapılan çok sayıdaki ameliyatta kaydedilen bilgilerin istatistiksel olarak değerlendirilmesiyle oluşturulmuştur.

Günümüzde cerrahi tekniklerinde gelişmeler ve ameliyatlardaki ölüm risklerinde düşüş görülmesine rağmen, hasta ve hasta yakınları için ölüm riskinin bilinmesi hala daha büyük önem taşımaktadır. Ayrıca, hastanın ölüm riskinin bilinmesi devlet ve özel sağlık sigorta şirketleri için gerekmektedir.

Bu araştırmada Türkiye'deki hastanelerde yapılan kalp-damar ameliyatlarında ölçülen parametrelerin kaydedilebileceği bir veri tabanı ve bu kayıtlar üzerinde makine öğrenmesi çalışmaları ile EuroSCORE'a benzer bir risk belirleme modelinin öğrenileceği bir sistem geliştirilmiştir. Bu araştırmada, özniteliklerin ROC alanı risk hesaplanmasında özniteliklerin ağırlığı olarak kullanılmaktadır. Bu şekilde, tüm ROC alanını maksimum hale getirerek daha iyi bir öznitelik tabanlı makine öğrenmesi ve risk tahmin modeli geliştirilmiştir.

Hastaların genetik özellikleri ve yaşam tarzları göz önüne alındığında, Türk hastaların kalp-damar ameliyatlarındaki ölüm risklerinin Avrupalı hastalardan farklı olması kuvvetle muhtemeldir. Bu çalışmada, bu farklılık araştırılmıştır.

Anahtar sözcükler: Makine öğrenmesi, ROC, ROC alanı, ameliyat risk faktörleri,

kardiyovasküler operasyon, veri madenciliği.

Acknowledgement

I would like to express my gratitude to all those who gave me the possibility to make this thesis real. This space for thankfulness can never be sufficient for a few special people. First of all, I am deeply indebted to my magnificent supervisor Prof. Dr. Halil Altay Güvenir whose inexhaustibly support with indefatigable energy, incredible guidance, unbelievable patience, precious help, stimulating suggestions, and a great deal of encouragement helped me in all the time of research for and writing of this thesis. It was a great pleasure of me to have a chance of being acquainted with him and to have a chance of being assistant of him.

The incredible people, Serkan and Çağın, in Department of Medicine at Ankara University supported me in my research project. Especially, I am obliged to Assoc. Prof. Dr. Rüçhan Akar for his profound help in completing this thesis. All those who knew him will admire him for his work.

I would like to give my special thanks to Assist. Prof. Dr. Çiğdem Gündüz for showing keen interest to the subject matter and accepting to read and review this thesis.

I would like to thank my bosom friends for filling my life with their eternal joy and love. Above all, I am obliged to my parents. I owe everything to a woman in my life who love me with unrequitable, my mother Gülfer Tunca and to a man of whom I trust blindfolded and I imitate, my father Alpay Tunca.

To My Parents,

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In every aspect of human being life, we live in an expanding universe of data in which there is too much data and too little information. The quantity of data in the Internet and the world roughly doubles every year, and as a somewhat surprising consequence, the amount of information decreases rapidly. Not only the availability of data that is vital but also the ability to interpret this data is the main focus by computer scientists today. The development of new techniques to find precious knowledge under a huge amount of data is one of the main challenges for computer scientists.

The unbridled growth of data will inevitably lead to a situation in which it is increasingly difficult to access the desired information; it will always be like looking for a needle in a haystack, only the amount of hay will be growing all the time.

The ability to learn is inherent in living things; even relatively simple organisms like plants have this capacity. Plants learn to maximize the amount of light they receive by turning their leaves towards the sun; this is an elementary form of adaptation to the environment. This capacity to learn seems to be an essential characteristic of life itself. Machine learning led a hidden life in universities and research centers.

Some tasks are extremely hard to solve with computers, and can be relatively easily solved by experienced people, for example to recognize a friend. On the other hand, some tasks are like a piece of cake for computers to accomplish in a short amount of time than for humans, for example some complex mathematical problems. Experts seem to be able to learn how to deal with complexities from experience. Attention turned to the construction of learning algorithms [3, 5, 60].

An intelligent expert system can be constructed by putting all the rules that were used by the expert to the system. Collecting the information to put in an expert system involved a painstaking and expensive process of interviewing relevant experts. Machine learning algorithms could generate the rules automatically. Instead of interviewing experts it appeared that we might be able to build systems that could learn from experience.

Michalski et al. have defined learning as "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E". Witten and Frank defined learning as "things learn when they change their behavior in a way that makes them perform better in the future" [60].

Application of machine learning method to large databases is called data mining. It is well known, in mining, enormous quantities of debris have to be removed before diamonds or gold can be found. In finance, banks analyze their past data to build models to use in credit applications, fraud detection, and stock marketing. In manufacturing, the learning models are used for optimization, control, and troubleshooting. In medicine, learning models are used for medical diagnosis. Machine learning is not just a database problem; it is also a part of artificial intelligence. To be intelligent, a system that is in a changing environment should have the ability to learn [3, 5, 10].

Machine Learning is programming the computers to optimize a performance criterion using example data or past experience. We have a model defined up to some parameters, and learning is the execution of a computer program to optimize the parameters of the model using the training data or past experience. The model may be predictive to make predictions in the future, or descriptive to

gain knowledge from data, or both.

Machine learning is the study of computer algorithms that improve automatically from experience. Machine learning has wide spectrum of applications including natural language processing, pattern recognition, medical diagnosis, computer vision, bioinformatics, and robotics.

Michalski et al. organize Machine Learning approaches into a taxonomy, based on the learning strategies :

- Rote learning or learning by being programmed consists of just recording the different objects supplied by an expert.
- Learning by instruction is learning by being told some new knowledge from an external source.
- Inductive learning is accomplished by reasoning from externally supplied examples to produce more general descriptions.
- Learning by observation is learning by observing the environment and making discoveries.

In machine learning literature, the inductive learning is heavily studied. Inductive learning methods extract rules and patterns out of massive data sets. Inductive Machine Learning algorithms can be divided into a number of categories differently in literature. Generally, Machine Learning algorithms are organized into a taxonomy, based on the desired output of the algorithm:

- Supervised learning algorithms generate a function from training data to map the inputs to desired outputs.
- Unsupervised learning algorithms model a set of input data. (labeled examples are not included)
- Semi-supervised learning algorithms generate a function or classifier from both labeled and unlabel data.

- Reinforcement algorithms assess the goodness of policies and learn from past good action sequences to be able to generate a policy of how to act given an observation of the world.
- Transduction algorithms are similar to supervised learning, but they do not explicitly construct a function: instead, they try to predict new outputs based on training inputs, training outputs, and test inputs which are available while training.
- Learning to learn algorithms learn its own inductive bias based on previous experience.

Supervised learning is also known as classification. Training data include instances with labeled class. Supervised learning techniques learn a classification rule from training data to correctly predict the class of a new instance. In this thesis, for example, the training data are the preoperative parameters of patients underwent a cardiovascular surgery, with actual (labeled) class of each patient (Dead or Alive). The goal of the learning system is to obtain a set of rules to correctly predict the mortality risk of a new patient after cardiovascular surgery [60, 61].

Machine learning is also called concept learning. There are two types of concept learning: single concept learning and multi-concept learning. According to our study, we have both dead and alive patients after the surgery. In single concept learning, the system learns a set of rules to predict only a single concept (class)- only dead class. In multi-concept learning systems, it learns a set of rules for both of the concepts. In this thesis, multi-concept learning system is used.

A wide range of multi-concept systems have been developed to predict mutually disjoint classes, such as Decision Trees [70, 71], Bayesian Classifiers [15, 16, 26], Instance-based learning algorithms [4], and Nearest Neighbor [13, 15].

This thesis proposes a multi-concept learning algorithm called, Risk Estimation by Maximizing the Area under ROC Curve (REMARC). The previously developed related algorithms have achieved success in a wide range of real world

problem domains [31, 32, 34, 36]. They are robust algorithms to irrelevant features and missing feature values, which are problems for other inductive and supervised learning models such as decision trees, and nearest neighbor algorithms.

This thesis proposes a risk estimation technique by maximizing the area under the Receiver Operating Characteristic (ROC) Curve of the algorithm. The Risk Estimation by Maximizing the Area under ROC curve (REMARC) algorithm is non-incremental risk learning algorithm that learns the risk of a test instance from preclassified instances in training set. Risk estimation of the test instance is done by risk estimation scheme where feature-value rules distribute their risk among classes.

Hang and Ling gave formal definitions of discriminancy and consistency in comparing evaluation measures for learning algorithms. The Accuracy and Area under the ROC Curve (AUC) are the two measures that are compared in their studies. They establish precise and objective criteria for comparing these two measures in general and show, both empirically and formally, that AUC is better measure than accuracy [49, 50].

The predictive ability (performance) of REMARC algorithm is measured by its area under the ROC curve (AUC). The heuristic in REMARC algorithm comes by the light and objective of maximizing the overall area under the ROC curve of the algorithm. That is to say, the aim is to maximize the performance of the algorithm. For this respect, if we measure and compare the performance of algorithms in terms of their Area under the receiver operating characteristic curve (AUC), the discriminative ability (weight) of each feature can be used as a weight in addition to rule's predicted risks. The feature's AUC over the testing instances is used to strengthen the feature's risk to overall risk of that test instance. High quality features, that have more discriminative ability, would have more effect on the overall predicted risk of a test instance to maximize the overall performance of the algorithm.

Since the multi-concept learning systems have a wide range of application areas in real-world problems, the system proposed in this thesis will evaluate a real patient data set in our project-TurkoSCORE.

1.1 Motivation

The first question that occurs in cardiac surgery patient's mind is "Am I going to die?". Sometimes giving realistic mortality risk is more trustworthy answer from patient's point of view than explaining the complications of the surgery. It is very important to inform the patient and his/her relatives about the risk of mortality before a cardiovascular surgery. Also, the risk of patient essentially tells the surgeon how a patient with a similar comorbidity would be expected to fare based on a national standard care.

It would be misleading to make a decision about the quality of care of hospitals and success of surgeries by looking only at crude mortality. In fact, the high risk patients underwent a surgery over medical treatment have higher percentage mortality. Nowadays, the mortality information is no longer sufficient for assessing the quality of care of hospitals or surgeries. It would also be fallacious to call an operation as success, if morbidity and poor long-term occurred after the surgery [59, 76, 77].

There are many reasons for predicting the risk of mortality in groups of cardiac patients. These range from helping determine the indication of surgery and proper informed consent to allowing quality monitoring of surgeons and institutions. The predictions have obvious applications in patient's counseling and medical decision-making for individual risk assessment. The predictions are also valuable for assessing if a surgical care is in keeping with an accepted norm. Operative mortality is a good measure of quality of a cardiac surgical care, as long as patient risk factors are taken into consideration. Therefore, a lot of machine learning models have been proposed all over the world to predict the mortality risks for patients undergoing cardiovascular surgery [47, 48, 62, 67, 69, 73, 75, 82, 83].

At Cardiovascular Surgery departments in Turkey, EuroSCORE method calculates the predicted mortality for patients [62]. In EuroSCORE, nearly 20 thousand consecutive patients from 128 hospitals in eight European countries were studied. Validation of EuroSCORE model in other countries have been analyzed. When the outcomes of these surgical operations were analyzed epidemiologically,

crucial differences across the nations were observed [86]. Some studies were done to assess the performance of EuroSCORE model in some other countries out of Europe. As a result of these analysis, the EuroSCORE model of risk prediction was not validated in the present population of cardiac surgical patients in some populations. The claim of this thesis is, since the characteristic and life styles of Turkish people taken into consideration, EuroSCORE may not be validated in our population. Also, since the EuroSCORE system learns a model using a data set occurred before the year 2000, afterwards, considerable improvements achieved in surgical techniques and applied medical treatment protocols. So, a scoring system special to Turkish population is essential in Turkey.

This thesis proposed a machine learning algorithm, called Risk Estimation by Maximizing the Area under the ROC Curve (REMARC), to construct a risk estimation system for the prediction of early mortality in patients undergoing cardiovascular surgeries on the basis of objective risk factors by using national TurkoSCORE data set.

1.2 Overview

Chapter 1 provided a broad introduction to the area of machine learning and gave a brief information about the proposed thesis. Motivation section was written for warming up to the subject.

Chapter 2 describes the background information. The main aim of this chapter is to give literature summary of the learning algorithm and some definitions about the proposed thesis.

Chapter 3 presents the most broadly used scoring system in Europe, called EuroSCORE. This chapter gives detailed information about this scoring system, which will be compared in terms of performance with REMARC algorithm.

Chapter 4 presents an extensive explanation of the TurkoSCORE project and the proposed algorithm.

Chapter 5 will demonstrate the experiments of the proposed algorithm evaluated and the results of its application to the dataset of the project.

Chapter 6 will conclude the thesis by indicating the contributions of the thesis, outcome of the experiments, and outlines the future work on this subject.

Chapter 2

Background

This chapter provides general literature summary and some definitions needed to understand the concepts in rest of the following chapters. Literature summary section explains early stages in study of risk estimation and classifying. The other section presents general information about cardiovascular surgeries. Receiver Operating Characteristic (ROC) section explicates how area under the curve calculation performed and how ROC curves are drawn, and why the Area Under ROC Curve (AUC) is chosen as a performance measure.

2.1 Literature Summary

The study of risk classifying in patients undergoing a medical treatment began at the beginning of 19th century. It is first attributed to Briton Florance Nightingale, who made major contributions to the statistical analysis of postoperative complications, morbidity, and mortality. It is hardly surprising that, the percentage of mortality in patients treated in hospitals was towering than the patients treated outside of hospitals. Her studies showed that the outcomes of surgeries could be changed from one hospital to another. She concluded her analysis by the percentage of mortality could also vary through patients having different stage of

the same illness. This analysis was known as the first example of risk degree analysis. Nightingale made unforgettable efforts to improve the hospital care service in London [56, 63, 80].

At the beginning of 1900s, increasing quality in medicine began with the challenges in the quality of medical education. Major changes made in medical education after an extensive on-site analysis of medical school in the USA and Canada. As a consequence of these analyses, a drastic decrease in the number of medical schools occurred. Also, the remaining medical schools were affiliated with the universities and became an academic educational enterprise, a situation that remains to this day [9, 24, 25, 54, 78].

Ernest Avery Codman created a form of anesthesia chart which is used even today. He undertook the idea of systematic follow-up of surgical patients. He created his own "End Result Hospital" in Boston, Massachusetts. In this hospital, every patient's end results, diagnosis errors, and treatments were followed even years after and reported annually [11].

There are many reasons for predicting the risk of mortality in groups of cardiac patients. These range from helping determine the indication for surgery and proper informed consent to allowing quality monitoring for surgeons and institutions. It is very significant to inform the patients undergoing cardiovascular surgery and their relatives about the risk of mortality before the operation. For this respect, in the USA and Europe, a lot of data mining systems for determining the risk factors in patients undergoing cardiovascular operations have been developed and applied in some clinics. APACHE III [55], Pennsylvania [81], New York's Cardiac Surgery Reporting System [38, 39, 40, 41, 42, 43, 44, 45, 46], Society of Thoracic Surgeons National Database [18, 47], Veterans Affairs [37], Parsonnet [67], Provincial Adult Cardiac Care Network of Ontario, Canada [83, 84], Northern New England Cardiovascular Disease Study Group [14, 64, 65, 66], Cleveland clinical severity score [20, 48], and EuroSCORE [62] are some examples of risk classification studies.

Much disparity subjected between the clinical parameters that increase the national source utilization and the parameters that affect mortality. In previous

studies, it is shown that the variables special to the cardiac disease (recent myocardial infarct, left ventricular dysfunction, hemodynamic instability) are the factors affecting the hospital mortality. On the other hand, it is observed that the external factors other than the cardiac disease (extracardiac arteriopathy, chronic pulmonary disease) affect the national source utilization such as the hospital staying duration, and hospital expenses [22, 23, 72].

There are many machine learning techniques used to predict the risk factors in cardiovascular surgery [1, 6, 8, 12, 17, 27, 28, 29, 48, 51, 53, 52, 57, 58, 62, 67, 68, 69, 73, 74, 82, 83, 85]. These studies were about predicting the risk of disease without concerning the operational risks. Magovern and his colleagues proposed univariate logistic regression analysis model that predicts the mortality and morbidity only after the coronary artery bypass graft surgery [58]. Also, Biagioli and his colleagues proposed a multivariate Bayesian model for assessing morbidity after coronary artery surgery by using 88 operation risk factors [7]. Both of the models are not suitable to be examined by experts.

The previously developed related algorithms acquire knowledge by obtaining a set of rules after training process [31, 35, 36]. These algorithms learn robust model, and have achieved success in a wide range of medicine problem domains [30, 32, 33, 34].

The algorithm of this thesis, REMARC (for Risk Estimation by Maximizing the Area under the ROC Curve) algorithm, is a risk estimation algorithm by maximizing the area under the receiver operating characteristic (ROC) curve.

2.2 Cardiac Surgery

Cardiac surgery is surgery on the heart and/or great vessels performed by a cardiac surgeon. Frequently, it is done to treat complications of ischemic heart disease (for example, coronary artery bypass grafting), correct congenital heart disease, or treat valvular heart disease created by various causes including endocarditis. It also includes heart transplantation.

When a patient applies or is directed by cardiologist to a cardiovascular surgery department, the primary procedure is to collect the preoperative data about patient's clinical symptoms. Preoperative data include identity, complete history recalled and recounted by a patient, physical examination, angiography and echography, the preoperative medication, laboratory analysis, and some general operational.

After the surgery has been carried out, the surgeon takes operative records down including operational procedures done during surgery, surgery crew list, and perfusion data. All data including intensive care unit, complication, laboratory test, medication while discharging from the hospital, and follow-up are some of the postoperative data recorded procedurally for each cardiac patient.

Mortality is the condition of being mortal, or susceptible to death. Mortality data are initially noted immediately after the performed surgery and continuously followed up in specific intervals.

2.3 Receiver operating characteristic

A ROC graph is a technique for visualizing, organizing, and selecting classifiers based on their performance. In signal detection theory, ROC has been used as a graphical plot of sensitivity versus (1 - specificity) since 1975 [19]. Spackman was the earliest scientist who demonstrated the value of ROC curves in evaluating and comparing algorithms in machine learning field [79].

2.3.1 Classifier Performance

We begin by considering a two-class prediction problem, in which the outcomes are labeled either as positive (p) or negative (n). A classification model is mapping from instances to predicted classes (p,n). The classifier result can be a continuous value (probability, score) to which different thresholds may be applied to predict class membership. Other classifiers can predict discrete class label indicating one

of the classes.

Given a classifier and an instance, there are four possible outcomes. If the instance is positive and the outcome of the classifier is positive, it is classified as true positive (TP); if it is classified as negative, it is counted as false negative (FN). If the instance is negative and it is classified as negative, it is counted as true negative (TN); if it is classified as positive, it is counted as false positive (FP).

Given a classifier and a set of test set with P positive and N negative instances, a two-by-two confusion matrix or contingency matrix can be constructed representing the disposition of the set of instances, as follows :

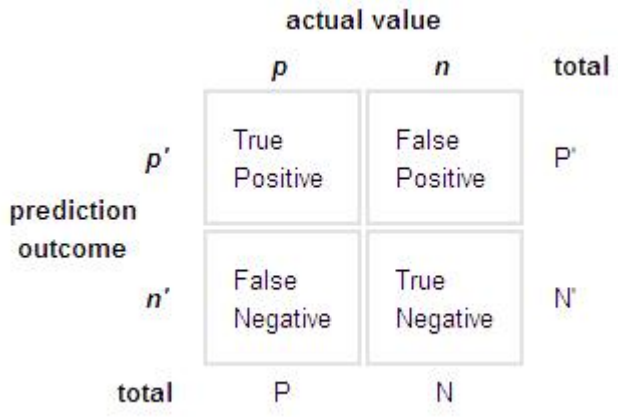

Figure 2.1: Confusion matrix

In Figure 2.1 [2], the numbers in diagonal represent the correct predictions, and the numbers off the diagonal represent the errors. The true positive rate (also called TPR, recall, hit rate, sensitivity) of a classifier is estimated as :

$$true\ positive\ rate = \frac{TP}{P}$$

The false positive rate (also called FPR, false alarm rate, (1 - specificity)) of the classifier is estimated as :

$$false\ positive\ rate = \frac{FP}{N}$$

2.3.2 ROC space

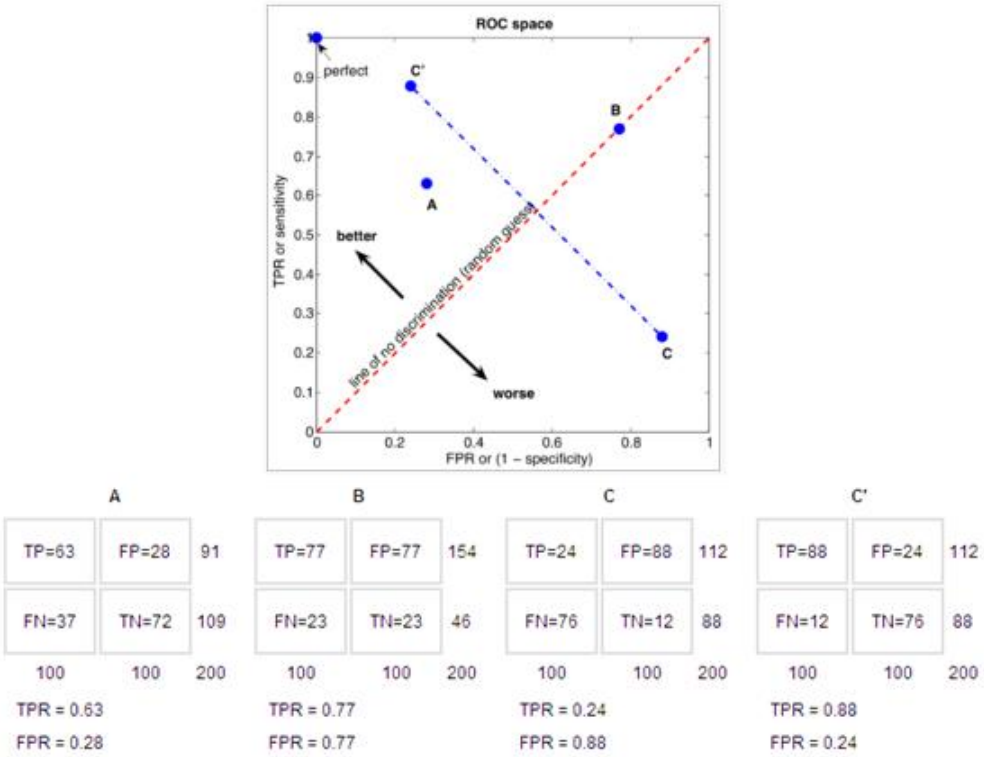

Figure 2.2: The ROC space and plots of four classifier example

ROC graphs are two-dimensional graphs in which TP rate (sensitivity) is plotted on the Y axis and FP rate (1- specificity) is plotted on the X axis, which depicts relative trade-offs between true positive (benefits) and false positive (costs). Each prediction result or one instance of a confusion matrix corresponds to a single point in ROC space.

In Figure 2.2 [2], all classifiers are discrete classifiers. The point (0, 1) represents a perfect classification. It represents a classifier that found all true positives and no false positives. A random guess classifier would give a point along a diagonal line, no-discrimination line. Points above the diagonal indicate good classifiers, while points below the line indicate bad classifiers. Informally, one point in ROC space is better than another if it is to the northwest of the first [21].

In Figure 2.2, Classifier B predicts random guess, actually it has no information. Classifier A is a good classifier, while classifier C is a bad classifier. Any classifier that produces a point below the diagonal line can be negated to produce a point above the diagonal line. Negating a classifier simply means reversing its classification decisions on every instance, as shown in Classier C'.

Inputs: L, the set of test examples; $f(i)$, the probabilistic classifier's estimate that example i is positive; P and N, the number of positive and negative examples.
Outputs: R, a list of ROC points increasing by *fp rate*.
Require: $P > 0$ and $N > 0$

```
1: L_sorted ← L sorted decreasing by f scores
2: FP ← TP ← 0
3: R ← ⟨⟩
4: f_prev ← −∞
5: i ← 1
6: while i ≤ |L_sorted| do
7:    if f(i) ≠ f_prev then
8:       push (FP/N, TP/P) onto R
9:       f_prev ← f(i)
10:   end if
11:   if L_sorted[i] is a positive example then
12:      TP ← TP + 1
13:   else                                   /* i is a negative example */
14:      FP ← FP + 1
15:   end if
16:   i ← i + 1
17: end while
18: push (FP/N, TP/P) onto R                 /* This is (1,1) */
19: end
```

Figure 2.3: Efficient method for generating ROC points

2.3.3 Curves in ROC space

The outcome of discrete classifiers are only the class labels, positive or negative. When a set is given to such classifiers, the result will be a single confusion matrix, which corresponds to a single point in ROC space. The other classifiers produce rank or score as outcome. For these classifiers, a predefined threshold can be used to produce a discrete classifier. For instance, if the score or probability is above or equal to the threshold, it can be classified as positive instance, otherwise classified as negative instance. Then, confusion matrix can be obtained corresponding a single point in ROC space. Different threshold values correspond to a different point in ROC space. A ROC curve can be imaginally drawn by varying a threshold

from $-\infty$ to $+\infty$. The algorithm to generate an efficient ROC curve is detailed in Figure 2.3 [2, 21].

ROC curve compares the classifiers' performance across the entire range of class distributions and error costs. In Figure 2.4, B seems to dominate the A. But it can be observed that B is not dominating A in the whole range. In those situation, the area under the ROC curve is a good summary for comparing the two ROC curves.

2.3.4 Area under a ROC curve (AUC)

A ROC curve is two-dimensional depiction of classifier performance. ROC performance can be represented by a single point to compare the performance of different classifiers. The area under the ROC curve (AUC) has been used in medical diagnosis since the 1970s. It has been proposed as an alternative single-number measure for evaluating the predictive ability of learning algorithms. AUC is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance [49, 50, 21].

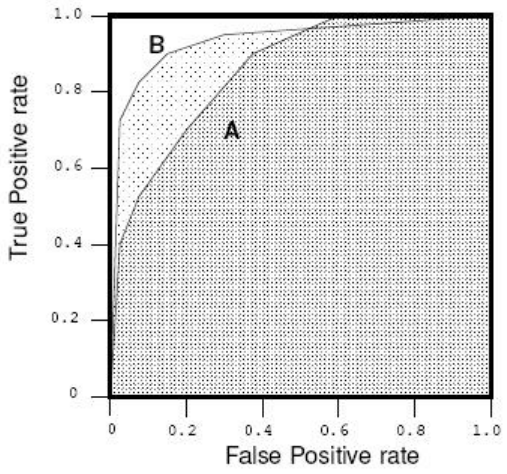

Figure 2.4: Area under two ROC curves

Figure 2.4 shows the area under two ROC curves, A and B. Classifier B has a greater area and therefore a better average performance.

2.3.5 AUC versus Accuracy

The predictive ability of a classification algorithm is measured by its predictive accuracy on the testing examples. However, the outcome of most classifiers can be probability or score of the class prediction. This information is completely ignored in accuracy.

In many data mining applications, accuracy is not enough; for instance, when ranking information of a test instance is needed instead of a mere class label. A perfect ranking result would be possible if there is a true ranking of the training set. This can be achieved by a ROC curve. The AUC provides a good measure for the performance of ROC curves.

The studies based on comparing two measures, AUC and accuracy, in general have been done. Hang and Ling [49, 50] gave formal definitions of discriminancy and consistency in comparing evaluation measures for learning algorithm. They establish precise and objective criteria for comparing two measures in general and show, both empirically and formally, that AUC is a better measure than accuracy. Thus, in this thesis, for evaluating the learning algorithm AUC has been used.

Chapter 3

EuroSCORE

This chapter presents the commonly used scoring system in Europe and Turkey, which is called EuroSCORE. Firstly, general information about the system will be given, the information about how the analysis have been done for determining risk factors and how the overall risk is calculated. In following sections, an analysis of EuroSCORE system has been performed on TurkoSCORE dataset to observe the validation of EuroSCORE on Turkish population. Demographic, calibration and discrimination results are all provided.

3.1 European System for Cardiac Operation Risk Evaluation

It would be misleading to make a decision about the quality of care of hospitals and success of surgeries by looking only at crude mortality. In fact, the high risk patients underwent a surgery over medical treatment have higher percentage mortality [59]. Nowadays, the mortality information is no longer sufficient for assessing the quality of care of hospitals or surgeries. It would also be fallacious to call an operation as success, if morbidity and poor long-term occurred after the surgery [76, 77].

Many of the cardiac risk factors studies have derived in North American patient population. In Europe, a model called EuroSCORE (The European System for Cardiac Operative Risk Evaluation) has been developed and commonly used by European cardiovascular surgeons. This system calculates the predicted operative risk of patients undergoing cardiac surgery during or 30-days after the surgery, based on the values of some parameters measured before the operation. The risk factors obtained in this study includes 68 preoperative and 29 operative parameters by the light and analysis of previous risk factors used in North American and European risk model studies. Most likely risk factors to be useful were identified by consultant cardiac surgeons. Although the risk factors selected for evaluation were largely similar to those in other American studies, whenever possible the definitions are simplified in EuroSCORE. The model used by EuroSCORE developed by data gathered from nearly 20 thousand consecutive patients from 128 hospitals in eight European countries (Germany, France, UK, Italy, Spain, Finland, Sweden, Switzerland) [62].

After some analysis and assessment of the performance of the effects of these potential preoperative and operative risk factors on EuroSCORE project data set, improvement of the performance of the model is obtained by the elimination of factors one at a time. Overall seventeen risk factors were found to be useful for calculating the predicted operative risk of patient underwent cardiac surgery. Definitions of each factor are detailed in Figure C.1, Appendix C. For the scoring system, these risk factors were weighted. The score of the system can be calculated in two different ways. First score is Additive (Standard) EuroSCORE and the other one is Logistic EuroSCORE. Additive EuroSCORE was designed to be a user-friendly scoring system, originally derived from a logistic regression methodology. Initially, Additive EuroSCORE was used. But after some studies on the validation of EuroSCORE system on other cardiac data sets in other European countries, the deficiency of Additive EuroSCORE was noted. Although calculation is simple, Additive EuroSCORE can sometimes underestimate in very high risk patients. Consequently, the Logistic regression version of the system was published [74].

Table 3.1 details the name, weights for Additive and coefficient for Logistic

Table 3.1: EuroSCORE risk factors, their additive weights and beta coefficients

Factor	**Additive weight**	**Logistic β_i coefficient**
Age	1	0.0666354
Sex(female)	1	0.3304052
Chronic pulmonary disease	1	0.4931341
Extracardiac arteriopathy	2	0.6558917
Neurological dysfunction disease	2	0.8416260
Previous cardiac surgery	3	1.0026250
Serum creatinine	2	0.6521653
Active endocarditis	3	1.1012650
Critical preoperative state	3	0.9058132
Unstable angina	2	0.5677075
LV dysfunction(moderate)	1	0.4191643
LV dysfunction(poor)	3	1.0944430
Recent myocardial infarct	2	0.5460218
Pulmonary hypertension	2	0.7676924
Emergency	2	0.7127953
Other than isolated CABG	2	0.5420364
Surgery on thoracic aorta	3	1.1597870
Postinfarct septal rupture	4	1.4620090

EuroSCORE of each risk factor. Definition of risk factors can be scaned in Appendix C, Figure C.1. The Additive EuroSCORE, as it can be guessed from its name, can be calculated simply as adding up the scoring of each existing risk factor of each patient. Logistic EuroSCORE can be computed with the following formula:

$$Predicted\ mortality = \frac{e^{\beta_0 + \sum \beta_i \chi_i}}{1 + e^{\beta_0 + \sum \beta_i \chi_i}}$$

where,

e is natural number = 2.718281828

β_0 is the constant of the logistic regression equation = -4.789594.

β_i is the coefficient of the variable χ_i in the logistic regression equation provided in Table 3.1.

$\chi_i = 1$ if a categorical risk factor is present and 0 if it is absent.

For age, $\chi_i = 1$ if $age < 60$; χ_i increases by one point for year thereafter. Hence

for age 59 or less $\chi_i = 1$, age 60 $\chi_i = 2$, age 61 $\chi_i = 3$, and so on.

EuroSCORE assumes that all the missing values of risk factors have been determined. Not selecting a risk factor means that the risk factor is not observed in the patient.

3.2 Validation of EuroSCORE on Turkish dataset

The purpose of this analysis in this section is to evaluate the performance of Additive and Logistic EuroSCORE in Turkish cardiac surgery by testing it on the TurkoSCORE database.

The definitions of some of the risk variables were not identical in both Europe and Turkey, so some adjustments or approximate assumptions were made to enable complete analysis, listed in Figure C.2, Appendix C.

The Turkish and European patient populations were compared in demographic characteristics, incidence of surgical procedures performed, and prevalence of risk factors, detailed in Table 3.2. Statistical analysis was by t-test for continuous variables and Chi square for categorical values. P values under 0.05 were considered as significant. The simple risk factors were then tested on TurkoSCORE database. This enabled the performance analysis of both calibration and discrimination of EuroSCORE on the TurkoSCORE database.

3.2.1 Demographic results

The prevalence of risk factors in the two populations are detailed in Table 3.2. The Turkish patients are younger in the dataset compared to the ones in EuroSCORE database. Turkish patients have higher incidence of Chronic pulmoner disease and Neurological dysfunction disease. Less patients in Turkish population have extracardiac arteriopathy disease. Turkish patients were more than fourfold as

Table 3.2: Prevalence of risk factors in TurkoSCORE and EuroSCORE populations

Risk Factor	**TurkoSCORE prevalence (%)**	**EuroSCORE prevalence (%)**	p **- value**
Age mean	59.22	62.5	<0.0001
<60	47.4	33.2	<0.0001
60-64	16.7	17.8	0.067
65-69	16.1	20.7	<0.0001
70-74	12.5	17.9	<0.0001
75+	7.3	9.6	<0.0001
Female	28.5	27.8	0.323
Chronic pulmonary disease	15.7	3.9	<0.0001
Extracardiac arteriopathy	5.5	11.3	<0.0001
Neurological dysfunction disease	6.6	1.4	<0.0001
Previous cardiac surgery	29.8	7.3	<0.0001
Serum creatinine	1	1.8	<0.0001
Active Endocarditis	0.1	1.1	<0.0001
Critical preoperative state	0.1	4.1	<0.0001
Unstable angina	10.9	8	<0.0001
LV dysfunction Moderate	28.2	25.6	<0.0001
Poor	4.1	5.8	<0.0001
Recent MI	24	9.7	<0.0001
Pulmonary hypertension	1.1	2	<0.0001
Emergency	4.7	4.9	0.566
Other than isolated CABG	16	36.4	<0.0001
Surgery on thoracic aorta	4	2.4	<0.0001
Postinfarc septal rupture	0.3	0.2	0.137

likely to have previous cardiac surgery. Turkish patients have lower incidence of Serum creatinine, Active endocarditis, preoperative critical state and pulmonary hypertension. Turkish patients were more likely to be labeled as having unstable angina and LV dysfunction Moderate. Poor LV dysfunction were more likely to be presented in Europeans than Turkish patients. More than twice Turkish patients over Europeans had recent myocardial infarction within 90 days before the surgery. Europeans were more likely to have surgery other than isolated CABG and less likely to have surgery on thoracic aorta. All differences were significant ($p < 0.05$) as depicted in Table 3.2. The similarities between two

populations were seen only in the percentage of the patients age between 60-64, the percentage of female patients, Emergency state of the surgery and postinfarc septal rupture.

3.2.2 Discrimination and calibration

Table 3.3: Predicted and observed mortality by EuroSCORE risk level for whole cohort

	Patients (deaths)	Observed mortality rate	Predicted mortality
EuroSCORE Additive			
0-3 (low risk)	2260(8)	0.35%	1.70%
4-6 (medium risk)	1687(22)	1.30%	4.96%
7 + (high risk)	1219(73)	5.99%	8.80%
Total	5166(103)	1.99%	4.44%
EuroSCORE Logistic			
Low risk	1722(4)	0.23%	0.82%
Medium risk	1722(21)	1.22%	1.39%
High Risk	1722(78)	4.53%	3.73%
Total	5166(103)	1.99%	1.98%

Of the 5166 patients, there were 103 deaths, giving an overall mortality rate of 1.99%. The additive EuroSCORE model predicted a mortality rate of 4.44% while the logistic EuroSCORE model predicted a mortality rate of 1.98%, as shown in Table 3.3. Thus, Additive model over estimated mortality at each risk tertile. In Figure 3.1, the discriminatory ability of the Additive (Standard) EuroSCORE model was good, with an area under the ROC curve of 81%. The discriminatory ability of Logistic EuroSCORE model was fair, with an area under the ROC curve of 74.41%. Additive model calibration was poor, the model over predicted deaths in each risk group, and the Logistic EuroSCORE underestimated mortality rate in high risk patients.

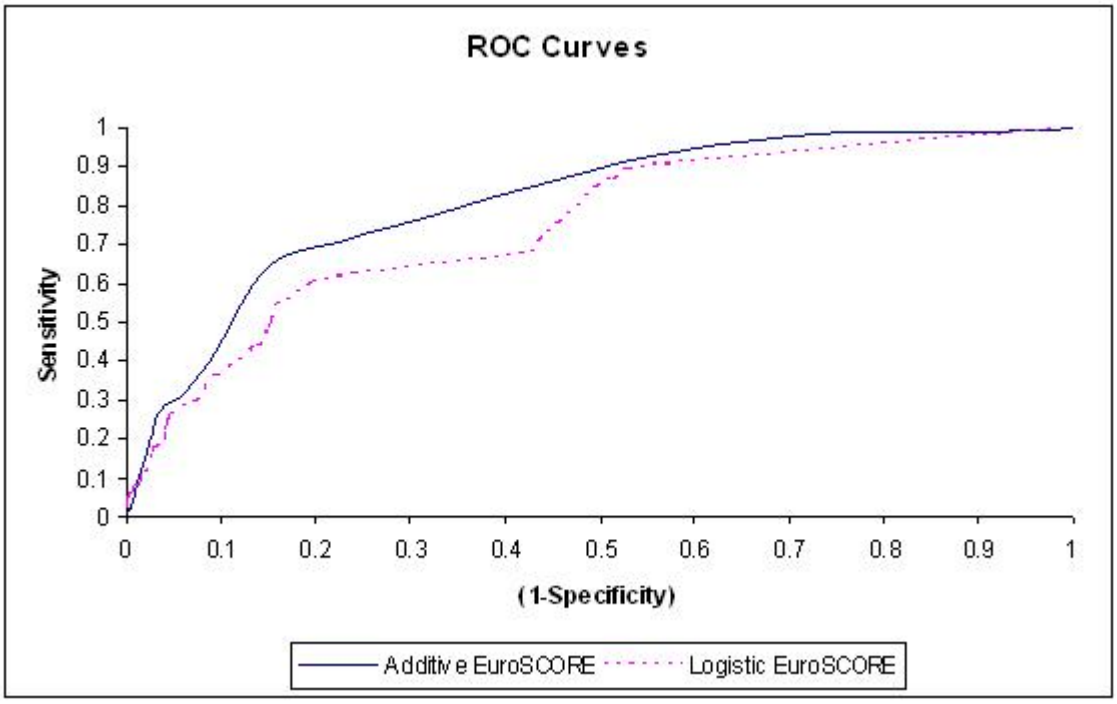

Figure 3.1: Receiver operating characteristic (ROC) curves for Additive and Logistic EuroSCORE

Chapter 4

TurkoSCORE

This chapter presents the deatiled information about the aim and scope of the TurkoSCORE project. TurkoSCORE system is composed of two parts; patient database and the learning system for estimating mortality risk. Database system, gathered data, and the REMARC algorithm are explained in details.

4.1 Aim and Scope

Feature projection based machine learning techniques learn a set of rules. For a query instance, the rules that match with the feature value of the query instance are selected. Each rule used in query distributes its risks to each class. The predicted class of the instance is then labeled as the highest risk class or the predicted score is the total class risk of the desired class. Various versions of this technique were studied and applied in medicine field as well. The results were successful.

The aim of the project is to estimate the mortality risk of patients undergoing cardiovascular surgeries. The predictive ability (performance) of REMARC algorithm is measured by the area under the ROC curve (AUC). The heuristic

in REMARC algorithm comes by the light and objective of maximizing the overall area under the ROC curve of the algorithm. That is to say, the aim is to maximize the performance of the algorithm. For this respect, if we measure and compare the performance of algorithms in terms of their area under the receiver operating characteristic (ROC) curve (AUC), the discriminative ability (weight) of each feature can be used as a weight in addition to rule's predicted risks. A single feature's AUC over the training instances is used to strengthen the feature's risk to overall risk of that test instance. High quality features, that have more discriminative ability, would have more effect on the overall predicted risk of a test instance to maximize the overall performance of the algorithm.

The aim of the project at the applied field, hospital, is to construct a risk estimation system for the prediction of early mortality in patients undergoing cardiovascular surgeries in Turkey on the basis of objective risk factors.

The scope of the project is to set up a database system for storing cardiovascular surgical patient's data in Turkey. These data will include personal, preoperative, operative, postoperative, and mortality parameters. The aim is not only to find risk factors of the patient or to estimate mortality risks of patients, but also to obtain shared extensive national Cardiac Database of Turkish patients. User friendly as well as comprehensive web application for gathering data through internet is planned to be designed. This web application will also be used by doctors to monitor, search, and print the patient health profile as far as one click away. Other purpose of TurkoSCORE project is to construct a data mining system on this database by using preoperative and postoperative parameters to develop a model to estimate the mortality risks of patients.

4.2 Project setup

The project group was set up to include a number of computer engineers from Computer Engineering Department at Bilkent University and Turkish cardiac

surgeons from Cardiovascular Surgery Department at Ankara University (Appendix A). The findings and the preliminary studies by members of the group, and the features of predominantly, European risk models, their refinements and their application were considered and analyzed. Consequently, cardiovascular parameters were selected and defined on the basis of credibility, objectivity, reliability, and prevalence. All the cardiovascular parameters and definitions are detailed in Appendix B.

4.3 Data collection

Database system on a server for storing data has been set up at Bilkent University. The aim is not only to find risk factors of the patient, but also to obtain shared extensive national Cardiac Database of Turkish patients for future researches in medicine and machine learning fields.

Database includes totally 18 tables having totally 921 fields. This data include the personal, preoperative, operative, postoperative and mortality information of each patient undergoing cardiovascular surgery.

A comprehensive web application has been designed for storing, searching, viewing, printing, and analyzing the data statistically [1]. A view of the web site can be seen in Appendix A.2. The total number of cardiovascular parameters (information collected by doctors) included in the system is detailed in Table 4.1. Definition of each cardiovascular parameter can be found in Appendix B.

The web site is authenticated to securely identify the users to the system. This is done to preserve the patients rights. Two levels of authorization presents; Administrator and Doctor. Different authorized users have different access rights to the system. Doctors have only the right to search, view, print, add new patient's data, and update an existing patient's information. Administrators have all the rights of Doctors and additionally have the right of deleting data, adding new user, adding new web application control information (e.g, adding

[1] http://turkoscore.cs.bilkent.edu.tr

Table 4.1: Cardiovascular parameters

Categories	# of parameters
Personal	21
Preoperative	244
Operative	189
Postoperative	111
Mortality	13
Total	565

new prosthesis brand), and downloading all patients data from database tables to SPSS format. Also, Doctor's rights have been secured. One patient belongs to one surgery group. A doctor from another surgery group is not allowed to update the data of a patient underwent cardiac operation by another surgery group.

Comprehensive information on data collection requirements and definitions of variables was provided to all participating institutions and summarized on a web form.

This database has been developed extensively, so that Turkish experts can benefit from extensive data set for future research. Most of the studies need a huge data set for validation of statistics, algorithms, or any analysis. This project intends to gather all Turkish patient's data undergoing cardiovascular surgery in all hospitals of Turkey into one shared database, TurkoSCORE Database, in course of time. The project has been announced in Turkish Cardiovascular Surgery Association as a new national Database system. Other hospitals desiring to join TurkoSCORE Project, are all welcomed by TurkoSCORE Project Group. Already, the Cardiovascular Surgery Department of Acıbadem Hospital in Istanbul has been joined the project. Two centers, the Cardiovascular Surgery Department of Ankara University and Acıbadem Hospital, participating in the project have totally 5166 patients.

All patients who underwent cardiovascular surgery during the project period and previous periods were all included in the study. Surgeries included in the system were done between February 1999 and August 2008.

Data were gathered and entered by the doctors in Ankara University onto the

database through Internet by using a web application. In order to ensure the correctness of data entered by the surgery assistants, the data were checked by the consultant surgeon.

4.4 Data

Totally, 5166 instances present in the TurkoSCORE dataset. 4933 (95.5%) of the instances were from Acıbadem Hospital and 233 (4.5%) were from Ankara University. Overall mortality for all the cardiac procedures was 103 patients (1.99%) of whom 85 (1.64%) from Acıbadem Hospital and 18 (0.35%) from Ankara University.

4.4.1 Patient- related factors

Mean age of the patients was 59.22 with standard deviation of 12.10. Age range was 0-91 years, 1855 patients (35.9%) were aged 65 or over. 3695 of the patients (71.5%) were male and 1471 (28.5%) of the patients were female. Chronic pulmonary disease was present in 811 (15.7%) patients. Extracardiac arteriopathy and Neurological dysfunction disease presented in 284 (5.5%) and 341 (6.6%) patients, respectively. Previous cardiac surgery had been carried out in 1539 (29.8%)patients of whom 77 (1.5%) had thoracic aorta surgery, 93 (1.8%) had Valve surgery, and 1369 (26.5%) had coronary artery bypass. 52 (1%) of the patients had exceeded 2.26 of preoperative serum creatinine. 5 (0.1%) had active endocarditis. Critical preoperative status affected 5 (0.1%) patients.

4.4.2 Cardiac related factors

563 (10.9%) had unstable angina pektoris. Left ventricular function was moderate in 1457 (28.2%) with ejection fraction of 30%-50% and poor in 212 (4.1%) with ejection fraction less than 30%. In patients undergoing cardiovascular surgery,

1240 (24%) of them had myocardial infarction within 90 days. Systolic pulmonary artery pressure exceeded 60mmHg in 57 (1.1%) patients.

4.4.3 Operational related factors

The emergent operations carried out on referral before the beginning of the next working day counted in 243 (4.7%) of the patients. 827 (16%) of the operations were major cardiac procedure other than or in addition to coronary artery bypass. Surgery on thoracic aorta carried out in 207 (4%) of the operations. Postinfarc septal rupture was noted in 15 (0.3%).

4.5 Algorithm

This section provides a detailed information about the learning algorithm for estimating the scores for instances. The algorithm is called REMARC for Risk Estimation by Maximizing the Area under the ROC Curve.

4.5.1 Introduction

The previously developed related algorithms acquire knowledge by obtaining a set of rules by different approaches. These studies have achieved success in a wide range of real world problem domains. They are robust algorithms to irrelevant features and missing feature values which are problems for other inductive and supervised learning models such as decision trees and nearest neighbor algorithms [32, 34, 36].

Classification by Feature Partitioning (CFP) is an inductive, incremental and supervised learning model [36]. Feature values are partitioned into disjoint generalized and specialized segments during training. Voting Feature Intervals (VFI) is a inductive, non-incremental, and supervised learning model. It constructs feature intervals on each feature dimension from training instances [32]. The feature

intervals can represent either a range of feature values or a point for a single categorical feature value. Benefit maximizing Classifier on Feature Projection (BCFP) is also inductive, non-incremental, and supervised model which learns a set of classification rules that maximizes the benefit of classification, given a benefit matrix [34].

The way the Risk Estimation by Maximizing the Area under the ROC Curve (REMARC) algorithm learns a model for risk estimation is to obtain a set of rules and each rule distributes its risk among classes. It can be illustrated by an example of four training instances, two features and one query instance in Figure 4.1. One of the feature is nominal (f_1) and other is linear (f_2). In these learning models, each nominal feature values partitioned into segments. Each feature-value combination constitute a rule. Each rule has an overall risk of 1 and distributes this risk among classes. The classes, in this example, are C_1 and C_2. The rules learned for the features are;
if f_1=a then risk[C_1]=1.0, risk[C_2]=0.0
if f_1=b then risk[C_1]=0.0, risk[C_2]=1.0
if f_2=-∞..3 then risk[C_1]=0.5, risk[C_2]=0.5
if f_2=3..+∞ then risk[C_1]=0.5, risk[C_2]=0.5

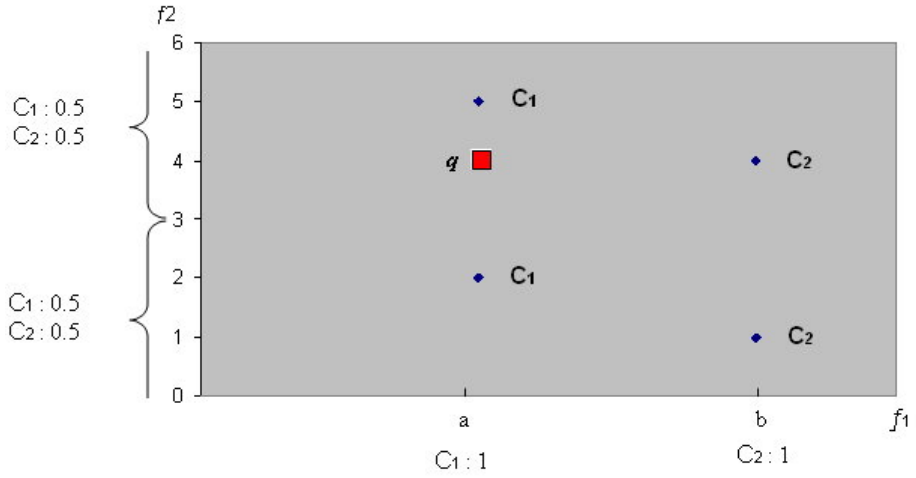

Figure 4.1: Learning a model and estimating risk by REMARC

In order to compute the risk for a query instance, the risk computed for all features are averaged. For the query instance q, the total risk of class C_1 is 0.75 and class C_2 is 0.25 (average of 1.5 and 0.5). This example shows the robustness of REMARC algorithms in presence of irrelevant features in learned rule set. In this case, feature f_2 is irrelevant feature, because it distributes its risk equally among classes. It actually has no effect on overall risk estimation.

Although the related algorithms learn robust models, they become deficient in risk estimation conditions where ranking of instances is important. Most risk estimation models estimate the same risk value for too many instances. Same risk scores complicate the target ranking. That is the situation when the rules distribute the same probability value. So, there is an extra need in weighted features to discriminate the instances that have different comorbidity but have the same risk. For example, Additive EuroSCORE model estimates 20 distinct risk values, Logistic EuroSCORE model estimates 109 distinct risk values, and REMARC algorithm estimates 873 distinct risk values for same 5166 patients.

REMARC model does not intend to give very high risky patients 80% or 90% mortality risk and to give less risky patients 10% or 20% mortality risk. That is to say, the important thing is not the absolute value of the risk. For the evaluation of the performance (reliability) of any score estimation algorithm, the important thing is to correctly order the instances. REMARC algorithm is trained to learn the correct rules. Correct rules here mean; the rules that can correctly order the test instances in terms of their risk and labeled class.

The technique to calculate the area under the ROC curve had been defined in background chapter. To maximize the area under the ROC curve, positive instances must be ranked in very most beginning of the order. So, to maximize the performance of the risk estimation algorithm, the risk of the positively (Dead) labeled instances must be greater than the risk of the negatively (Alive) labeled instances in training process. So, REMARC algorithm learns a rule set to maximize the AUC by using the posterior probabilities of each rule plus the feature's discriminative ability. The example below illustrates the feeling of how to calculate the weight values of each feature.

Assume the categorical feature Sex. It has two different values, Female and Male. The rule learned from only posterior probabilities is;
Feature: Sex (Categorical) Count= 5043,
Female, Count=1427, Rank=1
P: count=30 risk=0.021023126
N: count=1397 risk=0.97897685
Male, Count=3616, Rank=0
P: count=68 risk=0.01880531
N: count=3548 risk=0.9811947

The aim of REMARC algorithm is to correctly order the positive instances. As you can see from above example, an instance in training set with positive label can get either 0.021023126 (F) or 0.01880531 (M). These two risk values are used as a threshold to observe the discriminative ability of feature sex.

The discriminative ability (weight) of any feature is calculated as AUC value of the feature. An instance can at least have the min 0.01880531 risk value from feature sex. So, training set is traced to find the TPR and FPR values for 0.01880531 risk value. That constitutes all the training set. In general, the smallest given risk as a threshold forms the (1,1) point in ROC curve of a feature. For the other risk value, 0.021023126, the TPR and FPR values are also computed to form another point on ROC curve. So overall ROC curve for the feature Sex would be like in Figure 4.2. The area under the ROC curve for each feature is calculated and used as a weight in overall risk estimation.

To show the effect of weighted features on the order of instances, a simple example is given below. Consider a rule set learned from training instances are;
if f_1=a then risk[C_1]=1.0, risk[C_2]=0.0
if f_1=b then risk[C_1]=0.0, risk[C_2]=1.0
if f_2=m then risk[C_1]=1.0, risk[C_2]=0.0
if f_2=n then risk[C_1]=0.0, risk[C_2]=1.0
if f_3=x then risk[C_1]=1.0, risk[C_2]=0.0
if f_3=y then risk[C_1]=0.0, risk[C_2]=1.0

For the query instances q_1 (a,?,y) and q_2 (?,m,y), all rules distribute their

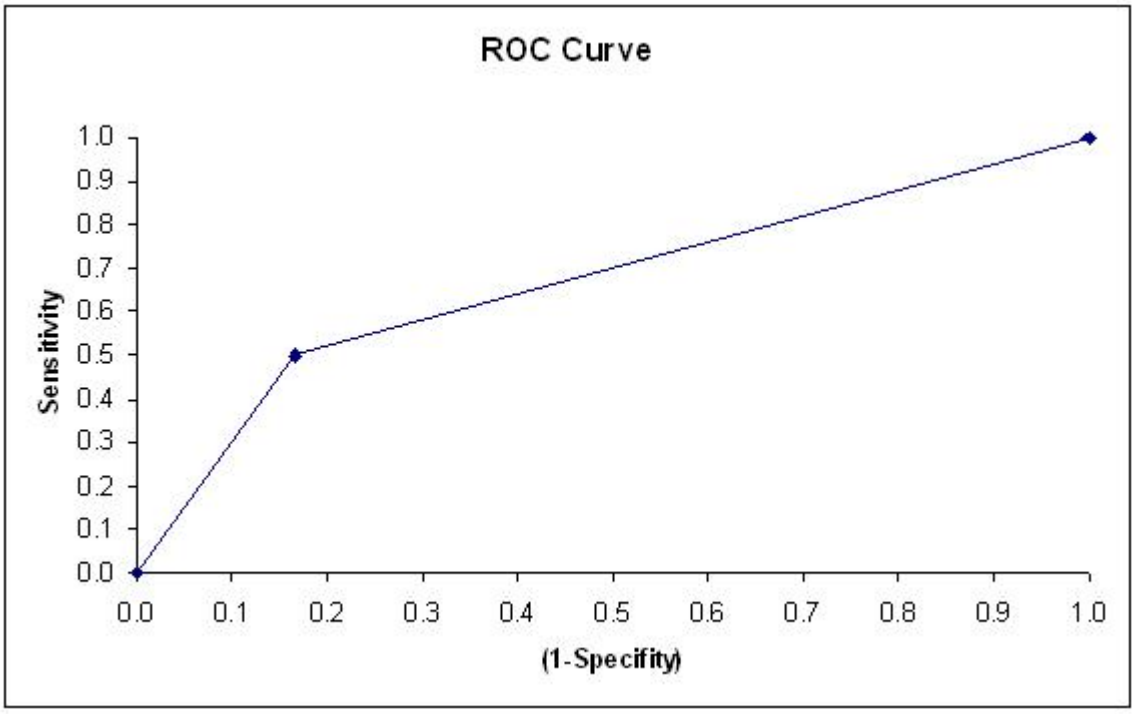

Figure 4.2: ROC Curve for a Feature with 2 categorical values

risks among classes resulting in total risks of C_1=1, C_2=0 and C_1=1, C_2=0 for q_1 and q_2, respectively. That risk estimation results in equal risks for different features for different test instances. REMARC algorithm includes the discriminatory ability of each feature by multiplying feature-AUC of each feature's risk estimate. Consider the receiver operating characteristic curve of each feature on training set in Figure 4.3 that details the discriminative ability of each feature on the training set. The AUC of each feature is computed and included in risk estimation scheme. Assume f_1 has 0.8, f_2 has 0.6 and f_3 has 0.5 of AUC. Then, the risks of q_1 among classes are C_1=0.65 and C_2=0.0. Also, the risks of q_2 among classes become C_1=0.55 and C_2=0.

REMARC algorithm is introduced to overcome such ranking problems by including the decisiveness effect of each risk factor to risk estimation. The feature is more decisive if it has higher AUC than other one. The risk for query instance q_1 is higher than the query instance q_2 according to the technique used in REMARC. This example also shows the robustness of the algorithm in missing feature values.

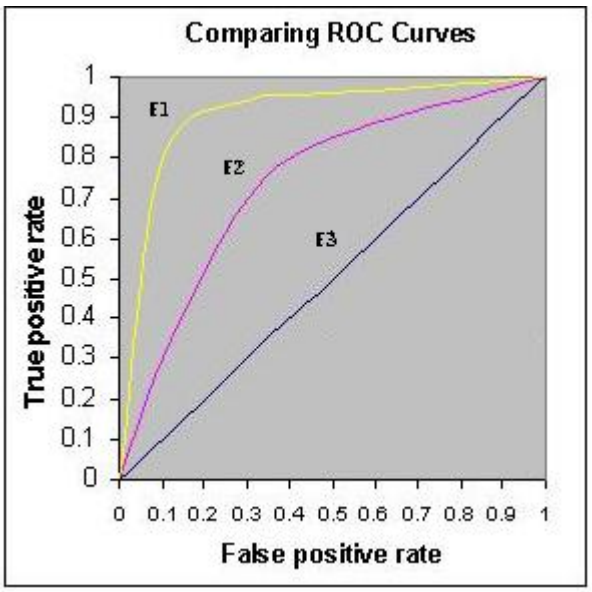

Figure 4.3: Comparing ROC of features f1, f2 and f3

4.5.2 Training

REMARC algorithm as shown in Figure 4.4 first runs the training procedure using a feature set previously analyzed and labeled as potential risk factors. Features can be categorical or numerical features. Firstly, the training part of REMARC algorithm converts numerical features to categorical (makeCategorical()). To find the categorical values of each feature, the mean value of all training instances for each class is found. Then, the means of each class for that feature are sorted in ascending order. Let m_p, m_n are the means of class p and n, respectively. Assume then, $m_p > m_n$, m_n, m_p is the ordered list of means. The categorical values for that feature are:

$$(-\infty..m_n), (m_n..m_p), (m_p.. + \infty)$$

The number of categorical values for that feature is equal to the number of classes plus 1. Each categorical value constitutes a range of numerical values.

After the conversion of each numerical feature to a categorical feature, for each instance, the numerical value of each feature is then replaced by the new

```
train(trainingSet)
        for each feature f
                if f is continous, makeCategorical(f)
                for each categorical value v of f
                        computeFeatureValueRisk(v, f)
                rankCatValues(f)
                computeAUC(f)
end // train

computeFeatureValueRisk(v, f )
        risk f,v = P(positive | f has value v) using instances in trainingSet
end // computeCatRisks

ComputeRisk(q)
        totalRisk=0, knownValues=0
        for each feature f
                if qf value is known
                        totalRisk += ( risk f,v ) * ( AUC of f )
                        Increment knownValues
        return (totalRisk / knownValues)
end // ComputeRisk
```

Figure 4.4: Risk Estimation by Maximizing Area under ROC curve (REMARC) Algorithm

categorical value representing the range that covers the numerical value.

Then, for each categorical value v of each feature f, the risk is computed (computeFeatureValueRisk()). The $risk_{f,v}$ is defined as the posterior probability that the instance, in the training set, with the value v for feature f is positive.

Training procedure, then, ranks the categorical values of each feature in decreasing order of $risk_f$. The features that are successful in correctly estimating the risk of an instance are given more weight in the REMARC algorithm. The success of a feature is based on its ability to correctly order the instances according to their risks. In other words, a feature that assigns higher risks to positive cases (patients who died during or 30-days after the operation) is considered as successful. Since the REMARC algorithm tries to maximize the overall AUC, it uses the AUC of a single feature as its measure of success, that is its weight.

Therefore, for each feature, the area under the receiver operating characteristic curve (AUC) is computed using the training set.

After the training process is accomplished, the REMARC algorithm is ready to determine the total risk of a query instance using the set of learned rules and feauture-AUCs.

4.5.3 Complexity of the REMARC Algorithm

The cost of this training algorithm is the sum of the cost of computeFeatureValueRisk(), rankCatValues(), and computeAUC(). Let n be the number of training instances, v be the number of categorical values of each feature, and f be the number of features. omputeFeatureValueRisk() estimates the probabilistic risks for each feature-value rule for each class. That's cost $O(\mathrm{n}) + O(\mathrm{v}) = O(\mathrm{n})$. RankCatValues() job is to reorder the categorical values in each feature in decreasing order of posterior probabilities of positive class. This part of the algorithm costs $O(\mathrm{v}log\mathrm{v})$ for sorting. Since the categorical values are in order, computeAUC() takes $O(\mathrm{v})$ to compute the feature-AUC weight. Totally, $O(\mathrm{n}) + O(\mathrm{v}log\mathrm{v}) + O(\mathrm{v}) = O(\mathrm{n})$ for each feature. So, the total cost of the training process is $O(\mathrm{fn})$.

4.5.4 Risk Estimation

Risk Estimation procedure is detailed in Figure 4.4 as ComputeRisk(). For a given query instance q, the risk estimation scheme collects the risks of each rule by multiplying each feature's risk by feature-AUC. If the value of q for a feature f, that is q_f, is unknown, that feature's rule does not participate in risk estimation process. After collecting the risks of each rule, the classifier predicts the positive class risk of q as the weighted average of the risks computed for each feature value.

Chapter 5

Experiments and Results

This chapter provides experiments accomplished and the results. TurkoSCORE dataset gathered during the project scope is used in all experiments, as described in previous chapter. The performance of REMARC algorithm which is also described in details in the previous chapter, has been compared with EuroSCORE scoring system in Experiment 1. In Experiment 2, most likely risk factors identified and filtered by consultant surgeons were used and the performance of REMARC algorithm is investigated. In Experiment 3, the effect of using different feature AUCs as a threshold for filtering the risk factors is investigated. REMARC algorithm is implemented in Java language. Areas under the ROC curves and the points for ROC curves are all calculated in Java programming language as well. Chart Wizard of Excel is used for drawing ROC curves.

5.1 Experiment 1

For comparing performance of REMARC algorithm with EuroSCORE study, the 17 risk factors identified in EuroSCORE study are used. The name and definition of risk factors can be found in Figure C.1, Appendix C. The definitions of some of the risk variables were not identical in both Europe and Turkey, so some adjustments or approximate assumptions were made to enable complete analysis,

detailed in Figure C.2, Appendix C. The AUCs of EuroSCORE risk factors are listed in Figure C.2, Appendix C.

Totally, dataset includes 5166 instances with 1.99% mortality rate. All the instances are used for both training and testing. The rules learned by REMARC algorithm for EuroSCORE features can be scanned in Section Appendix E.1.

The mortality risks estimated by REMARC algorithm are computed automatically for each instance. Additive EuroSCORE and Logistic EuroSCORE risks for each patient are also calculated. The performance of these three models are compared by area under the ROC curves. The ROC curves for these three approaches are illustrated in Figure 5.1 to monitor the performance disparities. AUCs of Additive EuroSCORE, Logistic EuroSCORE, and REMARC Algorithm are 80.95%, 74.41%, 84.11%, respectively. Performance measure results reflect the robustness of the REMARC algorithm in risk estimation. The risk estimation model used in REMARC algorithm is better than both of the Additive EuroSCORE and Logistic EuroSCORE.

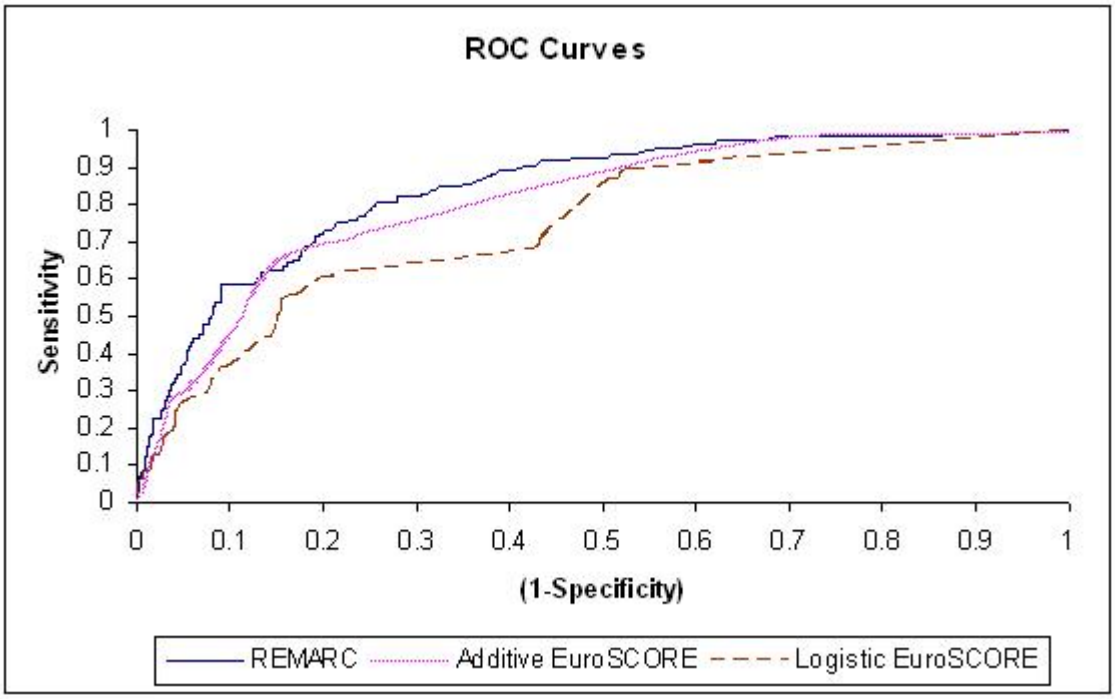

Figure 5.1: Receiver operating characteristic (ROC) curves of REMARC Algorithm, Additive and Logistic EuroSCORE with EuroSCORE risk factors

5.2 Experiment 2

Risk factors obtained in this study include 190 preoperative and 16 operative parameters by the light and analysis of cardiovascular operations in Turkey and Europe. Most likely risk factors to be useful were identified by consultant cardiac surgeons in Cardiovascular Surgery Department, Ankara University. Risk factors having few number of instances are excluded from identified risk factors list. Consequently, 104 risk factors are used as potential features for the REMARC algorithm. The definition and values of each risk factor can be seen in Appendix B. The risk factors and the feature-AUC values of these potential risk factors are listed in decreasing order in Appendix D.

The same dataset, with 5166 instances and 1.99% mortality rate is used in this experiment.

5.2.1 Experiment 2a

In this experiment, all instances in the dataset are used for both training and testing process. The rules learned for TurkoSCORE risk factors by REMARC algorithm are in Appendix E.2. The mortality risks are estimated for each instance automatically by the rules learned in REMARC algorithm.

In Figure 5.2, ROC curve illustrates the performance of the REMARC algorithm. The area under the REMARC ROC curve for these 104 features is 85.91487%. Risk estimation by risk factors identified in TurkoSCORE project and used in REMARC algorithm outperforms both the Additive EuroSCORE and Logistic EuroSCORE. The AUC of REMARC algorithm in Experiment 2a is higher than the AUC in Experiment 1. The result of this experiment shows that the risk factors identified in TurkoSCORE have more discriminative ability than the risk factors identified in EuroSCORE model.

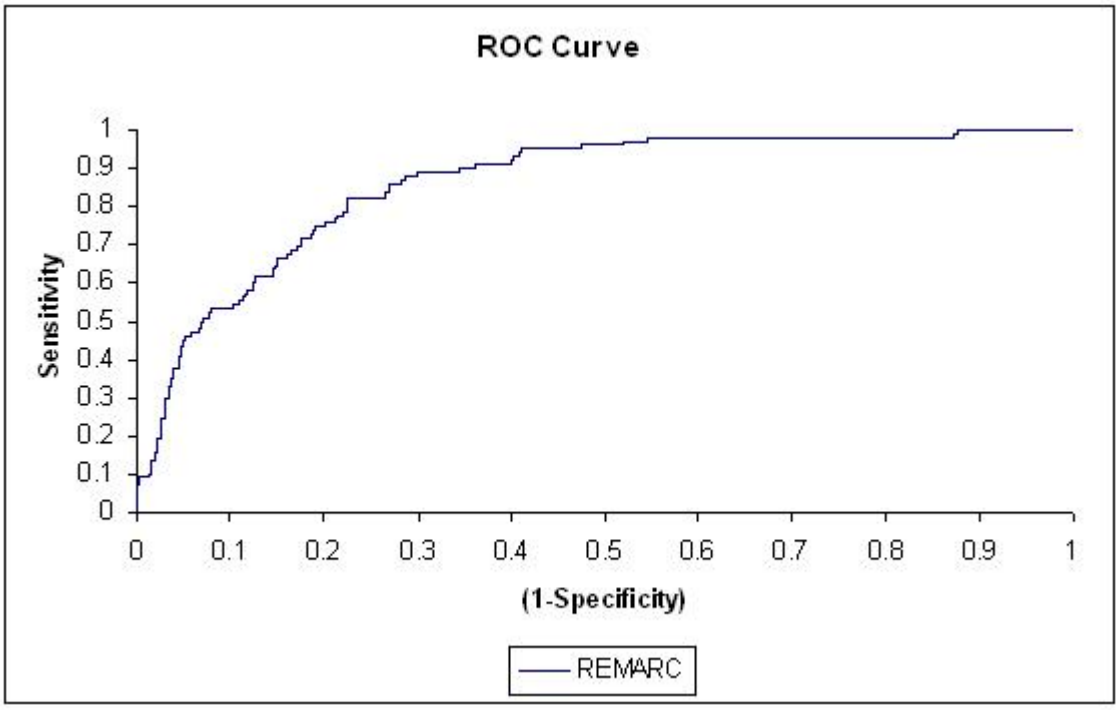

Figure 5.2: Receiver operating characteristic (ROC) curve of REMARC algorithm with TurkoSCORE risk factors

5.2.2 Experiment 2b

In this experiment, to make more realistic performance evaluation of the REMARC algorithm, 10-fold cross-validation technique is chosen. In 10-fold cross-validation, the original dataset is partitioned into 10 subsets. Of the 10 subsets, a single subset is retained as the validation data for testing the REMARC model, and the remaining 9 subsets are used as training data. The cross-validation process is then repeated 10 times, with each of the 10 subsets used exactly once as the validation data. So, each test instance would not be used in training process while estimating the risk of that instance. The Table 5.1 details the areas under the ROC curves of Thesis Algorithm for each fold. The 10 results from the folds then can be averaged to produce a single estimation. The average AUC of REMARC algorithm is 85.74%.

Table 5.1: REMARC AUC values for 10-fold cross-validation

Fold	AUC (%)
0	79.14%
1	90.11%
2	96.54%
3	90.28%
4	75.83%
5	90.94%
6	77.36%
7	81.29%
8	89.40%
9	86.46%
Average	85.74%

5.3 Experiment 3

The performance of REMARC algorithm is measured by its AUC. The heuristic in REMARC algorithm as it is described in previus chapter, comes by the light and objective of maximizing the overall AUC of the algorithm. The discriminative ability (weight) of each feature can be used as a weight in addition to rule's predicted risks. The feature's AUC over the testing instances is used to strengthen the feature's risk on the overall risk of that test instance. High quality features, that has more discriminative ability, would has more effect on the overall predicted risk of a test instance to maximize the overall performance of the algorithm.

In Appendix D, the features and their feature-AUC values are listed in decreasing order of feature-AUC values. All the instances are used in both training and testing. In this experiment, the effect of filtering features with low feature-AUC is investigated. For this respect, increasing threshold for feature AUC has been tested to observe how the REMARC algorithm would behave. The thresholds for feature-AUC and the count of risk factors satisfying the threshold constraint for each test are all detailed in Table 5.2.

For example, the first row indicates that the features having feature AUC greater than 51% are used in the test. There is 82 features satisfying this constraint. These features are first 82 features in Table Appendix D, and the overall

AUC of the REMARC algorithm is 85.88%.

The optimal feature AUC value to maximize the AUC of the REMARC algorithm has been observed at threshold 56%. The 49 risk factors having feature AUC value greater than 56% achieve the best REMARC algorithm performance. These 49 features are the first 49 features listed in Figure D.1, Appendix D.1.

Table 5.2: AUC results of REMARC algorithm in different feature AUC thresholds

Feature AUC Lower Limit	# of features	Overall AUC of Algorithm
51%	82	85.88%
52%	76	85.61%
53%	70	85.84%
54%	61	85.78%
55%	56	85.87%
56%	**49**	**86.15%**
57%	41	85.37%
58%	35	84.35%
59%	32	83.77%
60%	28	83.77%
61%	25	83.74%
62%	20	82.75%
63%	17	79.81%

Chapter 6

Conclusion and Future Work

In this project, a database system has been set up, web interface to gather data has been designed, risk factors has been identified, and risk estimation model, REMARC algorithm, has been modeled triumphantly.

In this thesis, two types of dataset are considered. First one includes the risk factors of commonly used scoring system-EuroSCORE and the second one includes the risk factors selected and defined on the basis of credibility, objectivity, reliability, and prevalence by cardiac surgeons participating in TurkoSCORE project. Both of the datasets are gathered from the TurkoSCORE database.

The area under the ROC curve of Additive EuroSCORE, Logistic EuroSCORE, and REMARC algorithms are measured and compared. It is explained why the rules learned by REMARC algorithm outperforms both of the EuroSCORE models in risk estimation with the same risk factors and the same dataset. The main reason for this is that REMARC model allows instances to be ranked according to a more fine-grained scale compared to other models by the heuristic of maximizing the AUC. Instances with different comorbidity can be better differentiated from other instances by feature-AUC weights.

The feature-AUC (weight) is not only used in risk estimation, but also used in risk factors selection. Different thresholds of weight have been tested to filter the

less discriminative features from risk factors list. REMARC Model also outperforms both of the EuroSCORE models in risk estimation by using TurkoSCORE risk factors. Also, the model shows its robustness in selecting the discriminative risk factors. Again, this allows instances to be ranked correctly that maximizes the AUC. As the threshold, for filtering risk factors used in the model, increases to an optimal value, the REMARC model observed its maximum performance.

REMARC algorithm is also robust to irrelevant features and missing feature values, as explained.

As a future work, first of all other future works, the dataset must be improved with more data. The risk estimation scheme will be better. Morbidity risk can be estimated in addition to mortality risk. The feature-AUC (weight) is multiplied with posterior probabilities. The effect of feature-AUC (weight) can be tested by different approaches (taking square, taking cube). Additive approach is used in estimation of the total risk from rules. Some other approaches can be generated such as logistic regression formulas. Each rule in REMARC model includes one feature. Feature construction techniques can be modeled so that the rules can include more than one feature.

Bibliography

[1] Coronary artery bypass surgery in new york state 19961998. [pdf] 2001 [cited 8 april 2005]. www.health.state.ny.us/nysdoh/consumer/heart/1996-98cabg.pdf.

[2] www.wikipedia.com.

[3] P. Adriaans and D. Zantinge. Data mining, 1998.

[4] D. Aha, D. Kibler, and M. Albert. Instance-based learning algorithms, *Machine Learning*, 6:37-66, 1991.

[5] E. Alpaydin. Introduction to machine learning, 2004.

[6] E. Antman, M. Cohen, P. Bernink, C. McCabe, T. Horacek, G. Papuchis, B. M. B, R. Corbalan, D. R. D, and J.-. E. Braunwald. Risk stratification and therapeutic decision making in acute coronary syndromes, 2000.

[7] B. Biagioli, S. Scolletta, G. Cevenini, E. Barbini, P. Giomarelli, and P. Barbini. A multivariate bayesian model for assessing morbidity after coronary artery surgery, crit care, 10(3), r94, 16813658, doi: 10.1186/cc4951, 2006.

[8] B. Bridgewater, H. Neve, N. Moat, T. Hooper, and M. Jones. Predicting operative risk for coronary artery surgery in the united kingdom: a comparison of various risk prediction algorithms. heart;79:350355, 1998.

[9] R. Brown. Rockefeller medicine men. berkeley: University of california press, 1979.

[10] J. Carbonell. Machine learning, paradigms and methods., 1990.

[11] E. Codman. A study in hospital efficiency as demonstrated by the case report of the first five years of a private hospital. boston, thomas todd company, 1917.

[12] I. Colombet, A. Ruelland, G. Chatellier, F. Gueyffier, P. Degoulet, and M. Jaulent. Models to predict cardiovascular risk: comparison of cart, multilayer perceptron and logistic regression. proc amia symp.;156-60, 2000.

[13] B. Dasarathy. *Nearest Neighbor(NN) Norms, NN Pattern Classification Techniques*. ieee computer society press, 1990.

[14] D. Disch, G. O'Connor, J. Birkmeyer, E. Olmstead, D. Levy, and S. Plume. Changes in patients undergoing coronary artery bypass grafting: 1987-1990. northern new england cardiovascular disease study group. ann.thorac surg; 57:416-423, 1994.

[15] R. Duda and P. Hart. *Pattern Classification and Scene Analysis*, new york: Wiley, 1973.

[16] R. Duda, P. Hart, and D. Stork. *Pattern Classification*, new york : Wiley-interscience publication, 2001.

[17] K. Eagle, R. Guyton, R. Davidoff, G. Ewy, J. Fonger, T. Gardner, J. Gott, H. Herrmann, R. Marlow, W. Nugent, G. OConnor, T. Orszulak, R. Rieselbach, W. Winters, S. Yusuf, R. Gibbons, J. Alpert, A. Garson, G. Gregoratos, R. Russell, T. Ryan, and S. Smith. Acc/aha guidelines for coronary artery bypass graft surgery: executive summary and recommendations.a report of the american college of cardiology/american heart association task force on practice guidelines (committee to revise the 1991 guidelines for coronary artery bypass graft surgery). circulation; 100:14641480, 1999.

[18] F. Edwards, R. Clark, and M. Schwartz. Coronary artery bypass grafting: the society of thoracic surgeons national database experience. ann.thorac surg; 57:12-19, 1994.

[19] J. Egan. Signal detection theory and roc analysis, series in cognitition and perception. new york: Academic press, 1975.

[20] F. Estafanous, F. Loop, T. Higgins, S. Tekyi-Mensah, B. Lytle, D. C. DM, M. Roberts-Brown, and N. Starr. Increased risk and decreased morbidity of coronary artery bypass grafting between 1986 and 1994. ann.thorac surg; 65:383-389, 1998.

[21] T. Fawcett. Roc graphs: Notes and practical considerations for researchers. kluwer academic publishers, netherlands, 2004.

[22] V. Ferraris and S. Ferraris. Risk factors for postoperative morbidity. j thorac cardiovasc surg; 111:731-738, 1996.

[23] V. Ferraris, S. Ferraris, and A. Singh. Operative outcome and hospital cost. j thorac cardiovasc surg; 115:593-602, 1998.

[24] A. Flexner. Carnegie foundation bulletin 4. new york: Carnegie foundation for the advancement of teaching; on medical education in the united states and canada, 1910.

[25] A. Flexner. An autobiography. new york: Simon and schuster, 1960.

[26] K. Fukunaga. *Introduction to Statistical Pattern Recognition*, academic press, san diego, 1990.

[27] F. Gabrielle, F. Roques, P. Michel, A. Bernard, C. de Vicentis, X. Roques, R. Brenot, E. Baudet, and M. David. Is the parsonnets score a good predictive score of mortality in adult cardiac surgery: assessment by a french multicentre study. eur j cardiothorac surg; 11:406414, 1997.

[28] D. Gamberger, G. Krstacic, and T. Smuc. Medical expert evaluation of machine learning results for a coronary heart disease database, lncs 1933, 159-168, 2000.

[29] F. Grover, R. Johnson, G. Marshall, and K. Hammermeister. Factors predictive of operative mortality among coronary artery bypass subsets. ann thorac surg;56:12961306; discussion 13061307, 1993.

[30] H. Güvenir, B. Acar, G. Demirz, and A. Cekin. A supervised machine learning algorithm for arrhythmia analysis, computers in cardiology; 24:433-436, 1997.

[31] H. Güvenir, G. Demirz, and N. Ilter. A classification learning algorithm robust to irrelevant features, in artificial intelligence: Methodology, systems applications(proceedings of aimsa'98), fausto giunchiglia(ed.), springer-verlag, lnai 1480, sozopol, bulgaria, (sept. 21-23), 281-290, 1998.

[32] H. Güvenir, G. Demirz, and N. Ilter. Learning differential diagnosis of erythemato-squamous diseases using voting feature intervals, artificial intelligence in medicine, 13(3):147-165, 1998.

[33] H. Güvenir and N. Emeksiz. An expert system for the differential diagnosis of erythemato-squamous diseases, expert systems with applications; 18(1):43-49, 2000.

[34] H. Güvenir, N. Emeksiz, N. Ikizler, and N. merci. Diagnosis of gastric carcinoma by classification on feature projections, artificial intelligence in medicine, 31(3):231-240, 2004.

[35] H. Güvenir and H. Koc. Concept representation with overlapping feature intervals, cybernetics and systems: An international journal; 29(3):263-282, 1998.

[36] H. Güvenir and I. Sirin. Classification by feature partitioning, machine learning, 23(1):47-67, 1996.

[37] K. Hammermeister, R. Johnson, G. Marshall, and F. Grover. Continuous assessment and improvement in quality of care. a model from the department of veterans affairs cardiac surgery. ann.surg; 219:281-290, 1994.

[38] E. Hannan, H. Bernard, J. O. JF, and H. Kilburn. A methodology for targeting hospital cases for quality of care record reviews. am.j public health; 79:430-436, 1989.

[39] E. Hannan, H. K. H.R. Bernard, and J. O'Donnell. Gender differences in mortality rates for coronary artery bypass surgery. am.heart j; 123:866-872, 1992.

[40] E. Hannan, H. Kilburn, M. Lindsey, and R. Lewis. Clinical versus administrative data bases for cabg surgery. does it matter? med care; 30:892-907, 1992.

[41] E. Hannan, H. Kilburn, J. O'Donnell, H. Bernard, E. Shields, M. Lindsey, and A. Yazici. A longitudinal analysis of the relationship between in-hospital mortality in new york state and the volume of abdominal aortic aneurysm surgeries performed. health serv.res.; 27:517-542, 1992.

[42] E. Hannan, H. Kilburn, J. O'Donnell, G. Lukacik, and E. Shields. Adult open heart surgery in new york state. an analysis of risk factors and hospital mortality rates. jama; 264:2768-2774, 1990.

[43] E. Hannan, H. Kilburn, M. Racz, E. Shields, and M. Chassin. Improving the outcomes of coronary artery bypass surgery in new york state. jama; 271:761-766, 1994.

[44] E. Hannan, J. O'Donnell, H. Kilburn, H. Bernard, and A. Yazici. Investigation of the relationship between volume and mortality for surgical procedures performed in new york state hospitals. jama; 262:503-510, 1989.

[45] E. Hannan, A. Siu, D. Kumar, H. Kilburn, and M. Chassin. The decline in coronary artery bypass graft surgery mortality in new york state. the role of surgeon volume. jama; 273:209-213, 1995.

[46] E. Hannan, C. Wu, E. Bennett, R. Carlson, A. Culliford, J. Gold, R. Higgins, O. Isom, C. Smith, and R. Jones. Risk stratification of in-hospital mortality for coronary artery bypass graft surgery. j am.coll.cardiol; 47:661-668, 2006.

[47] B. Hattler, C. Madia, and C. Jhonson. Risk stratification using the society of thoracic surgeons program. ann thorac surg; 52:1348-52., 1994.

[48] T. Higgins, F. Estafanous, F. Loop, G. Beck, J. Blum, and L. Paranandi. Stratification of morbidity and mortality outcome by preoperative risk factors in coronary artery bypass patients. a clinical severity score. jama; 267:2344-2348, 1992.

[49] J. Huang and C. Ling. Using auc and accuracy in evaluating learning algorithms, ieee transactions on knowledge and data engineering, vol. 17, no. 3, 2005.

[50] J. Huang, C. Ling, and H. Zhang. Auc: a statistically consistent and more discriminating measure than accuracy, 2005.

[51] R. Huijskes, P. Rosseel, and J. Tijssen. Outcome prediction in coronary artery bypass grafting and valve surgery in the netherlands: development of the amphiascore and its comparison with the euroscore. eur j cardiothorac surg; 24:741749, 2003.

[52] J. Ivanov, M. Borger, T. David, G. Cohen, N. Walton, and C. Naylor. Predictive accuracy study: comparing a statistical model to clinicians estimates of outcomes after coronary bypass surgery. ann thorac surg; 70:162168, 2000.

[53] J. Ivanov, J. Tu, and C. Naylor. Ready-made, recalibrated, or remodeled? issues in the use of risk indexes for assessing mortality after coronary artery bypass graft surgery. circulation; 99:20982104, 1999.

[54] P. James. Fifty years of baylor university hospital. dallas: Baylor university hospital, 1953.

[55] W. Knaus, D. Wagner, J. Zimmerman, and E. Draper. Variations in mortality and length of stay in intensive care units. ann.intern.med; 118:753-761, 1993.

[56] E. Kopf. Florence nightingale asn statistician, publ am med assoc; 15:388-404, 1916.

[57] T. Kurki and M. Kataja. Preoperative prediction of postoperative morbidity in coronary artery bypass grafting. ann thorac surg; 61:17401745, 1996.

[58] J. Magovern, T. Sakert, G. Magovern, D. Benckart, J. Burkholder, G. Liebler, and G. Magovern. A model that predicts morbidity and mortality after coronary artery bypass graft surgery, j am coll cardiol; 28:1147-1153, 1996.

[59] D. Mark. Mark db. implications of cost in treatment selection for patients with coronary disease. ann thorac surg, 61:12-15, 1996.

[60] R. Michalski, J. Carbonell, and T. Mitchell. Machine learning, an artificial intelligence approach, los altos: Morgan kaufmann, 1983.

[61] K. Morik. Knowledge representation and organization in machine learning. new york: Springer-verlag, 1989.

[62] S. Nashef, F. Roques, and P. Michel. European system for cardiac operative risk evaluation (euroscore). eur j cardio thorac surg; 16:9-13., 1999.

[63] F. Nightingale. Notes on hospitals. london: Longman, 1863.

[64] G. O'Connor, J. Morton, M. Diehl, E. Olmstead, L. Coffin, D. Levy, C. Maloney, S. Plume, W. Nugent, and D. Malenka. Differences between men and women in hospital mortality associated with coronary artery bypass graft surgery. the northern new england cardiovascular disease study group. circulation; 88:2104-2110, 1993.

[65] G. O'Connor, S. Plume, E. Olmstead, L. Coffin, J. Morton, C. Maloney, E. Nowicki, D. Levy, J. Tryzelaar, and F. Hernandez. Multivariate prediction of in-hospital mortality associated with coronary artery bypass graft surgery. northern new england cardiovascular disease study group. circulation; 85:2110-2118, 1992.

[66] G. O'Connor, S. Plume, and J. Wennberg. Regional organization for outcomes research. ann.n.y.acad.sci; 703:44-50, 1993.

[67] V. Parsonnet, D. Dean, and A. Bernstein. A method of uniform stratification of risk factor evaluating the results of surgery in acquired adult heart disease. circulation; 79:3-12, 1989.

[68] S. Pocock, V. McCormack, F. Gueyffier, F. Boutitie, R. Fagard, and J. Boissel. A score for predicting risk of death from cardiovascular disease in adults with raised blood pressure, based on individual patient data from randomised controlled trials, bmj; 323:75-81, 2001.

[69] J. Pons, A. Granados, and J. Espinas. Assessing open heart surgery mortality in catalonia (spain) through a predictive risk model. eur j cardio thorac surg; 11:415-23., 1997.

[70] J. Quinlan. Introduction to decision trees, *Machine Learning* 1:81-106, 1986.

[71] L. Rendell. A new basis for state-space learning systems and a successful implementation, *Artificial Intelligence* 20:369-392, 1983.

[72] C. Riordan, M. Engoren, A. Zacharias, T. Schwann, G. Parenteau, S. Durham, and R. Habib. Resource utilization in coronary artery bypass operation: does surgical risk predict cost? ann.thorac surg; 69:1092-1097, 2000.

[73] F. Roques, F. Gabrielle, and P. Michel. Quality of care in adult heart surgery: Proposal for a self-assessment approach based on a french multicenter study. eur j cardiothorac surg; 9:440-3, 1995.

[74] F. Roques, P. Michel, A. Goldstone, and S. Nashef. The logistic euroscore, eur heart j.; 24(9):882-3, 2003.

[75] F. Roques, S. Nashef, and P. Michel. Risk factors and outcome in european cardiac surgery: Analysis of the euroscore multinational database of patients. eur j cardio-thorac surg; 15:816-23., 1999.

[76] P. Sergeant, E. Blackstone, and B. Meyns. Validation and interdependence with patient variables of the influence of procedural variables on early and late survival after cabg. eur j cardiothorac surg, 12:1-19., 1997.

[77] P. Sergeant, F. Roques, F. Gabrielle, P. Michel, C. DeVincentiis, M. David, and E. Baudet. Quality of care in adult heart surgery: proposal for a self-assessment approach based on a french multicenter study. eur j cardiothorac surg, 9:440., 1995.

[78] R. Sorelle. The quest for excellence: Baylor college of medicine, 1900-2000. houston: Office of public affairs at baylor college of medicine, 2000.

[79] K. Spackman. Signal detection theory: Valuable tools for evaluating inductive learning. in: Proceedings of the sixth international workshop on machine learning. san mateo, ca, pp. 160-163, morgan kaufman, 1989.

[80] D. Speigenhalter. Surgical audit: statistical lessons from nightingale and codman. j r stat soc.; 162(part 1):45-58, 1999.

[81] P. Steen, A. Brewster, R. Bradbury, E. Estabrook, and J. Young. Predicted probabilities of hospital death as a measure of admission severity of illness. inquiry; 30:128-141, 1993.

[82] N. Tremblay, J. Hardy, and J. Perault. A simple classification of the risk in cardiac surgery: The first decade. can j anaesth; 40:103-11., 1993.

[83] J. Tu, S. Jaglal, and C. Naylor. Multicenter validation of a risk index for mortality, intensive care unit stay, and overall hospital length of stay after cardiac surgery. steering committee of the provincial adult cardiac care network of ontario. circulation; 91:677-684., 1995.

[84] J. Tu and K. Wu. The improving outcomes of coronary artery bypass graft surgery in ontario, 1981 to 1995. cmaj.; 159:221-227, 1998.

[85] K. Tuman, R. McCarthy, R. March, H. Najafi, and A. Ivankovich. Morbidity and duration of icu stay after cardiac surgery. a model for preoperative risk assessment. chest; 102:3644, 1992.

[86] C. Yap, M. Mohajeri, B. Ihle, A. Wilson, S. Goyal, and M. Yii. Validation of euroscore model in an australian patient population. anz j surg; 75(7):508-12., 2005.

Appendix A

TurkoSCORE project

A.1 TurkoSCORE Study Group

Prof. Dr. H. Altay Güvenir
Computer Engineering Department, Bilkent University

Doc. Dr. A. Rüçhan Akar
Cardiovascular Surgery Department, Ankara University

Ayşen Tunca
Computer Engineering Department, Bilkent University

Op. Dr. Serkan Durdu
Cardiovascular Surgery Department, Ankara University

Dr. Elif Kuzgun Çetinkanat
Cardiovascular Surgery Department, Ankara University

Dr. Çağın Zaim
Cardiovascular Surgery Department, Ankara University

A.2 TurkoSCORE web application

Figure A.1: A view from web site

Appendix B

TurkoSCORE parameters

Figure B.1: Identity parameters

Kimlik Bilgileri	
Parameter Name	**Options**
Dosya No	Text
Adı	Text
Soyadı	Text
Cinsiyet	K = Kadın
	E = Erkek
TC Kimlik No	Text
KKTC Kimlik No	Text
Doğum Tarihi (gün/ay/yıl)	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Yaş	Text
Eğitim	0 = Bilinmiyor
	1 = İlkokul
	2 = Ortaokul
	3 = Lise
	4 = Üniversite
	-1 = Seçilmedi
Doğum Yeri	List
Şehir	List
Adres	Text
Telefon Ev	Text
Telefon Cep	Text
Telefon İş	Text
Meslek	Text
Medeni Durumu	0 = Evli
	1 = Bekar
	-1 = Seçilmedi

Kimlik Bilgileri	
Parameter Name	**Options**
Kurum	1 = Emekli Sandığı
	2 = SSK
	3 = Bağkur
	4 = Yeşil Kart
	5 = Özel Kurum
	6 = Diğer
	-1 = Seçilmedi
Birinci Derece Yakınının adı, soyadı ve telefonu	Text
Prospektif çalışma hastası	
Hayır	True/False
Coronary trial	True/False
Steroid trial	True/False
Transfüzyon	True/False
AF Apoptosis	True/False
Stentless AVR	True/False
Mitral Kapak Onarımları	True/False
Kardiyak Kök Hücre	True/False
Seçilmedi	True/False
Diğer çalışma hastası	Text
AllowedUser	Hidden

Figure B.2: Hospital stay up parameters

Yatış Bilgileri	
Parameter Name	**Options**
Hastane Adı	Text
Hastayı refere eden doktor	Text
Diğer	Text
Hastaneye Giriş Tarihi	Text
	Text
	Text
Hastaneden Çıkış Tarihi	Text
	Text
	Text
Operasyon Tarihi	Text
	Text
	Text
Yapılan Operasyon	Text
Yoğun Bakım Yatış Tarihi	Text
	Text
	Text
Yoğun Bakım Çıkış Tarihi	Text
	Text
	Text
Yoğun Bakım yatış süresi (saat)	Text
Yoğun Bakım Ek yatış süresi (saat)	Text
Yoğun Bakım toplam yatış süresi (saat)	Text

Figure B.3: Complete clinical history parameters recalled and recounted by a patient

Risk Faktörleri	
Parameter Name	**Options**
Ağırlık (kg)	Text
Boy (cm)	Text
BSA	otomatik
Vücut kitle indeksi (BMI)	otomatik
Kategorik BMI	0 = Normal - BMI <25
	1 = Kilolu - BMI >= 25 ve <30
	2 = Obez - BMI >= 30
	-1 = Seçilmedi
Bel çevresi uzunluğu (cm)	Text
Kalça çevresi uzunluğu (cm)	Text
Ameliyat öncesi stabil Angina Pektoris (CCS klasifikasyonuna göre)	0 = CCS0 → Anjina pektoris mevcut değil
	1 = CCS1 → ağır fiziksel aktivite ile anjina pektoris olması
	2 = CCS2 → orta derecede aktivite ile anjina pektoris olması (>2 kat merdiven çıkma veya 2 blok yürüme ile)
	3 = CCS3 → hafif aktivite ile anjina pektoris olması (<2 kat merdiven çıkma vaya 2 blok yürüme ile)
	4 = CCS4 → istirahat veya minimal aktivite ile anjina pektoris olması, unstabil anjina pektoris
	-1 = Seçilmedi
Unstabil Angina (CCS klasifikasyonuna göre)	0 = Unstabil angina yok
	1 = CCS4A → istirahat veya minimal aktivite ile AP (hastanın hastaneye başvurması sonrasıda agresif ilaç tedavisi ile AP olmuyorsa)
	2 = CCS4B → istirahat veya minimal aktivite ile AP (hastanın hastaneye başvurması sonrasında agresif ilaç tedavisine rağmen AP oluyorsa, bu nedenle taburcu edilemiyorsa ancak intravenöz nitrogliserine ihtiyacı olmuyor ise)
	3 = CCS4C → istirahat veya minimal aktivite ile AP (hastanın hastaneye başvurması sonrasında, agresif ilaç tedavisine ve intravenöz nitrogliserine rağmen semptomları kontrol altına alınamıyor ise veya hemodinamik stabilite sağlanamıyor ise)
	4 = CCS4D → kardiyojenik şok tablosunda ise
	-1 = Seçilmedi
Yatış sırasında göğüs ağrısının tanımlanması	0 = Anjina pektoris mevcut değil
	1 = Semptomlar kardiyak iskemi ile ilgisiz
	2 = Stabil anjina
	3 = Unstabil anjina
	4 = Non-ST Elevasyonlu MI (Non-STEMI)
	5 = ST Elevasyonlu MI (STEMI)
	-1 = Seçilmedi
Ameliyat öncesi dispne (NYHA klasifikasyonuna göre)	1 = NYHA1 → fiziksel aktivitesinde kısıtlanma yok, günlük aktivitelerini rahat yapabiliyor
	2 = NYHA2 → fiziksel aktivitesinde çok hafif kısıtlama var, istirahatta sorunsuz veya hafif egzersizleri rahat yapabiliyor
	3 = NYHA3 → fiziksel aktivitesinde belirgin kısıtlanma var, sadece istirahat halinde rahat

Risk Faktörleri	
Parameter Name	**Options**
Ameliyat öncesi dispne (NYHA klasifikasyonuna göre)	4 = NYHA4 → fiziksel aktivitesi ileri derecede kısıtlanmış, yatağa veya sandalyeye bağımlı ve istirahatta dahi rahat değil
	-1 = Seçilmedi
Konjestif Kalp Yetmezliği	0 = Yok
	1 = Var
	-1 = Seçilmedi
Hemodinamik Status	1 = Stabil -- vital bulguları (kalp hızı, sistemik tansiyonu, idrar çıkışı normal sınırlarda, takipne, ortopne, PND yok)
	2 = Unstabil -- vital bulguları değişken
	3 = Kardiyojenik şok
	-1 = Seçilmedi
Kritik Preoperatif status	
Seçilmedi	True/False
Yok	True/False
VT / VF	True/False
Resüsitasyon	True/False
IABP	True/False
Ventilasyon	True/False
Akut renal yetmezlik	True/False
Diabetes Mellitüs	
Seçilmedi	True/False
Hastada Diabetes Mellitus yok	True/False
Hastaneye yatış sonrası diyabet tanısı almış	True/False
Diyet kontrollü diabet	True/False
Oral antidiabetik ilaç ile kontrol edilen diabet	True/False
İnsülin ile kontrol edilen diabet	True/False
İnsülin + Oral antidiabetik ilaçlarla kontrol edilen diabet	True/False
Dokümente edilmemiş	True/False
Diabetes Mellitüs (yıl süreyle)	Text
Hipertansiyon kategorik	0 = NORMAL - Sistolik KB <140 mmHg, Diastolik KB <90 mmHg
	1 = ORTA DERECEDE HT - Sistolik KB ≥140 ve <160 mmHg, Diastolik KB ≥90 ve <100 mmHg
	2 = CİDDİ HT - Sistolik KB ≥160 mmHg, Diastolik KB ≥100 mmHg
	3 = Hipertansiyon yok
	-1 = Seçilmedi
Son 1 yılda antihipertansif ilaç kullanmış mı?	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Sigara Hikayesi	0 = Bilinmiyor
	1 = Hiç sigara içmemiş
	2 = Sigara içmeyi bırakmış > 1 ay - 1 yıl
	3 = Sigara içmeyi bırakmış > 1 yıl
	4 = Halen içiyor
	-1 = Seçilmedi
Sigara İçme Süresi (yıl süreyle)	Text
Sigara İçme Miktarı (adet/günde)	Text
Ömür boyu içtiği sigara paketi adeti	otomatik

Risk Faktörleri	
Parameter Name	**Options**
Koroner Arter Hastalığı Aile Hikayesi	0 = Yok
	1 = Var -- Birinci derece akrabalarında erkek <45 yaş önce, kadın <55 yaş önce tanı almış koroner arter hastalığı veya kalp krizi hikayesi
	-1 = Seçilmedi
Hiperlipidemi	0 = Hiperlipidemi yok
	1 = Hiperlipidemi, ilaçla kontrol altında
	2 = Hiperlipidemi, ilaçla kontrol altında değil
	3 = Bilinmiyor
	-1 = Seçilmedi
Kronik Obstrüktif Akciğer Hastalığı (KOAH)	0 = Yok -- normal spirometri test sonuçları, KOAH ile ilgili herhangi bir semptomun olmaması (öksürük,balgam), ilaç kullanımı olmaması
	1 = KOAH Risk var -- spirmetrik testler normal, kronik semptomları mevcut (öksürük, balgam)
	2 = Hafif KOAH -- FEV1/FVC <%70, FEV1≥%80 predicted, kronik semptomlar var veya yok (öksürük, balgam)
	3 = Orta KOAH -- FEV1/FVC <%70, FEV1≥%30 <%80 predicted, kronik semptomlar var veya yok (öksürük, balgam, dispne) -- FEV1 ≥%50 <%80 predicted
	4 = Orta KOAH -- FEV1/FVC <%70, FEV1≥%30 <%80 predicted, kronik semptomlar var veya yok (öksürük, balgam, dispne) -- FEV1≥%30 <%50 predicted
	5 = Ciddi KOAH -- FEV1/FVC <%70, FEV1 <%30 predicted veya FEV1 < %50 predicted ve respiratuar yetmezlik veya sağ kalp yetmezliğinin klinik semptomlarının olması
	-1 = Seçilmedi
FEV1 (sayı olarak)	Text
%FEV1 Predicted (sayı olarak)	Text
Renal Yetmezlik	0 = Yok
	1 = Var
	2 = Diyaliz gereksinimi
	3 = Fonsiyone renal transplant
	-1 = Seçilmedi
Son Preoperatif Kreatinin Düzeyi	0 = Kreatinin < 1.2 mg/dL
	1 = Kreatinin 1.2 - 1.5 mg/dL
	2 = Kreatinin 1.5 - 2.26 mg/dL
	3 = Kreatinin > 2.26 mg/dL
	-1 = Seçilmedi
Karaciğer Hastalığı	0 = Yok
	1 = Child-Pugh Grade A (Asit yok, Bilirubin<2mg/dL, Albumin>3.5 g/dL, INR<1.8, ensefalopati yok) – kompanze KC hastalığı
	2 = Child-Pugh Grade B (Hafif derecede asit var, Bilirubin = 2-3mg/dL, Albumin= 2.8-3.5 g/dL, INR < 1.8, ensefalopati grade 1-2) – Ciddi fonksiyonel yetmezlik
	3 = Child-Pugh Grade C (Orta derecede asit var, Bilirubin>3mg/dL, Albumin<2.8 g/dL, INR>2.3, ensefalopati grade 3-4) – Dekompanze KC hastalığı
	-1 = Seçilmedi

Risk Faktörleri	
Parameter Name	**Options**
Peptik ülser hastalık hikayesi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Geçirilmiş Gastrointestinal kanama	0 = Yok
	1 = Var
	-1 = Seçilmedi
Alkol Kullanımı	0 = Yok
	1 = < 25 gram / gün (2 bardak şarap)
	2 = >= 25 ve< 50 gram/ gü;n
	3 = >= 50 ve < 100 gram / gün
	4 = >= 100 gram / gün
	-1 = Seçilmedi
Alkol kullanım sıklığı	0 = Her gün, günde iki kez
	1 = Her gün
	2 = Haftada 5-6 kez
	3 = Haftada 3-4 kez
	4 = Haftada 1-2 kez
	5 = Ayda 2-3 kez
	6 = Ayda bir kez veya daha az
	-1 = Seçilmedi
Periferik Arter Hastalığı	0 = Yok
	1 = Var, istirahat veya egzersiz ile kladikasyo intermitant
	2 = Var, arteriyel yetmezlik nedeniyle geçirilmiş amputasyon
	3 = Var, aorto-iliak oklusiv hastalık nedeniyle geçirilmiş rekonstriksiyon
	4 = Var, periferik damar hastalığı nedeniyle vasküler rekonstriksiyon, bypass cerrahisi veya perkütan angioplasti veya stent
	5 = Var, aort anevrizma varlığı, onarım yapılmış veya yapılmamış
	6 = Var, non-invasiv veya invasive testlerle dokümente edilmiş
	-1 = Seçilmedi
Serebrovasküler Hastalık	0 = Yok
	1 = RIND
	2 = TİA (24 saat içinde iyileşmenin sağladığı akut serebrovasküler atak)
	3 = CVA (Semptomların 24 saatten fazla sürdüğü vasküler etyolojili olduğu düşünülen atak)
	4 = Non-invaziv karotis incelemesinde çapta %79 daralma
	5 = Geçirilmiş Karotis Cerrahisi veya perkutan karotis girişimi
	6 = Diğer Nörolojik hastalıklar (myastania gravis gibi)
	-1 = Seçilmedi
24 saatten fazla süren koma hikayesi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Serebrovasküler hastalık zamanı	1 = 2 hafta içinde
	2 = > 2 hafta
	3 = Bilinmiyor
	-1 = Seçilmedi

Risk Faktörleri	
Parameter Name	**Options**
İnfektif Endokardit	0 = Yok
	1 = Pozitif kan kültürü ile infektif endokardit öntanısı
	2 = Ekokardiyografide vejetasyon veya görüntüleme yöntemleri ile endokardit öntanısı
	3 = Prostetik kapak endokarditi
	4 = Geçirilmiş ve tadavi edilmiş infektif endokardit
	-1 = Seçilmedi
Koagulopati	0 = Yok
	1 = Var
	-1 = Seçilmedi
Tiroid hastalık hikayesi	0 = Ötiroid
	1 = Hipertiroidi hikayesi
	2 = Hipotiroidi hikayesi
	3 = Subklinik hipotiroid (serbest T3 ve T4 normal, TSH üst sınırda veya artmış)
	-1 = Seçilmedi
Psikiyatrik hastalık hikayesi	0 = Yok
	1 = Major depresif hastalık hikayesi
	2 = Bipolar hastalık hikayesi
	3 = Şizofreni hikayesi
	4 = Madde bağımlılığı hikayesi
	-1 = Seçilmedi
Malignite hikayesi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Malignite Detayı	Text
Geçirilmiş ciddi aritmi hikayesi	0 = Yok
	1 = Venriküler fibrilasyon (cerrahi öncesi 2 hafta içinde)
	2 = Venriküler fibrilasyon (cerrahi öncesi 2 haftadan fazla)
	3 = Atrial fibrilasyon (cerrahi öncesi 2 hafta içinde)
	4 = Atrial fibrilasyon (cerrahi öncesi 2 haftadan fazla)
	5 = Atrial flutter (cerrahi öncesi 2 hafta içinde)
	6 = Atrial flutter (cerrahi öncesi 2 haftadan fazla)
	7 = Üçüncü derece kalp bloğu (cerrahi öncesi 2 hafta içinde)
	8 = Üçüncü derece kalp bloğu (cerrahi öncesi 2 haftadan fazla)
	-1 = Seçilmedi
Geçirilmiş aritmi tedavi yöntemleri	0 = Yok
	1 = Ablasyon tedavisi
	2 = Automatic implantable cardioverter/defibrillator(AICD)
	3 = Kalıcı Pacemaker
	4 = Farmakolojik tedavi
	5 = Elektrokardiyoversiyon
	-1 = Seçilmedi
Geçirilmiş Perkütan Koroner girişim	0 = Yok
	1 = Balon Kateter Anjioplasti
	2 = Perkütan Transluminal Koroner Anjioplasti(PTCA)
	3 = Rotational Atherektomi
	4 = Directional Atherektomi
	5 = Extractional Atherektomi

Risk Faktörleri	
Parameter Name	**Options**
Geçirilmiş Perkütan Koroner girişim	6 = Laser Atherektomi
	7 = Intrakoroner Stent(bare metal)
	8 = Intrakoroner Stent(ilaç kaplı)
	9 = Perkütan Koroner Anjiografi
	-1 = Seçilmedi
Perkütan Koroner girişim ile operasyon arası süre	0 = Yok
	1 = < 6saat
	2 = >6 saat
	-1 = Seçilmedi
En son geçirilmiş perkütan koroner girişim Tarihi	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
6 saat içinde geçirilmiş başarısız PTCA	0 = Yok
	1 = Var
	-1 = Seçilmedi
Geçirilmiş MI Sayısı	0 = Operasyon öncesi MI geçirmemiş
	1 = Bir kez MI geçirmiş
	2 = İki veya daha fazla MI geçirmiş
	3 = Bilinmiyor
	-1 = Seçilmedi
Operasyon öncesi geçirilmiş MI	0 = Yok
	1 = MI < 6 saat
	2 = MI 6-24 saat
	3 = MI 1-7 gün
	4 = MI 8-21 gün
	5 = MI > 21 gün ve < 6 ay
	6 = MI > 6 ay
	-1 = Seçilmedi
En son geçirilmiş MI tarihi	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Preoperatif respiratör gereksinimi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Preoperatif resüstasyon	0 = Yok
	1 = Var
	-1 = Seçilmedi

Figure B.4: Physical examination parameters

FizikMuayene Table	
Parameter Name	**Options**
Ritm statusu	
Seçilmedi	True/False
Sinus ritmi	True/False
AF/flutter	True/False
Geçirilmiş VT/VF	True/False
VES	True/False
1. derece AV blok	True/False
2. derece AV blok	True/False
AV-tam blok	True/False
Preoperatif Sistolik kan basıncı (mmHg)	Text
Preoperatif Diyastolik kan basıncı (mmHg)	Text
Preoperatif Ortalama kan basıncı (mmHg)	Text
Ankle - brachial indeks	0 = <0.50
	1 = 0.50-0.59
	2 = 0.60-0.69
	3 = 0.70-0.79
	4 = 0.80-0.89
	5 = 0.90-0.99
	6 = >1.0
	-1 = Seçilmedi
Karotis Üfürümü Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Karotis Üfürümü Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Pulmoner raller	0 = Yok
	1 = Var
	-1 = Seçilmedi
Pulmoner wheezing	0 = Yok
	1 = Var
	-1 = Seçilmedi
Toraks deformitesi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Mitral diastolik rulman	0 = Yok
	1 = Var
	-1 = Seçilmedi
Mitral sistolik üfürüm	0 = Yok
	1 = I/VI
	2 = II/VI
	3 = III/VI
	4 = IV/VI
	5 = V/VI
	6 = VI/VI
	-1 = Seçilmedi

FizikMuayene Table	
Parameter Name	**Options**
Aort diastolik üfürüm	0 = Yok
	1 = Var
	-1 = Seçilmedi
Aort sistolik üfürüm	0 = Yok
	1 = I/VI
	2 = II/VI
	3 = III/VI
	4 = IV/VI
	5 = V/VI
	6 = VI/VI
	-1 = Seçilmedi
Pulmoner arter diastolik üfürüm	0 = Yok
	1 = Var
	-1 = Seçilmedi
Pulmoner arter sistolik üfürüm	0 = Yok
	1 = I/VI
	2 = II/VI
	3 = III/VI
	4 = IV/VI
	5 = V/VI
	6 = VI/VI
	-1 = Seçilmedi
Abdomen	
Hepatomegali	0 = Yok
	1 = Var
	-1 = Seçilmedi
Splenomegali	0 = Yok
	1 = Var
	-1 = Seçilmedi
Kitle	0 = Yok
	1 = Var
	-1 = Seçilmedi
Üfürüm	0 = Yok
	1 = Var
	-1 = Seçilmedi
Asit	0 = Yok
	1 = Var
	-1 = Seçilmedi

FizikMuayene Table	
Parameter Name	**Options**
Vasküler	
Varis Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Varis Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - Femoral arter Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - Femoral arter Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - Popliteal arter Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - Popliteal arter Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. dorsalis pedis Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. dorsalis pedis Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. tibialis posterior Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. tibialis posterior Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. radialis Sağ	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nabızlar - A. radialis Sol	0 = Yok
	1 = Var
	-1 = Seçilmedi
Allen Testi	
Dominant el	0 = Sağ
	1 = Sol
	-1 = Seçilmedi
Non-Dominant el	0 = Pozitif (inkomplet palmar arkus dolaşımı)
	1 = Negatif (yeterli palmar arkus dolaşımı)
	-1 = Seçilmedi
Dominant el	0 = Pozitif (inkomplet palmar arkus dolaşımı)
	1 = Negatif (yeterli palmar arkus dolaşımı)
	-1 = Seçilmedi

Figure B.5: Angiography and echography parameters

Anjio/EKO	
Parameter Name	**Options**
Anjiografi raporu	Text
Dominant koroner arter	0 = Circumflex
	1 = Sağ koroner arter
	-1 = Seçilmedi
Hasta koroner arter sayısı (> %50 darlık)	0 = Yok
	1 = 1 damar
	2 = 2 damar
	3 = 3 damar
	-1 = Seçilmedi
Sol ana koroner arter (LMCA) hastalığı (> %50 darlık)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Left anterior descending (> %50 darlık)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Circumflex (> %50 darlık)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Sağ koroner arter (> %50 darlık)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Sol Ventrikül Ejeksiyon fraksiyonu kategorik (Cardiac Care Network (CCN) of Ontario grading)	0 = Ölçülmedi
	1 = Grade I (>%50)
	2 = Grade II (%35-%49)
	3 = Grade III (%20-%34)
	4 = Grade IV (<%20)
	-1 = Seçilmedi
Ejeksiyon fraksiyon değeri (%)	Text
Ejeksiyon fraksiyonu ölçüm metodu	0 = Diğer yöntemler ile
	1 = Ekokardiyografi
	2 = LV anjiografi
	3 = MUGA
	-1 = Seçilmedi
Fractional shortening (FS) değeri	Text
Sistolik pulmoner arter basıncı değeri (mmHg)	Text
Mean pulmoner arter basıncı (normal değer : 9-17 mmHg) değeri	Text
Sol ventrikül diastol-sonu basıncı-LVEDP (mmHg)	Text
Sol ventrikül anevrizması	0 = Yok
	1 = Var
	-1 = Seçilmedi
Sol atriumda trombüs	0 = Yok
	1 = Var
	-1 = Seçilmedi
Sol ventrikül sistol-sonu çapı - LVESD değeri (mm)	Text
Sol ventrikül diastol-sonu çapı -LVEDD değeri (mm)	Text
Sol ventrikül sistol-sonu volümü-LVESV (ml)	Text
Sol ventrikül diastol-sonu volümü-LVEDV (ml)	Text
Interventriküler septum kalınlığı-IVSd (8-11 mm) (HOCM hastalarında mutlaka doldurulacak)	Text
Posterior duvar kalınlığı	Text

Anjio/EKO	
Parameter Name	**Options**
Sol atrium çapı değeri (mm)	Text
E dalgası (m/s)	Text
A dalgası (m/s)	Text
E/A oranı	Text
E dalgası deselerasyon zamanı-EDT (ms)	Text
Diastolik disfonksiyon	0 = Normal doluş paterni
	1 = Relaksasyonda azalma
	2 = Pseudonormal
	3 = Restriktif doluş paterni
	-1 = Seçilmedi
Aort Kapağı	
Aort stenozu	0 = Yok
	1 = Var
	-1 = Seçilmedi
Aort stenozu etyolojisi	0 = Yok
	1 = Dejeneratif
	2 = Romatizmal
	3 = Konjenital (bikuspid, unikuspid aort kapak gibi)
	4 = Endokardit
	5 = Diğer
	-1 = Seçilmedi
Aort kapak maksimum gradienti (mmHg)	Text
Aort kapak ortalama gradienti (mmHg)	Text
Subaortik kapak gradienti (LVOT) (mmHg)	Text
Aort Yetmezlik	0 = Yok
	1 = 1. derece
	2 = 2. derece
	3 = 3. derece
	4 = 4. derece
	-1 = Seçilmedi
Aort yetmezlik etyolojisi	0 = Yok
	1 = Primer aort kapak hastalığı
	2 =Aort kökü hastalığı
	3 = Kombine
	-1 = Seçilmedi
Sinotübüler bileşke çapı değeri (mm)	Text
Valsalva sinüs çapı değeri (mm)	Text
Aort anülüs çapı değeri (mm)	Text
Kalsifiye aort	0 = Yok
	1 = Yaygın
	2 = Bölgesel
	-1 = Seçilmedi
Mitral Kapağı	
Mitral stenozu	0 = Yok
	1 = Var
	-1 = Seçilmedi

Anjio/EKO	
Parameter Name	**Options**
Mitral stenozu etyolojisi:	0 = Yok
	1 = Romatizmal
	2 = Mitral annuler kalsifikasyon
	3 = Neoplazm (sol atrial mikzoma gibi)
	4 = Konjenital (paraşüt deformitesi gibi)
	5 = Endokardit
	6 = SLE, romatoid artrit, Hunter-Hurler sendromu, Fabry hastalığı, Whipple hastalığı, Metiserjid
	7 = Karsinoid sendrom
	8 = Diğer
	-1 = Seçilmedi
Mitral kapak maksimum gradienti	Text
Mitral kapak mean gradienti	Text
Mitral kapak alanı (Doppler)	Text
Mitral kapak alanı (Planimetrik)	Text
Mitral kapak skoru	Text
Mitral annuler kalsifikasyon	0 = Yok
	1 = Hafif derecede (Annulusun 1/3'ünden azında)
	2 = Orta derecede (Annulusun 1/3 ile 2/3'ü arasında tutulum)
	3 = Ciddi (Annulusun 2/3'ünden fazlasında kalsifikasyon)
	-1 = Seçilmedi
Mitral Yetmezlik	0 = Yok
	1 = 1. derece
	2 = 2. derece
	3 = 3. derece
	4 = 4. derece
	-1 = Seçilmedi
Mitral Yetmezlik Etyolojisi	0 = Yok
	1 = Dejeneratif
	2 = İskemik
	3 = Romatizmal
	4 = Endokardit
	5 =Konjenital
	6 = Toraks travması
	7 = Diğer
	-1 = Seçilmedi
Mitral Yetmezlik Klasifikasyonu	
CarpentierTip I, normal kapakçık (santral yetersizlik, annüler dilatasyon veya leaflet perforasyonu)	True/False
CarpentierTip II, kapakçık prolapsı (kordal rüptür veya elongasyonu, papiller kas rüptürü veya elongasyonu)	True/False
CarpentierTip IIIa, diastol sırasında sınırlanmış kapakçık hareketi (romatik subvalvular fibrosis, kalsifikasyon)	True/False
CarpentierTip IIIB, sistol sırasında sınırlanmış kapakçık hareketi (iskemik veya dilate kardiyomiyopati)	True/False
Seçilmedi	True/False
Mitral Yetmezliğin hangi scallop'tan kaynaklandığı	
Santral yetmezlik	True/False
P1	True/False
P2	True/False
P3	True/False

Anjio/EKO	
Parameter Name	**Options**
A1	True/False
A2	True/False
A3	True/False
ALC (Anterolateral kommisur)	True/False
PMC (Posteromedial kommisur)	True/False
Mitral yetmezlikte regürjitan volüm	0 = Yok
	1 = <30ml
	2 = 31-60ml
	3 = >60ml
	-1 = Seçilmedi
Mitral yetmezlikte Efektif orifis area (ERO)	Text
Triküspid Kapağı	
Triküspid stenozu	0 = Yok
	1 = Var
	-1 = Seçilmedi
Triküspid stenozu etyolojisi	0 = Yok
	1 = Romatizmal
	2 = Konjenital
	3 = Sağ atrial neoplazm
	4 = Karsinoid sendrom
	5 = Endomiyokardiyal fibrozis
	6 = Endokardit
	7 = Kalp dışı tümör basısı
	8 = Diğer
	-1 = Seçilmedi
Trikuspid kapak maksimum gradienti (mmHg)	Text
Trikuspid kapak mean gradienti (mmHg)	Text
Triküspid yetmezlik	0 = Yok
	1 = 1. derece
	2 = 2. derece
	3 = 3. derece
	4 = 4. derece
	-1 = Seçilmedi
Triküspid yetmezlik etyolojisi	0 = Yok
	1 = Sekonder fonksiyonel trikuspid yetmezliği
	2 = Endokardit
	3 = Karsinoid sendrom
	4 = Romatizmal
	5 = Mikzamatöz
	6 = Ebstein anomalisi
	7 = Travma
	8 = İyatrojenik (pace teli, RV biyopsi gibi)
	9 = Diğer
	-1 = Seçilmedi
Pulmoner Kapağı	
Pulmoner stenoz	0 = Yok
	1 = Var
	-1 = Seçilmedi
Pulmoner kapak maksimum gradienti	Text
Pulmoner kapak mean gradienti	Text
Pulmoner kapak yetmezliği	0 = Yok
	1 = 1. derece
	2 = 2. derece
	3 = 3. derece
	4 = 4. derece

Figure B.6: Preoperative medication parameters

Preoperatif Medikasyon	
Parameter Name	**Options**
Preoperatif Antiagregan tedavi	
Seçilmedi	True/False
Kullanmıyor veya 1 hafta önce kesilmiş	True/False
Acetilsalisilik asid (ASA, Aspirin)	True/False
Klopidogrel (İscover, Plavix, Karum)	True/False
Diğer	True/False
Preoperatif Antikoagülan tedavi	
Seçilmedi	True/False
Kullanmıyor veya 1 hafta önce kesilmiş	True/False
Warfarin (Kumadin, Coumadin, Orfarin)	True/False
Unfraksiyone heparin	True/False
LMWH	True/False
IV Heparin (Heparin Sodium, Nevparin, Liquiemin, Calciparin, Fragmin)	True/False
Preoperatif Trombolitik veya Glikoprotein IIbIIIa İnhibitörü (son 48 saat içerisinde)	
Seçilmedi	True/False
Kullanılmamış	True/False
Aggrestat (Tirofiban)	True/False
Abciximab (ReoPro)	True/False
Streptokinaz/ürokinaz (Kabikinaz, Streptaz, Varidaz)	True/False
tPA (Actilyse Flakon)	True/False
Preoperatif Lipid düşürücü	
Seçilmedi	True/False
Yok	True/False
Atorvastatin (Alvastin, Ateroz, Ator, Caduet, Cardyn, Divator, Kolestor, Lipitaksin, Lipitor, Saphire, Tarden)	True/False
Bezafibrate (Befibrat, Azufibrat)	True/False
Colestyramine (Efensol)	True/False
Clofibrate (Klofibrat)	True/False
Colestipol (Colestid)	True/False
Ezetimibe (Ezetrol, İnegy)	True/False
Fenofibrate (Fenogal, Liphanthyl, Lipofen-Sr)	True/False
Fluvastatin (Lescol, Lescol XL)	True/False
Gemfibrozil (Lopid)	True/False
Lovastatin (Mevacor, Altocor)	True/False
Pravastatin (Pravachol)	True/False
Rosuvastatin (Crestor)	True/False
Simvastatin (İnegyZocor, Lipovas, Simvakol, Zocor, Zovatin)	True/False
Preoperatif Betablocker (< 24 saat)	0 = Yok
	1 = Acebutolol (Prent)
	2 = Atenolol (Atexal, Nortan, Tenoretic, Tensinor)
	3 = Betaxolol (Kerlone, Betoptic)
	4 = Bisoprolol (Concor, Lodoz)
	5 = Carteolol (Carteol)
	6 = Carvedilol (Carvexal, Coronis, Dilatrend, Kinetra)
	7 = Esmolol (Brevibloc)
	8 = Labetolol (Normodyne, Trandate)
	9 = Metoprolol Succinate (Beloc Zok)
	10 = Metoprolol (Beloc, Beloc Durules, Lopresor-Sr, Lopresor, Problok)

Preoperatif Medikasyon	
Parameter Name	**Options**
Preoperatif Betablocker (< 24 saat)	11 = Nadolol (Corgard, Anabet, Corzid)
	12 = Nebivolol (Vasoxen)
	13 = Penbutolol (Levatol)
	14 = Pindolol (Visken)
	15 = Propanolol (Dideral)
	16 = Sotalol (Darob, Sotarit, Talozin)
	17 = Timolol (Cosopt, Nyolol, Timabak, Timocomod, Timoftal, Timolol-Pos, Timoptic-Xe, Timosol, Xalacom)
	-1 = Seçilmedi
Preoperatif ACE İnhibitörü (< 24 saat)	0 = Yok
	1 = Benazepril (Cibacen, Cibadrex)
	2 = Captopril (Kapril, Kaptoril)
	3 = Cilazapril (İnhibace, İnhibace Plus)
	4 = Enalapril (Enalap, Enapril, Enapril Plus, Eneas, Konveril, Konveril Plus, Renitec, Vasolapril)
	5 = Fosinopril (Monopril, Monopril Plus)
	6 = Lisinopril (Acerilin, İnhibril, Rilace, Rilace Plus, Sinopryl, Sinoretik, Zestoretik, Zestril)
	7 = Moexipril (Univasc)
	8 = Perindopril (Coversyl, Conversyl Plus, Preterax)
	9 = Quinapril (Accuzide, Accuzide Fort, Acuitel)
	10 = Ramipril (Blokace, Blokace Plus, Delix, Delix Plus, Delix Protect)
	11 = Trandolapril (Gopten, Tarka)
	12 = Zofenopril (Zoprotec)
	13 = Enalaprilat (Vasotec IV)
	-1 = Seçilmedi
Preoperatif ARB	0 = Yok
	1 = Candersartan (Atacand, Atacand Plus, Ayra)
	2 = Eprosartan (Teveten, Teveten Plus)
	3 = Losartan (Cozaar, Eklips, Eklips Plus, Hyzaar, Loxibin, Loxibin Plus, Sarvas, Sarvastan)
	4 = Olmesartan Medoxomil (Hipersar, Olmetec)
	5 = Telmisartan (Micardis, Micardis Plus, Pritor, Pritor Plus)
	6 = İrbesartan (Karvea, Karvezide)
	7 = Valsartan (Diovan, Co-Diovan)
	-1 = Seçilmedi
Preoperatif Kalsiyum antagonisti	0 = Yok
	1 = Amlodipine (Amplodis, Amlokard, Amlovas, Caduet, Dilopin, Monovas, Nipidol, Norlopin, Normopres, Norvadin, Norvasc, Vasocard, Vasonorm, Vazkor)
	2 = Barnidipine (Libradin)
	3 = Bepridil (Vascor)<
	4 = Felodipine (Plendil)
	5 = Isradipine (Dynacirc Sro)
	6 = Lacidipine (Lacipil)
	7 = Lercanidipine (Lercadip)
	8 = Nicardipine (Cardene)
	9 = Nimodipine (Nimotop)
	10 = Nilvadipine (Nilvadis)
	11 = Nifedipine (Adalat Crono, Nidicard, Nidilat)

Preoperatif Medikasyon	
Parameter Name	**Options**
Preoperatif Kalsiyum antagonisti	12 = Verapamil (Fibrocard, İsoptin, İsoptin Kkh, İsoptin-Sr, Tarka, Veroptin)
	13 = Dilitiazem (Altizem-Sr, Dilticard, Diltizem, Diltizem-Sr, Kardil-Sr)
	-1 = Seçilmedi
Preoperatif Nitrogliserin (dermal veya oral)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Preoperatif İV. Nitrat (< 48 saat)	0 = Yok
	1 = Var
	-1 = Seçilmedi
Preoperatif Diüretik	
Seçilmedi	True/False
Yok	True/False
Furosemide (Lasix, Desal, Ürever, Furomid, Lizik, Ürex)	True/False
Amiloride Spironolactone (Moduretic, Aldactone, Adactazide)	True/False
Chlorthalidone Hydrochlorothiazide (Regreton, Hygroton, Akuadon, Triamteril, Moduretic, Aldactezide, Adelphan)	True/False
Indapamide Metolazone (Fludex, Flupamid, İndurin, Metozalon)	True/False
Bumetanide (Butinate, Burinex)	True/False
Torsemide (Toracard, Duprac, Torrem)	True/False
Triamterene (Triamteril)	True/False
Preoperatif Antiaritmik	
Seçilmedi	True/False
Yok	True/False
Moricizine (Ethmozine)	True/False
Quinidine (Longacor, Natisedin)	True/False
Procainamide (Pronestyle, Pronestyle-Sr, Procan-Sr, Procanbid)	True/False
Disopyramide (Norpace, Rthmodan)	True/False
Tocainide (Tonocard)	True/False
Lidocaine (Aritmal, Jetmonal, Jetokain Simplex, Jetokain, Jetosel)	True/False
Phenytoin (Epanutin, Epdantoin, Hidantin, Phenhydan)	True/False
Mexiletine (Mexitil)	True/False
Flecainide (Tambocor)	True/False
Propafenone (Rhytmonorm)	True/False
Acebutolol (Prent, Sectral)	True/False
Esmolol (Brevibloc)	True/False
Propranolol (Dideral)	True/False
Amiodarone (Cordarone)	True/False
Dofetilide (Tikosin)	True/False
İbutilide (Corvert)	True/False
Sotalol (Darob, Sotarit, Talozin)	True/False
Diltiazem (Altizem-Sr, Dilticard, Diltizem, Diltizem-Sr, Kardil)	True/False
Verapamil (Fibrokard, İsoptin, İsoptin Kkh, İsoptin-Sr, Tarka, Veroptin)	True/False
Bretylium Tosilate	True/False

Preoperatif Medikasyon	
Parameter Name	**Options**
Preoperatif Inotrop kullanımı (µg/kg/dak)	
Seçilmedi	True/False
Yok	True/False
Dopamin (Dopmin, Giludop, Dopadren)	True/False
Dobutamin (Dobutabag, Dobutrex)	True/False
Noradrenalin (Xylonor)	True/False
Adrenalin (Epipen)	True/False
Levosimendan (Syndax)	True/False
Preoperatif Dijital	0 = Yok
	1 = Var (Digoksin, Lanoksin)
	-1 = Seçilmedi
Preoperatif İnsulin	0 = Yok
	1 = Var
	-1 = Seçilmedi
Preoperatif oral antidiyabetik	
Seçilmedi	True/False
Yok	True/False
Gliclazide (Betanorm, Diamicron, Efikas, Glikron, Glumikron, Oramikron)	True/False
Gliburide (Diyanorm, Gliben, Diyaben)	True/False
Tolbutamide (Diaboral)	True/False
Pioglitazone (Actos)	True/False
Rosiglitazone (Avandia)	True/False
Preoperatif Steroid	
Seçilmedi	True/False
Kullanmıyor	True/False
Oral steroid	True/False
İnhaler steroid	True/False
IV steroid	True/False
Preoperatif H2 Antagonisti veya proton pompa inhibitörü	0 = Yok
	1 = Cimetidine (Ulkamet)
	2 = Ranitidine (Pylorid, Ranitab, Ulcuran, Zantac, Rozon, Ranobel)
	3 = Famotidine (Famodin Nevofam Famoser Duovel Famo, Famogast, Famec, Famotsan, Gasterol, Gastifam, Gastover, Gastrosidin, Neotab, Pepdif, Ulcusar, Notidin)
	4 = Nizatidine (Axid)
	-1 = Seçilmedi
Preoperatif İmmünsupressif tedavi (Operasyon öncesi son 1 ayda)	0 = Yok
	1 = Var
	-1 = Seçilmedi

Figure B.7: Laboratory analysis parameters

Laboratuar	
Parameter Name	**Options**
Preoperatif veya Postoperatif Laboratuar	Preoperatif/Postoperatif/Seçilmedi
Laboratuar Tarihi	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Açlık Glukoz	Text
BUN (Kan Üre Azotu)	Text
Kreatinin	Text
Ürik asit	Text
Sodyum	Text
Potasyum	Text
Klor	Text
Kalsiyum	Text
Fosfor	Text
Magnezyum	Text
Total Protein	Text
Albumin	Text
Total Bilirubin	Text
Direkt Bilirubin	Text
AST	Text
ALT	Text
Gamma Glutamil Transferaz (GGT)	Text
Alkalen fosfataz (ALP)	Text
Laktat dehidrogenaz (LDH)	Text
Total Kolesterol	Text
HDL Kolesterol	Text
LDL Kolesterol	Text
VLDL	Text
Trigliserit	Text
HbA1c	Text
CRP	Text
Serbest T3	Text
Serbest T4	Text
TSH	Text
HBsAg	0 = Negative
	1 = Positive
	-1 = Seçilmedi
Anti-HBS	0 = Negative
	1 = Positive
	-1 = Seçilmedi
Anti-HCV	0 = Negative
	1 = Positive
	-1 = Seçilmedi
Anti-HIV	0 = Negative
	1 = Positive
	-1 = Seçilmedi
WBC (Beyaz küre)	Text
Hgb (Hemoglobin)	Text
Hct (Hematokrit)	Text
Plt (Trombosit)	Text

Laboratuar	
Parameter Name	**Options**
Sedim	Text
ASO	Text
PT	Text
INR	Text
aPTT	Text
CK-MB Kütle	Text
Troponin I	Text
Demir	Text
Total demir bağlama kapasitesi	Text
% Saturasyon	Text
Ferritin	Text
Vitamin B12 düzeyi	Text
Folat düzeyi	Text
Amilaz	Text
Pankreatik Amilaz	Text
Lipaz	Text

Figure B.8: Operation related parameters

Operatif Bilgiler	
Parameter Name	**Options**
Operasyon Önceliği	0 = Elektif
	1 = Urgent (1 hafta)
	2 = Acil (24 saat)
	3 = Salvaj (Hemen)
	-1 = Seçilmedi
Operasyon aciliyet nedeni	0 = Yok
	1 = Akut miyokard infarktüsü (AMI)
	2 = Intra-Aortik Balon Pompa destek gereksinimi (IABP)
	3 = Medikal tedaviye refrakter anstabil anjina
	4 = Konjestif kalp yetmezliği
	5 = Koroner anatomi
	6 = Kapak disfonksiyonu (Nativ veya prostetik)
	7 = Aort disseksiyonu
	8 = İnfektif endokardit
	9 = Anjiografi komplikasyonu
	10 = Kardiak Travma
	-1 = Seçilmedi
Operasyon insidansı	1 = İlk kardiyovasküler operasyon
	2 = İlk re-op kardiyovaskü;ler operasyon
	3 = İkinci re-op kardiyovasküler operasyon
	4 = Üçüncü re-op kardiyovasküler operasyon
	5 = Dördüncü veya daha fazla re-op kardiyovasküler operasyon
	-1 = Seçilmedi
Geçirilmiş Operasyon	
Yok	True/False
Koroner Cerrahisi	True/False
	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Kapak Cerrahisi	True/False
	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
İntraperikardial veya büyük damar Cerrahisi	True/False
	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Operasyon gruplaması	
Seçilmedi	True/False
Koroner Bypass Cerrahisi	True/False
Kapak Cerrahisi	True/False
Kalp Nakli	True/False
Aort Cerrahisi	True/False
Karotis Cerrahisi	True/False
Konjenital Cerrahisi	True/False
Periferik damar cerrahisi	True/False
Diğer Torasik prosedürler	True/False
Kardiyak Tümör	True/False
Perikard Cerrahisi	True/False

Operatif Bilgiler	
Parameter Name	**Options**
Diğer kardiak prosedürler	
Seçilmedi	True/False
Yok	True/False
Sol Ventrikül Anevrizma Onarımı	True/False
Batista operasyonu	True/False
Sol Ventrikül Restorasyon	True/False
Kök Hücre İmplantasyonu	True/False
Transmiyokardiyal laser revaskülarizasyon	True/False
Ventriküler septal defekt/rüptür Onarımı	True/False
Atrial septal defekt (ASD) Onarımı	True/False
Konjenital diğer defektlerin onarımı	True/False
Aritmi cerrahisi Radyo-Frekans veya microwave Ablasyon	True/False
Aritmi cerrahisi Cerrahi Maze prosedürü	True/False
Aritmi cerrahisi Kalıcı Pacemaker	True/False
Aritmi cerrahisi Kalıcı Pacemaker, kardiyak resenkronizasyon	True/False
Aritmi cerrahisi AICD	True/False
Aritmi cerrahisi AICD, kardiyak resenkronizasyon	True/False
Kardiyak travma	True/False
İHSS (idiyopatik hipertrofik subaortik stenoz septal myektomi)	True/False
PVR (pulmoner kapak replasmanı), stentsiz biyolojik kapak veya homogreft ile	True/False
Pulmoner kapak onarımı	True/False
Kardiyak kist hidatik eksizyonu	True/False
Bentall operasyonu	True/False
Çıkan aort anevrizma onarımı (David, Yacoup teknikleri)	True/False
Torakoabdominal EVAR	True/False
Sternal revizyon	True/False
Diğer	True/False
Sol Atrial Miksoma	True/False
Konstriktif Perikardit	True/False
MI mekanik komplikasyonu	0 = Yok
	1 = Var
	-1 = Seçilmedi
Preoperatif Antibiyotik seçimi	0 = Verilmedi
	1 = Birinci jenerasyon sefalosporin
	2 = İkinci jenerasyon sefalosporin
	3 = Vancomisin
	4 = Allerji nedeniyle diğer antibiyotikler
	-1 = Seçilmedi
Preoperatif IV Steroid kullanıldı mı?	0 = Hayır
	1 = Düşük doz (< 250mg)
	2 = Orta doz (250mg - 499mg)
	3 = Yüksek doz (> 500mg)
	-1 = Seçilmedi

Operatif Bilgiler	
Parameter Name	**Options**
İnsizyon	
Standart Median Sternotomi	True/False
Ministernotomi	True/False
Anterior Torakotomi	True/False
Posterolateral Torakotomi	True/False
Minitorakotomi	True/False
Klemshell	True/False
Servikal	True/False
Median Laparotomi	True/False
Diğer Laparotomi	True/False
Diğer	True/False
Seçilmedi	True/False
Hibrid operasyon yapıldımı?	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Hibrid operasyonun zamanı	0 = Perkütan girişimden önce
	1 = Perkütan girişimden sonra
	-1 = Seçilmedi
Perkütan girişim yapılan koroner arter	
Diag1/intermediate	True/False
Diag2	True/False
OM1	True/False
OM2	True/False
Cx-posterolateral	True/False
RCA Crux öncesi	True/False
RCA - PDA dalı	True/False
RCA - LV dalı	True/False
Seçilmedi	True/False

Figure B.9: Coronary artery bypass surgery parameters

Koroner Baypas	
Parameter Name	**Options**
Distal koroner anastomoz sayısı	0 = Seçilmedi / 1-10
Arterial kondüit distal anastomoz sayısı	0 = Seçilmedi / 1-5
Venöz kondüit distal anastomoz sayısı	0 = Seçilmedi / 1-5
Greft 1	True/False
GreftProksimal1	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi
GreftKonduit1	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal1	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft1KoronerArterCapi	List
Greft1KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 2	True/False
GreftProksimal2	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi

Koroner Baypas	
Parameter Name	**Options**
GreftKonduit2	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal2	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft2KoronerArterCapi	List
Greft2KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 3	True/False
GreftProksimal3	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi
GreftKonduit3	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal3	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft3KoronerArterCapi	List

Koroner Baypas	
Parameter Name	**Options**
Greft3KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 4	True/False
GreftProksimal4	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi
GreftKonduit4	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal4	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft4KoronerArterCapi	List
Greft4KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 5	True/False
GreftProksimal5	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi

Koroner Baypas	
Parameter Name	**Options**
GreftKonduit5	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal5	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft5KoronerArterCapi	List
Greft5KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 6	True/False
GreftProksimal6	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi
GreftKonduit6	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal6	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft6KoronerArterCapi	List

Koroner Baypas	
Parameter Name	**Options**
Greft6KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
Greft 7	True/False
GreftProksimal7	0 = Aorta
	1 = LIMA - in situ
	2 = RIMA - in situ
	3 = Vena Safena Magna (sequential)
	4 = LIMA (sequential)
	5 = RIMA (sequential)
	6 = Radial
	7 = Gastroepiploik in situ
	8 = Arkus aorta dalları
	-1 = Seçilmedi
GreftKonduit7	0 = LIMA
	1 = RIMA
	2 = Radial Arter
	3 = Vena Safena Magna
	4 = Vena Safena Parva
	5 = Gastroepiploik Arter
	6 = Diğer
	-1 = Seçilmedi
GreftDistal7	0 = LAD
	1 = Diag1 / Intermediate
	2 = Diag2
	3 = OM1
	4 = OM2
	5 = CX - posterolateral (CX-distal)
	6 = RCA Crux öncesi
	7 = RCA - PDA dalı
	8 = RCA - LV dalı
	-1 = Seçilmedi
Greft7KoronerArterCapi	List
Greft7KoronerArterKalitesi	0 = Distal damar kalitesi iyi
	1 = Skip lezyonlar mevcut
	2 = Diffüz olarak tutulum mevcut
	3 = Çok ciddi diffüz hastalık mevcut
	-1 = Seçilmedi
İMA distal anastomoz sayısı	0 = Seçilmedi / 1-4
İMA hazırlanış tekniği	0 = İskeletize
	1 = Pedikül olarak
	-1 = Seçilmedi
Radial arter distal anastomoz sayısı	0 = Seçilmedi / 1-4
Safen ven distal anastomoz sayısı	0 = Seçilmedi / 1-10

Koroner Baypas	
Parameter Name	**Options**
Endarteraktomi yapıldı mı	0 = LAD
	1 = Diagonal dalları
	2 = Cx-Om dalları
	3 = Distol Cx
	4 = RCA Crux öncesi
	5 = RCA-PDA dalı
	6 = RCA-LV dalı
	7 = Hayır
	-1 = Seçilmedi
İMA'ya kullanılan vasodilatör ajan	0 = Papaverin
	1 = Diltiazem
	2 = İliyomedin
	3 = Nitrogliserin
	4 = Niprus
	-1 = Seçilmedi

Figure B.10: Valve surgery parameters

Kapak Cerrahisi	
Parameter Name	**Options**
Aort kapak cerrahisi	
Aort kapak cerrahi tekniği	0 = Yok
	1 = Aort kapak replasmanı (AVR)
	2 = Aort kapak onarımı/rekonstrüksiyonu
	3 = Kondüitli kapakla aort kökü rekonstrüksiyonu
	4 = AVR + aort greft (kapaklı kondüit kullanılmadı)
	5 = Kapak koruyucu aort kökü rekonstrüksiyonu
	6 = Aort kapak resuspansiyonu + çıkan aort replasmanı
	7 = Yalnızca aort kapak resuspansiyonu
	8 = Subaortik stenoz rezeksiyonu
	9 = Bentall operasyonu (çıkan aort kapak replasmanı + AVR)
	10 = Sinüs valsalva anevrizma onarımı
	-1 = Seçilmedi
Aort Kapak Morfolojisi	0 = Trikuspid
	1 = Bikuspid
	2 = Monokuspid
	3 = Dört veya daha fazla kuspisli
	-1 = Seçilmedi
Aort Anüler genişletme	0 = Yok
	1 = Var
	-1 = Seçilmedi
Aort kapak protez	1 = Mekanik
	2 = Biyolojik
	3 = Homogreft
	4 = Otogreft (ROSS prosedürü)
	-1 = Seçilmedi
Aort kapak protez çapı (mm)	0 = Seçilmedi / 18-30
Aort kapak protez markası	Table
Mitral kapak cerrahisi	
Mitral kapak cerrahi tekniği	0 = Yok
	1 = Mitral Kapak replasmanı (MVR) posterior subvalvular aparat korunarak
	2 = Mitral Kapak replasmanı (MVR) anterior ve posterior subvalvular aparat korunarak
	3 = Mitral Kapak replasmanı (MVR) subvalvular aparat korunmaksızın
	4 = Mitral kapak onarımı, yalnızca annuloplasti
	5 = Mitral kapak onarımı, quadrangüler rezeksiyon + annuloplasti
	6 = Mitral kapak onarımı, sliding plasti + annuloplasti
	7 = Mitral kapak onarımı, kordal tamir + annuloplasti
	8 = Mitral kapak onarımı, perikardiyal yama + annuloplasti
	9 = Mitral kapak onarımı, Alfieri sütür + annuloplasti
	10 = Mitral kapak onarımı, diğer onarım teknikleri
	11 = Açık Mitral Kommissurotomi (AMK)
	-1 = Seçilmedi
Mitral kapağa yaklaşım	0 = Yok
	1 = Sol atriotomi
	2 = Trans-septal
	-1 = Seçilmedi

Kapak Cerrahisi	
Parameter Name	**Options**
LA trombektomi	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
LA apendaj plikasyonu	0 = Yok
	1 = İnternal
	2 = External
	-1 = Seçilmedi
Mitral kapak protez	1 = Annuloplasti ring/bant
	2 = Mekanik kapak
	3 = Biyolojik kapak
	4 = Homogreft
	-1 = Seçilmedi
Mitral kapak protez çapı (mm)	0 = Seçilmedi / 18-34
Mitral protez markası	Table
Mitral Ring & Band çapı (mm)	0 = Seçilmedi / 18-34
Mitral Ring & Band markası	Table
Trikuspid kapak cerrahisi	
Trikuspid kapak cerrahi tekniği	0 = Yok
	1 = Trikuspid kapak replasmanı (TVR)
	2 = Yalnızca annuloplasti
	3 = Trikuspid kapak rekonstrüksiyonu + annuloplasti
	4 = Trikuspid kapak rekonstrüksiyonu, annuloplasti yapılmadan
	5 = Valvektomi
	-1 = Seçilmedi
Triküspid kapak protez	1 = Annuloplasti ring/bant
	2 = Mekanik kapak
	3 = Biyolojik kapak
	4 = Homogreft
	-1 = Seçilmedi
Triküspid kapak protez çapı (mm)	0 = Seçilmedi / 18-34
Triküspid protez markası	Table
Triküspid Ring & Band çapı (mm)	0 = Seçilmedi / 18-34
Triküspid Ring & Band markası	Table
Pulmoner kapak cerrahisi	
Pulmoner kapak cerrahi tekniği	0 = Yok
	1 = Pulmoner kapak replasmanı (PVR)
	2 = Pulmoner kapak rekonstrÜksiyonu
	-1 = Seçilmedi
Pulmoner kapak protez	0 = Biyolojik
	1 = Mekanik
	-1 = Seçilmedi
Pulmoner kapak protez çapı (mm)	0 = Seçilmedi / 18-34
Pulmoner protez markası	Table
Aritmi cerrahisi	
Ablasyonda kullanılan enerji kaynağı :	1 = Yok
	2 = Kesme ve dikme tekniği (Cox-Maze)
	3 = Radyofrekans
	4 = Mikrodalga
	5 = Kriyotermi
	6 = Laser
	7 = Yüksek yoğunluk odaklı ultrasound
	-1 = Seçilmedi

Kapak Cerrahisi	
Parameter Name	**Options**
Ablasyon tekniği	1 = Cox-Maze III
	2 = Yalnızca ablasyon ile pulmoner ven izolasyonu (sol atriyel)
	3 = Pulmoner ven izolasyonu, apandaj ablasyonu, mitral kapağa uzanan ablasyon (kombine sol atriyel)
	4 = Biatrial ablasyon
	5 = Yalnızca sağ atriyel ablasyon
	-1 = Seçilmedi
Ablasyon uygulaması	1 = Yok
	2 = Unipolar
	3 = Bipolar
	4 = Kombine (unipolar +bipolar)
	-1 = Seçilmedi
Ablasyon süresi (dakika)	

Figure B.11: Thoracic aorta surgery parameters

Aort Cerrahisi	
Parameter Name	**Options**
Aort patolojisi	
Anevrizma	True/False
Disseksiyon	True/False
Transeksiyon	True/False
Rüptür	True/False
Koarktasyon	True/False
Ateramatöz	True/False
Marfan sendromu veya diğer konnektif doku hastalıkları	True/False
Mikotik	True/False
Sfilitik	True/False
Konjenital	True/False
Seçilmedi	True/False
Aort Anevrizması	
Yok	True/False
Çıkan Aort	True/False
Arkus Aorta	True/False
İnen Torasik Aort	True/False
Torakoabdominal	True/False
Abdominal	True/False
Aort kökü	True/False
Seçilmedi	True/False
Aort Disseksiyonu	0 = Yok
	1 = Tip A
	2 = Tip B
	-1 = Seçilmedi
Aort Disseksiyonu Süresi (gün olarak) :	
Aort girişimleri	1 = Çıkan aort replasmanı
	2 = Çıkan aort + hemiarkus replasmanı
	3 = Torakal inen aort anevrizma onarımı
	4 = Torako-abdominal aort anevrizma onarımı
	5 = Abdominal aort anevrizma onarımı
	6 = Torako abdominal aort EVAR
	7 = Abdominal aort EVAR
	8 = Aorta-bifemoral bypass
	9 = Aorta-subclavien bypass
	-1 = Seçilmedi
Aort protez çapı (mm)	18-34
Protez markası	Table

Figure B.12: Surgery crew parameters

Ameliyat Ekibi	
Parameter Name	**Options**
Konsültan Hekim	Text
1. Cerrah	Text
Asistan cerrah	Text
2. asistan	Text
3. asistan	Text
Konsültan Anestezist	Text
Asistan Anestezist	Text
Anestezi Teknikeri	Text
Ameliyat Hemşiresi	Text
Diğer Ameliyat Hemşiresi	Text
Perfüzyonist	Text
Diğer Perfüzyonist	Text

Figure B.13: Perfusion parameters

Perfüyonist	
Parameter Name	**Options**
Cilt kesişi başlama saati	Text
	Text
Cilt kapatılma saati	Text
	Text
Operasyon süresi (dk)	Text
Kan Grubu	0 = 0
	1 = A
	2 = B
	3 = AB
	-1 = Seçilmedi
	0 = Rh Negatif
	1 = Rh Pozitif
	-1 = Seçilmedi
Sistolik Pulmoner Arter Basıncı (mm-Hg)	Text
Diastolik Pulmoner Arter Basıncı (mm-Hg)	Text
Mean Arter Basıncı (mm-Hg)	Text
Pulmoner Kapiller Wedge Basıncı (mm-Hg)	Text
CVP (mm-Hg)	Text
Mix Venöz Saturasyon	Text
Kardiyopulmoner bypas	0 = Off-pump
	1 = On-pump beating heart
	2 = Total CPB
	3 = Parsiyel CPB
	-1 = Seçilmedi
Off-pump'tan kardiyopulmoner bypass'a geçme nedeni	0 = Gerek duyulmadı, operasyon planlandığı gibi Off-pump tamamlandı
	1 = Exposure ve görüntüleme yetersizliği
	2 = Kanama
	3 = Koroner anatominin uygunsuzluğu ve diffüz distal damar hastalığı
	4 = Hemodinamik instabilite (hipotansiyon/aritmi)+E16
	5 = Konduit kalitesinin iyi olmaması veya travma nedeniyle hasarlı olması
	6 = Diğer nedenler
	-1 = Seçilmedi
Off-pump'ta Stabilizasyon metodu	0 = Kompresyon
	1 = Suction (aspirasyon metodu)
	-1 = Seçilmedi
Oksijenatör	0 = Affinity (Medtronic)
	1 = Jostra / MAQUET (GST medical)
	2 = Dideco
	3 = Edwards
	4 = Terimo
	5 = COBE
	6 = MEDOS
	-1 = Seçilmedi
Prime volüme (ml)	Text
FLOW 2.4	Text
FLOW 2.0	Text
AORT (mm)	Text
AXİLER (mm)	Text

Perfüyonist	
Parameter Name	**Options**
FEMORAL (mm)	Text
Balon Uçlu (fr)	Text
Basket (fr)	Text
Düz (fr)	Text
Kıvrık (fr)	Text
Kıvrık Demir Uçlu (fr)	Text
Intraoperatif antifibrinolitik kullanımı	
Seçilmedi	True/False
Kullanılmadı	True/False
Aprotinin (Trasylol) tam doz	True/False
Tranexamic Acid	True/False
Epsilon-aminocaproic acid (Amicar)	True/False
Diğer	True/False
Aprotinin (Trasylol) yarım doz	True/False
Desmopressin	True/False
Kombinasyon ise	Text
Kombinasyon nedeni	Text
Kanülasyon metodu	Text
Aort Oklüzyonu	0 = Yok
	1 = X-Klemp
	2 = Intravaskuler balon
	3 = Diğer
	-1 = Seçilmedi
Parsiyel aortik klemp (side biter) kullanıldımı?	0 = Hayır
	1 = 1 kez
	2 = 2 kez
	3 = 3 kez
	4 = >3 kez
	-1 = Seçilmedi
CPB süresi (dk)	Text
Kros klemp zamanı (dk)	Text
Hipotermik dolaşım arresti kullanıldımı ?	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Hipotermik dolaşım arrest süresi (dk)	Text
Kardiyopleji	0 = Yok
	1 = Kristaloid kardiyopleji
	2 = Kan kardiyoplejisi
	3 = Kombine
	-1 = Seçilmedi
Kardiyopleji verilme yolu	1 = Antegrad
	2 = Retrograd
	3 = Kombine
	-1 = Seçilmedi
İNDÜKSİYON (derece)	Text
İDAME (derece)	Text
HOTSHOT (derece)	Text
Root Kanül (ga)	Text
Hemofiltrasyon	0 = Yok
	1 = Var
	-1 = Seçilmedi
Hemofiltrasyon miktarı (cc)	0 = Yok

Perfüyonist	
Parameter Name	**Options**
ECMO	0 = Yok
	1 = Var
	-1 = Seçilmedi
Ventriküler asist device	
Seçilmedi	True/False
Yok	True/False
LVAD	True/False
RVAD	True/False
BVAD	True/False
İABP	0 = Yok
	1 = Preoperatif takıldı
	2 = İntraoperatif takıldı
	3 = Postoperatif takıldı
	4 = Bilinmiyor
	-1 = Seçilmedi
İABP endikasyonu	
Seçilmedi	True/False
Bilinmiyor	True/False
Hemodinamik İnstabilite	True/False
PTCA Desteği	True/False
Unstabil Angina	True/False
CPB Çıkışı	True/False
Proflaktik	True/False
CPB'tan çıkışta ritim	0 = NSR
	1 = AF / Flutter
	2 = 1. derece AV blok
	3 = 2. derece AV blok
	4 = AV-tam blok
	-1 = Seçilmedi
CPB'tan çıkışta pacemaker modu	0 = Gereksinim yok
	1 = VVI
	2 = DDD
	-1 = Seçilmedi
CPB'tan çıkışta inotrop gereksinimi (µg/kg/dak)	
Yok	True/False
Dopamin	True/False
	Text
Dobutamin	True/False
	Text
Adrenalin	True/False
	Text
Noradrenalin (Levophed)	True/False
	Text
Phenylephrine (Neo-Synephrine)	True/False
	Text
Milrinone (Primacor)	True/False
	Text
Isoprenalin (Isoproternol, Isuprel)	True/False
	Text
Aramine (Metaraminol)	True/False
	Text
Levosimendan	True/False
	Text

Perfüyonist	
Parameter Name	**Options**
Kardiyopulmoner bypasstan çıkışta Swan-Ganz Parametreleri	
Sistolik Pulmoner Arter Basıncı (mm-Hg)	Text
Diastolik Pulmoner Arter Basıncı (mm-Hg)	Text
Mean Arter Basıncı (mm-Hg)	Text
Pulmoner Kapiller Wedge Basıncı (mm-Hg)	Text
CVP (mm-Hg)	Text
Mix Venöz Saturasyon	Text
İntraoperatif kan ürünleri (ünite)	
Eritrosit	Text
Taze donmuş plazma	Text
Trombosit	Text
Kryopersipitat	Text
CPB sırasında kan gazı değerleri	
En düşük Ph	Text
En yüksek BE	Text
En düşük Hb	Text
En düşük Hct	Text
En yüksek PCo2	Text

Figure B.14: Postoperative and intensive care unit parameters

Postoperatif ve Yoğun Bakım Bilgileri	
POSTOPERATİF BİLGİLER	
Parameter Name	**Options**
Göğüs tüp dranajı ilk 8 saat (ml)	Text
Göğüs tüp dranajı ilk 24 saat (ml)	Text
Postoperatif kan ürünleri (ünite)	
Otolog tam kan	Text
Homolog tam kan	Text
Eritrosit	Text
Taze donmuş plazma (FFP)	Text
Trombosit	Text
Kryopersipitat	Text
Ameliyathane ekstübe edildi	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Toplam postoperatif ventilasyon süresi (saat)	Text
İlk 24 saatteki peak kan şekeri	Text
İlk 24 saatte verilen insülin dozu	Text
YOĞUN BAKIM BİLGİLERİ	
Yoğun Bakımda inotropik destek (µg/kg/dak):	
Yok	True/False
Dopamin	True/False
	Text
Dobutamin	True/False
	Text
Adrenalin	True/False
	Text
Noradrenalin (Levophed)	True/False
	Text
Phenylephrine (Neo-Synephrine)	True/False
	Text
Milrinone (Primacor)	True/False
	Text
Isoprenalin (Isoproternol, Isuprel)	True/False
	Text
Aramine (Metaraminol)	True/False
	Text
Levosimendan	True/False
	Text
Swan-Ganz Parametreleri	
Sistolik Pulmoner Arter Basıncı (mmHg)	Text
Diastolik Pulmoner Arter Basıncı (mmHg)	Text
Mean Arter Basıncı (mmHg)	Text
Pulmoner Kapiller Wedge Basıncı (mmHg)	Text
CVP (mmHg)	Text
Mix Venöz Saturasyon	Text
Redon dren	0 = 1.
	1 = 2.
	2 = 3.
	3 = 4.
	4 = > 4.
	-1 = Seçilmedi
Redon drenden drenaj miktarı	Text

Figure B.15: Complication parameters

Komplikasyon Bilgileri	
Parameter Name	**Options**
Tarih	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Operatif Komplikasyonlar	
Seçilmedi	True/False
Yok	True/False
Kanamalı tamponat nedeniyle reoperasyon	True/False
Kapak disfonksiyonu nedeniyle reoperasyon	True/False
Greft oklüzyonu nedeniyle reoperasyon	True/False
İMA spasmı nedeniyle reoperasyon	True/False
Diğer kardiyak nedenlerle reoperasyon	True/False
Düşük kalp debisi sendromu (Low cardiac output syndrom	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Perioperatif MI	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Yeni gelişmiş atrial fibrilasyon	0 = Yok
	1 = Var
	-1 = Seçilmedi
Elektrik kardiyoversiyon gereksinimi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Kalp bloğu	0 = Yok
	1 = Var
	-1 = Seçilmedi
Kalıcı kalp pili gereksinimi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Nörolojik komplikasyonlar	0 = Yok
	1 = Postoperatif stroke > 72 saat fazla
	2 = Geçici nörolojik defisit
	3 = Koma > 24 saat
	-1 = Seçilmedi
Pulmoner komplikasyonlar	
Seçilmedi	True/False
Yok	True/False
Reentübasyon	True/False
Uzamış ventilasyon	True/False
Pulmoner emboli	True/False
Pnömoni	True/False
Renal komplikasyonlar	0 = Yok
	1 = Böbrek yetmezliği
	2 = Diyaliz gereksinimi
	-1 = Seçilmedi
Peak postoperatif kreatinin (mg/dL)	
Vasküler komplikasyonlar	0 = Yok
	1 = İliak/femoral disseksiyon
	2 = Akut ekstremite iskemisi
	3 = Derin ven trombozu
	-1 = Seçilmedi

Komplikasyon Bilgileri	
Parameter Name	**Options**
Gastrointestinal komplikasyonlar	
Seçilmedi	True/False
Yok	True/False
Gastrointestinal kanama	True/False
Gastrointestinal perforasyon	True/False
Pankreatit	True/False
Kolesistit	True/False
Mezenterik iskemi	True/False
İnfeksiyon	
Seçilmedi	True/False
Yok	True/False
Sternum-yüzeyel	True/False
Sternum-derin	True/False
Torakotomi	True/False
Bacak	True/False
Radial trasesi	True/False
Septisemi	True/False
Diğer	True/False
İdrar yolu	True/False
Multi-organ yetmezliği	0 = Yok
	1 = Var
	-1 = Seçilmedi
Kardiyak arrest	0 = Yok
	1 = Var
	-1 = Seçilmedi
Antikoagülasyon komplikasyonları	0 = Yok
	1 = Var
	-1 = Seçilmedi
Aort disseksiyonu	0 = Yok
	1 = Var
	-1 = Seçilmedi
Perikardial tamponad	0 = Yok
	1 = Var
	-1 = Seçilmedi
Trakeostomi gereksinimi	0 = Yok
	1 = Perkütan
	2 = Cerrahi
	-1 = Seçilmedi
Trakeostomi Lokal komplikasyonları	0 = Hayır
	1 = Evet
	-1 = Seçilmedi

Figure B.16: Medication parameters while discharging from hospital

Taburculukta Medikasyon Bilgileri	
Parameter Name	**Options**
Taburculuk sırasında Antiagregan tedavi	
Seçilmedi	True/False
Kullanmıyor	True/False
Aspirin	True/False
Klopidogrel (İscover, Plavix, Karum)	True/False
Diğer	True/False
Taburculuk sırasında Antioagülan tedavi	0 = Kullanmıyor
	1 = Kumadin
	-1 = Seçilmedi
Taburculuk sırasında Lipid düşürücü	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında Betabloker	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında ACE inhibitörü	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında ARB	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında Kalsiyum antagonisti	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında Diüretik	
Seçilmedi	True/False
Yok	True/False
Loop diüretikleri	True/False
K tutucu diüretik	True/False
Taburculuk sırasında Dijital	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında Antiaritmik	0 = Yok
	1 = Cordarone
	2 = Diğer
	-1 = Seçilmedi
Taburculuk sırasında Steroid	
Seçilmedi	True/False
Kullanmıyor	True/False
Oral steroid	True/False
İnhaler steroid	True/False
Taburculuk sırasında İmmünsupressif tedavi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Taburculuk sırasında Analjezik gereksinim	0 = Yok
	1 = NSAIDS
	2 = COX - Z inhibitörleri
	3 = Narkotik analjesi
	-1 = Seçilmedi

Figure B.17: Follow-up parameters

Takip Bilgileri	
Parameter Name	**Options**
Takibe geldiği tarih	Text
	Text
	Text
Operasyondan sonra kaçıncı gün	otomatik
Tekrar başvuru nedeni	0 = Yok
	1 = Antikoagülan komplikasyonu-Valvular
	2 = Antikoagülan komplikasyonu-Farmakolojik
	3 = Aritmi/Kalp Bloğu
	4 = Konjestif Kalp Yetmezliği
	5 = Myokard İnfarktüsü ve/veya Tekrarlayan Angina
	6 = Perikardiyal Efüzyon ve/veya Tamponat
	7 = Pnömoni vey diğer pulmoner komplikasyonlar
	8 = Kapak Disfonksiyonu
	9 = Derin Sternal infeksiyon/ mediastinit
	10 = İnfeksiyon-Kondüit çıkarılma Yeri
	11 = Böbrek Yetmezliği
	12 = Geçici Nörolojik problemler (TİA, CVA gibi)
	13 = Kalıcı Cerebrovasküler Hasar
	14 = Akut Vaskülar Komplikasyon
	15 = Subakut Endokardit
	16 = Diğer – İlişkili Tekrar Başvuru
	17 = Diğer – İlişkisiz Tekrar Başvuru
	18 = Perkütan Koroner girişim
	19 = Redo CABG
	20 = IABP veya LVAD gereksinimi
	21 = Derin Ven Trombozu
	22 = Pulmoner Emboli
	23 = Heparin induced trombositojeni
	-1 = Seçilmedi
Ritm statusu	
Seçilmedi	True/False
Sinüs ritmi	True/False
AF/flutter	True/False
Geçirilmiş VT/VF	True/False
VES	True/False
Yeni gelişmiş atrial fibrilasyon	0 = Yok
	1 = Var
	-1 = Seçilmedi
Elektrik kardiyoversiyon gereksinimi	0 = Yok
	1 = Var
	-1 = Seçilmedi
MI	0 = Yok
	1 = Var
	-1 = Seçilmedi
Stroke	0 = Yok
	1 = Var
	-1 = Seçilmedi

Takip Bilgileri	
Parameter Name	**Options**
İnfeksiyon	
Seçilmedi	True/False
Yok	True/False
Sternum-yüzeyel	True/False
Sternum-derin	True/False
Torakotomi	True/False
Bacak	True/False
Radial trasesi	True/False
Diyaliz gereksinimi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Aort protez gradienti Maksimum	Text
Aort protez gradienti Ortalama	Text
Mitral protez gradienti Maksimum	Text
Mitral protez grafienti Ortalama	Text
Taburculuk sonrası mortalite	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Taburculuk sonrası primer ölüm nedeni	
Seçilmedi	True/False
Bilinmiyor	True/False
MI	True/False
Stroke (Nörolojik)	True/False
Ventriküler takiaritmi	True/False
Kötüleşen kalp yetmezliği	True/False
Kardiyak tamponad	True/False
Kardiyojenik şok	True/False
Kapak protez komplikasyonu	True/False
Pulmoner embolizm	True/False
Periferik arter hastalığı	True/False
Aort disseksiyon / rüptürü	True/False
Pulmoner yetmezlik	True/False
Renal yetmezlik	True/False
İnfeksiyon, septik şok	True/False
Hemoraji	True/False
Multiorgan yetmezliği	True/False
Kanser	True/False
Diğer	True/False
Otopsi yapılmış mı?	0 = Hayır
	1 = Evet
	-1 = Seçilmedi
Otopsi Raporu	Text
Follow-up bulgular	Text
EKO Raporu	Text
Tekrar Hataneye Yatış	Text
Takip sırasında Antiagregan tedavi	
Seçilmedi	True/False
Kullanmıyor	True/False
Aspirin	True/False
Klopidogrel (İscover, Plavix, Karum)	True/False
Diğer	True/False

Takip Bilgileri	
Parameter Name	**Options**
Takip sırasında Antioagülan tedavi	0 = Kullanmıyor
	1 = Kumadin
	-1 = Seçilmedi
Takip sırasında Lipid düşürücü	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında Betabloker	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında ACE inhibitörü	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında ARB	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında Kalsiyum antagonisti	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında Diüretik	
Seçilmedi	True/False
Yok	True/False
Loop diüretikleri	True/False
K tutucu diüretik	True/False
Takip sırasında Dijital	0 = Yok
	1 = Var
	-1 = Seçilmedi
Takip sırasında Antiaritmik	0 = Yok
	1 = Cordarone
	2 = Diğer
	-1 = Seçilmedi
Takip sırasında Steroid	
Seçilmedi	True/False
Kullanmıyor	True/False
Oral steroid	True/False
İnhaler steroid	True/False
Takip sırasında İmmünsupressif tedavi	0 = Yok
	1 = Var
	-1 = Seçilmedi

Figure B.18: Mortality parameters

Mortalite Bilgileri	
Parameter Name	**Options**
Ölüm tarihi	0 = Seçilmedi
	0 = Seçilmedi
	0 = Seçilmedi
Mortalite; operasyondan sonra kaçıncı gün	
Ölüm yeri	1 = Operasyonda
	2 = Hastanede
	3 = Evde
	4 = Başka Bir Departmanda
	5 = Reoperasyon sonrasında
	-1 = Seçilmedi
Operatif mortalite	0 = Yok
	1 = Var
	-1 = Seçilmedi
Hastane mortalitesi	0 = Yok
	1 = Var
	-1 = Seçilmedi
Operasyondan sonra ilk 30 günde mortalite	0 = Yok
	1 = Var
	-1 = Seçilmedi
Operasyondan sonra ilk yil mortalite	0 = Yok
	1 = Var
	-1 = Seçilmedi
Operasyondan sonra ilk 5 yil mortalite	0 = Yok
	1 = Var
	-1 = Seçilmedi
Postoperatif hastanede kalış süresi (gün)	
Operasyondan sonra 30 gün içinde tekrar hastaneye yatış	0 = Yok
	1 = Kanama ile ilgili antikoagulan komplikasyonu
	2 = Kapak trombozu ile ilgili antikoagulan komplikasyonu
	3 = Aritmi, kalp bloğu
	4 = Konjestif kalp yetmezliği
	5 = Miyokard infarktüsü
	6 = Rekürren anjina pectoris
	7 = Perikardiyal efüzyon veya tamponad
	8 = Pnömoni veya diğer respiratuar komplikasyonlar
	9 = Kapak disfonksiyonu
	10 = Derin sternal enfeksiyon
	11 = Yüzeyel sternal enfeksiyon
	12 = Konduit alma bölgesinde enfeksiyon
	13 = Renal yetmezlik
	14 = TIA
	15 = Kalıcı CVA
	16 = Akut vasküler komplikasyon
	17 = Subacute Endokardit
	18 = VAD komplikasyonu
	19 = Transplant Rejeksiyonu
	20 = Tekrar yatışa neden olan diğer nedenler (operasyonla ilgili)
	21 = Tekrar yatışa neden olan diğer nedenler (operasyonla ilgisiz)
	-1 = Seçilmedi

Mortalite Bilgileri	
Parameter Name	**Options**
Operasyondan sonra ilk 30 günde tekrar yatışta uygulanan prosedürler	0 = Yok
	1 = Kanama nedeniyle tekrar operasyona alındı
	2 = Kalıcı pacemaker veya AICD takıldı
	3 = Perkütan koroner girişimi uygulandı
	4 = Perikardiotomi / pericardiosentez gereksinimi
	5 = Koroner arter cerrahisi gereksinimi
	6 = Kapak cerrahisi gereksinimi
	7 = Sternal debritman veya pektoral muscle flep gereksinimi
	8 = Diyaliz gereksinimi
	9 = Vasküler nedenli operasyon gereksinimi
	-1 = Seçilmedi
Primer ölüm nedeni	
Seçilmedi	True/False
Bilinmiyor	True/False
MI	True/False
Stroke (Nörolojik)	True/False
Ventriküler takiaritmi	True/False
Kötüleşen kalp yetmezliği	True/False
Kardiyak tamponad	True/False
Kardiyojenik şok	True/False
Kapak protez komplikasyonu	True/False
Pulmoner embolizm	True/False
Periferik arter hastalığı	True/False
Aort disseksiyon / rüptürü	True/False
Pulmoner yetmezlik	True/False
Renal yetmezlik	True/False
İnfeksiyon, septik şok	True/False
Hemoraji	True/False
Multiorgan yetmezliği	True/False
Kanser	True/False
Diğer	True/False
Otopsi yapılmış mı ?	0 = Hayır
	1 = Evet
	-1 = Seçilmedi

Appendix C

EuroSCORE

Figure C.1: Description of EuroSCORE Risk Factors

Risk factor	Definition
Age	(per 5 years or part thereof over 60 years)
Sex	female
Chronic pulmonary disease	longterm use of bronchodilators or steroids for lung disease
Extracardiac arteriopathy	any one or more of the following: claudication, carotid occlusion or >50% stenosis, previous or planned intervention on the abdominal aorta,limb arteries or carotids
Neurological dysfunction disease	severely affecting ambulation or day-to-day functioning
Previous cardiac surgery	requiring opening of the pericardium
Serum creatinine	>200m micromol/L preoperatively
Active endocarditis	patient still under antibiotic treatment for endocarditis at the time of surgery
Critical preoperative state	any one or more of the following: ventricular tachycardia or fibrillation or aborted sudden death, preoperative cardiac massage, preoperative ventilation before arrival in the anaesthetic room,preoperative inotropic support, intraaortic balloon counterpulsation or preoperative acute renal failure (anuria or oliguria<10 ml/hour)
Unstable angina	rest angina requiring iv nitrates until arrival in the anaesthetic room
LV dysfunction	moderate or LVEF30-50%
	poor or LVEF <30
Recent myocardial infarct	(<90 days)
Pulmonary hypertension	Systolic PA pressure>60 mmHg
Emergency	carried out on referral before the beginning of the next working day
Other than isolated CABG	major cardiac procedure other than or in addition to CABG
Surgery on thoracic aorta	for disorder of ascending, arch or descending aorta
Postinfarct septal rupture	

Figure C.2: TurkoSCORE approximations

Risk Factor in EuroSCORE	Approximation in TurkoSCORE
Age	Yaş
Sex	Cinsiyet
Chronic pulmonary disease	Kronik obstrüktif akciğer hastalığı (KOAH)
Extracardiac arteriopathy	Periferik arter hastalığı
Neurological dysfunction disease	Serebrovasküler hastalık
Previous cardiac surgery	Geçirilmiş Koroner arter bypass cerrahisi, Kapak cerrahisi, İntraperikardial veya büyük damar cerrahisi
Serum creatinine	Preoperatif Kreatinin değeri >2.26 mg/Dl
Active endocarditis	Infektif Endokardit; Pozitif kan kültürü ile infektif öntanısı, Ekokardiyografide vejetasyon veya görüntüleme yöntemleri ile endokardit öntanısı, Prostetik kapak endokarditi
Critical preoperative state	Kritik preoperatif status; VT/VF , Resüsitasyon, IABP, Ventilasyon, Akut renal yetmezlik
Unstable angina	Unstabil angina pektoris
LV dysfunction	Moderate; Sol ventrikül ejeksiyon fraksiyonu kategorik olarak (Grade II) Poor; Sol venrikül ejeksiyon fraksiyonu kategorik olarak (Grade III veya Grade IV)
Recent myocardial infarct	Ameliyat öncesi geçirilmiş MI zamanı
Pulmonary hypertension	Sistolik pulmoner arter basıncı değeri >60mmHg
Emergency	Ameliyat önceliği (Acil veya Salvaj)
Other than isolated CABG	Koroner arter bypass cerrahisinin dışında veya ek olarak yapılan kalp ameliyatı; Kapak cerrahisi, kalp nakli, aort cerrahisi, karotis cerrahisi, Konjenital cerrahisi, Periferik damar cerrahisi, diğer Torasik prosedürler, Kardiyak tümör, perikard cerrahisi
Surgery on thoracic aorta	Torasik aort cerrahisi
Postinfarct septal rupture	MI mekanik komplikasyon

Figure C.3: AUCs of EuroSCORE Risk Factors

EuroSCORE Risk Factor	Feature AUC
Age	0.66380847
Sex	0.51788723
Chronic pulmonary disease	0.60317480
Extracardiac arteriopathy	0.55110460
Neurological dysfunction disease	0.55567807
Previous cardiac surgery	0.52613000
Serum creatinine	0.52943784
Active endocarditis	0.50465690
Critical preoperative state	0.50445930
Unstable angina	0.55356680
LV dysfunction	0.62603694
Recent myocardial infarct	0.53118860
Pulmonary hypertension	0.51913655
Emergency	0.57011170
Other than isolated CABG	0.62655780
Surgery on thoracic aorta	0.56366193
Postinfarct septal rupture	0.50832620

Appendix D

Experiments

Figure D.1: TurkoSCORE Feature-AUC values

#	Risk Factor	AUC of risk factor
1	Operasyon aciliyet nedeni	0.78746766
2	Mitral Sistolik Üfürüm	0.77480160
3	Pulmoner Raller	0.74305560
4	Sistolik pulmoner arter basıncı değeri(mmHg)	0.71272560
5	Ameliyat öncesi dispne (NYHA kasifikasyonuna göre)	0.70084625
6	Yatış sırasında göğüs ağrısını tanımlanması	0.69107145
7	Vücut kitle indexi(BMI)	0.68315970
8	Pulmoner Wheezing	0.68055560
9	Unstabil Angina (CCS klasifikasonuna göre)	0.67287785
10	Yas	0.67075970
11	Kalsifiye aort	0.66417910
12	Operasyon öncesi geçirilmiş MI	0.65748220
13	Sol Ventrikül Ejeksiyon Fraksiyonu kategorik(Cardiak Cara Network(CCN) of Ontario grading	0.64966154
14	Ameliyat öncesi stabil Angina Pektoris(CCS kasifikasyonuna göre)	0.64818656
15	Ejeksiyon Fraksiyon değeri	0.64637196
16	Geçirilmiş aritmi tedavi yöntemleri	0.64062500
17	Circumflex(>%50 darlık)	0.63928570
18	Operasyon Önceliği	0.62798440
19	Kronik Obstriktif Akciğer Hastalığı (KOAH)	0.62369543
20	Konjestif Kalp Yetmezliği	0.62231183
21	Aort Sistolik Üfürüm	0.61971840
22	infektif Endokardit	0.61908780
23	Kapak Cerrahisi	0.61627805
24	Aort Kapak maksimum gradienti (mmHg)	0.61422414
25	Toraks deformitesi	0.61071430

#	Risk Factor	AUC of risk factor
26	Triküspid Yetmezlik	0.60776940
27	Aort Diastolik Üfürüm	0.60662526
28	Ağırlık(kg)	0.60416130
29	Geçirilmiş ciddi aritmi hikayesi	0.59806293
30	Sinus ritmi	0.59670870
31	Son Preoperatif Kreatinin Düzeyi	0.59443325
32	Hasta Koroner Arter Sayısı(>%50 darlık)	0.59061766
33	Varis Sağ	0.58768654
34	Aort Yetmezlik	0.58562790
35	Hipertansyon kategorik	0.58226470
36	Mitral Yetmezlik	0.57874200
37	Operasyon insidansı	0.57860010
38	Sağ Koroner Arter(>%50 darlık)	0.57678574
39	Preoperatif Diastolik kan basıncı (mmHg)	0.57632095
40	Preoperatif Ortalama kan basıncı (mmHg)	0.57259953
41	Pulmoner Arter Sistolik Üfürümü	0.57142860
42	Sigara hikayesi	0.56858940
43	Bentall operasyonu	0.56837870
44	Malignite hikayesi	0.56457925
45	Serebrovasküler Hastalık	0.56422440
46	Sol Ventrikül sistol-sonu çapı-LVESD değeri (mm)	0.56329966
47	Preoperatif resüsitasyon	0.56250000
48	Nabızlar-A.tibialis posterior Sağ	0.56250000
49	Nabızlae-A.tibialis posterior Sol	0.56250000
50	Periferik Arter Hastalığı	0.55843130
51	Preoperatif respiratör gereksinimi	0.55764160
52	BSA	0.55555560
53	Nabızlar-A.dorsalis pedis Sol	0.55514705
54	Preoperatif Sistolik kan basıncı (mmHg)	0.55381610
55	Koroner Bypass Cerrahisi	0.55271970
56	Karaciğer Hastalığı	0.55059520
57	Boy(cm)	0.54863140
58	Left Anterior Decending (>%50 darlık)	0.54861110
59	Perkütan Koroner girişim ile operasyon arası süre	0.54723500
60	Sol Ana Koroner Arter(LMCA)hastalığı (>%50 darlık)	0.54109883
61	Hepatomegali	0.54044120
62	Hiperlipidemi	0.53863910
63	Geçirilmiş Koroner Cerrahisi	0.53782940
64	Geçirilmiş MI sayısı	0.53658766
65	Hemodinamik Status	0.53495175
66	AF/Flutter	0.53473306
67	Geçirilmiş İntraperikardial veya büyük damar Cerrahisi	0.53365180
68	Geçirilmiş Kapak Cerrahisi	0.53282845
69	Renal Yetmezlik	0.53132780
70	MI mekanik komplikasyon	0.53069770
71	Dominant Koroner Arter	0.52754235
72	Karotis Üfürümü Sol	0.52452530
73	Karotis Üfürümü Sağ	0.52438100
74	Geçirilmiş Perkütan Koroner girişim	0.52385220
75	Tiroit hastalık hikayesi	0.52341480
76	Mitral Diastolik Rulman	0.52281750

#	Risk Factor	AUC of risk factor
77	Varis Sol	0.51838230
78	Karotis Cerrahisi	0.51757705
79	Aritmi cerrahisi Radyo-Frekans veya microwave ablasyon	0.51413924
80	Periferik Damar Cerrahisi	0.51237386
81	Cinsiyet	0.51180744
82	Sol Ventrikül diastol-sonu çapı-LVEDD değeri (mm)	0.51013290
83	Carpentier Tip I,normal kapakçık (santral yetersizlik,annüler dilatasyon veya leaflet perforasyonu)	0.50939520
84	Santral Yetmezlik	0.50939520
85	Koroner Arter HastalığıAile Hikayesi	0.50894480
86	Sol Ventrikül Anevrizma Onarımı	0.50853163
87	Nabızlar-A.dorsalis pedis Sağ	0.50704230
88	VT/VF	0.50510204
89	AV-tam blok	0.50510204
90	Carpentier Tip IIIb,sistol sırasında sınırlanmış kapakçık hareketi(iskemik veya dilate kardiyomiyopati)	0.50510204
91	Aritmi cerrahisi AICD	0.50510204
92	IABP	0.50500090
93	A2	0.50479870
94	Carpentier Tip II,kapakçık prolapsı(kordal rüptür veya elongasyonu,papiller kas rüptürü veya elongasyonu)	0.50429314
95	Ventrküler Septal Defekt/rüptür onarımı	0.50429314
96	Diğer Kardiyak Prosedür	0.50227094
97	Diabetes Mellitus	0.50200780
98	Nabızlar-Femoral arter Sağ	0.50000000
99	Nabızlar-Femoral arter Sol	0.50000000
100	Nabızlar-Popliteal arter Sağ	0.50000000
101	Nabızlar-Popliteal arter Sol	0.50000000
102	Nabızlar-A.radialis Sağ	0.50000000
103	Nabızlar-A.radialis Sol	0.50000000
104	Dominant El	0.50000000

Appendix E

Rules Learned

E.1 Euroscore Risk factors

Rules learned:
If Age="64.99 .. PosInfinity" Then Risk=0.035772357, #cases=1845
If Age="59.103092 .. 64.99" Then Risk=0.013904982, #cases=863
If Age="NegInfinity..59.103092" Then Risk=0.009031199, #cases=2436

If Sex="K" Then Risk=0.02238806, #cases=1474
If Sex="E" Then Risk=0.018959913, #cases=3692

If Chronic pulmonary disease="Yes" Then Risk=0.045622688, #cases=811
If Chronic pulmonary disease="No" Then Risk=0.015154994, #cases=4355

If Extracardiac artertiopathy="Yes" Then Risk=0.056140352, #cases=285
If Extracardiac artertiopathy="No" Then Risk=0.017824216, #cases=4881

If Neurological dysfunction disease="Yes" Then Risk=0.053097345, #cases=339
If Neurological dysfunction disease="No" Then Risk=0.017609281, #cases=4827

If Previous cardiac surgery="Yes" Then Risk=0.023361454, #cases=1541
If Previous cardiac surgery="No" Then Risk=0.018482758, #cases=3625

If Serum Creatinine="Yes" Then Risk=0.13207547, #cases=53
If Serum Creatinine="No" Then Risk=0.01877567, #cases=5113

If Active Endocarditis="Yes" Then Risk=0.33333334, #cases=3
If Active Endocarditis="No" Then Risk=0.019755956, #cases=5163

If Critical preoperative state="Yes" Then Risk=0.2, #cases=5
If Critical preoperative state="No" Then Risk=0.019763611, #cases=5161

If Unstable angina="Yes" Then Risk=0.039215688, #cases=561
If Unstable angina="No" Then Risk=0.017589577, #cases=4605

If LV dysfunction="Poor" Then Risk=0.06666667, #cases=210
If LV dysfunction="Moderate" Then Risk=0.021932831, #cases=1459
If LV dysfunction="Good" Then Risk=0.011516315, #cases=3126

If Recent myocardial infarct="Yes" Then Risk=0.025020178, #cases=1239
If Recent myocardial infarct="No" Then Risk=0.018334607, #cases=3927

If Pulmonary hypertension="Yes" Then Risk=0.0877193, #cases=57
If Pulmonary hypertension="No" Then Risk=0.019181836, #cases=5109

If Emergency="Yes" Then Risk=0.0781893, #cases=243
If Emergency="No" Then Risk=0.017062766, #cases=4923

If Other than isolated CABG="Yes" Then Risk=0.05090909, #cases=825
If Other than isolated CABG="No" Then Risk=0.014052061, #cases=4341

If Surgery on thoracic aorta="Yes" Then Risk=0.08173077, #cases=208
If Surgery on thoracic aorta="No" Then Risk=0.017345704, #cases=4958

If Postinfarct septal rupture="Yes" Then Risk=0.125, #cases=16
If Postinfarct septal rupture="No" Then Risk=0.019611651, #cases=5150

E.2 Turkoscore Risk factors

Rules learned:
If Cinsiyet="K" Then Risk=0.021023126,#cases=1427
If Cinsiyet="E" Then Risk=0.01880531, #cases=3616

If Yas="65.4 .. PosInfinity" Then Risk=0.036285363, #cases=1626
If Yas="59.1083 .. 65.4" Then Risk=0.015625, #cases=1024
If Yas="NegInfinity..59.1083" Then Risk=0.008385744, #cases=2385

If Agirlik="NegInfinity..63.39796" Then Risk=0.034418605, #cases=1075
If Agirlik="63.39796 .. 71.584175" Then Risk=0.02017291, #cases=1041
If Agirlik="71.584175 .. PosInfinity" Then Risk=0.013679891, #cases=2924

If Boy="NegInfinity..148.11224" Then Risk=0.034782607, #cases=460
If Boy="148.11224 .. 156.74161" Then Risk=0.021520803, #cases=697
If Boy="156.74161 .. PosInfinity" Then Risk=0.0172547, #cases=3883

If BSA="NegInfinity..1.8646389" Then Risk=0.11764706, #cases=34
If BSA="1.8876595 .. PosInfinity" Then Risk=0.0952381, #cases=42
If BSA="1.8646389 .. 1.8876595" Then Risk=0.0, #cases=4

If BMI="33.022263 .. PosInfinity" Then Risk=0.2857143, #cases=7
If BMI="NegInfinity..27.636835" Then Risk=0.11627907, #cases=43
If BMI="27.636835 .. 33.022263" Then Risk=0.033333335, #cases=30

If AmeliyatOncesiAnjinaPektoris="Zero" Then Risk=0.060240965, #cases=83
If AmeliyatOncesiAnjinaPektoris="Four" Then Risk=0.038674034, #cases=543

If AmeliyatOncesiAnjinaPektoris="One" Then Risk=0.025996534, #cases=1154
If AmeliyatOncesiAnjinaPektoris="Three" Then Risk=0.019812305, #cases=959
If AmeliyatOncesiAnjinaPektoris="Two" Then Risk=0.009713229, #cases=2162

If UnstablAnjina="Four" Then Risk=1.0, #cases=1
If UnstablAnjina="Two" Then Risk=0.5, #cases=2
If UnstablAnjina="Zero" Then Risk=0.07575758, #cases=66
If UnstablAnjina="One" Then Risk=0.0, #cases=6
If UnstablAnjina="Three" Then Risk=0.0, #cases=1

If KardiyakPrezantasyon="Four" Then Risk=1.0, #cases=1
If KardiyakPrezantasyon="Zero" Then Risk=0.0882353, #cases=34
If KardiyakPrezantasyon="Two" Then Risk=0.05263158, #cases=19
If KardiyakPrezantasyon="Three" Then Risk=0.0, #cases=5
If KardiyakPrezantasyon="One" Then Risk=0.0, #cases=1
If KardiyakPrezantasyon="Five" Then Risk=0.0, #cases=1

If AmeliyatOncesiDispne="Four" Then Risk=0.14166667, #cases=120
If AmeliyatOncesiDispne="Three" Then Risk=0.049152542, #cases=590
If AmeliyatOncesiDispne="Two" Then Risk=0.015881708, #cases=1826
If AmeliyatOncesiDispne="One" Then Risk=0.009716941, #cases=2367

If KojestifKalpYetmezligi="One" Then Risk=0.14438502, #cases=187
If KojestifKalpYetmezligi="Zero" Then Risk=0.015040825, #cases=4654

If HemodinamikStatus="Three" Then Risk=0.35, #cases=20
If HemodinamikStatus="One" Then Risk=0.017989207, #cases=5003
If HemodinamikStatus="Two" Then Risk=0.0, #cases=2

If VT/VF="Yes" Then Risk=1.0, #cases=1
If VT/VF="No" Then Risk=0.019238397, #cases=5042

If IABP="Yes" Then Risk=0.5, #cases=2

If IABP="No" Then Risk=0.019242214, #cases=5041

If DM="Yes" Then Risk=0.019704433, #cases=1421
If DM="No" Then Risk=0.019326339, #cases=3622

If HipertansiyonHikayesi="Zero" Then Risk=0.14285715, #cases=28
If HipertansiyonHikayesi="One" Then Risk=0.11764706, #cases=34
If HipertansiyonHikayesi="Two" Then Risk=0.022123894, #cases=2260
If HipertansiyonHikayesi="Three" Then Risk=0.01472754, #cases=2716

If SigaraKullanimi="Two" Then Risk=0.1, #cases=10
If SigaraKullanimi="One" Then Risk=0.022564102, #cases=1950
If SigaraKullanimi="Four" Then Risk=0.021558871, #cases=1206
If SigaraKullanimi="Three" Then Risk=0.012419007, #cases=1852

If AiledeKronerArter="Yes" Then Risk=0.019425675, #cases=2368
If AiledeKronerArter="No" Then Risk=0.018106375, #cases=2651

If Hiperlipidemi="Zero" Then Risk=0.021421617, #cases=3081
If Hiperlipidemi="Two" Then Risk=0.015665796, #cases=1915
If Hiperlipidemi="One" Then Risk=0.0, #cases=27

If KOAH="Three" Then Risk=1.0, #cases=2
If KOAH="Two" Then Risk=0.375, #cases=8
If KOAH="One" Then Risk=0.05263158, #cases=19
If KOAH="Four" Then Risk=0.04144385, #cases=748
If KOAH="Zero" Then Risk=0.013653484, #cases=4248
If KOAH="Five" Then Risk=0.0, #cases=1

If RenalYetmezlik="One" Then Risk=0.2, #cases=15
If RenalYetmezlik="Two" Then Risk=0.2, #cases=15
If RenalYetmezlik="Zero" Then Risk=0.016924959, #cases=4904
If RenalYetmezlik="Three" Then Risk=0.0, #cases=1

If SonPreopKreatinin="Three" Then Risk=0.13461539, #cases=52
If SonPreopKreatinin="One" Then Risk=0.083333336, #cases=12
If SonPreopKreatinin="Zero" Then Risk=0.06451613, #cases=62
If SonPreopKreatinin="Two" Then Risk=0.04488778, #cases=401

If KaracigerHastaligi="One" Then Risk=0.25, #cases=4
If KaracigerHastaligi="Zero" Then Risk=0.08, #cases=75

If PeriferikArterHastalik="Four" Then Risk=0.6666667, #cases=3
If PeriferikArterHastalik="One" Then Risk=0.050724637, #cases=276
If PeriferikArterHastalik="Zero" Then Risk=0.016799483, #cases=4643

If SerebrovaskulerHastalik="Six" Then Risk=0.22222222, #cases=9
If SerebrovaskulerHastalik="Three" Then Risk=0.0882353, #cases=34
If SerebrovaskulerHastalik="Two" Then Risk=0.04761905, #cases=273
If SerebrovaskulerHastalik="Zero" Then Risk=0.016999574, #cases=4706
If SerebrovaskulerHastalik="One" Then Risk=0.0, #cases=13
If SerebrovaskulerHastalik="Five" Then Risk=0.0, #cases=2
If SerebrovaskulerHastalik="Four" Then Risk=0.0, #cases=5

If Endokardit="Four" Then Risk=1.0, #cases=1
If Endokardit="Two" Then Risk=0.5, #cases=2
If Endokardit="Zero" Then Risk=0.07594936, #cases=79

If Tiroid="Two" Then Risk=0.056074765, #cases=107
If Tiroid="Zero" Then Risk=0.01764831, #cases=4703
If Tiroid="One" Then Risk=0.0, #cases=3
If Tiroid="Three" Then Risk=0.0, #cases=1

If MaligniteHikayesi="Yes" Then Risk=0.5, #cases=2
If MaligniteHikayesi="No" Then Risk=0.07692308, #cases=78

If AritmiHikayesi="One" Then Risk=1.0, #cases=1
If AritmiHikayesi="Four" Then Risk=0.125, #cases=8
If AritmiHikayesi="Zero" Then Risk=0.08928572, #cases=56
If AritmiHikayesi="Three" Then Risk=0.0, #cases=1

If AritmiTedavi="Two" Then Risk=1.0, #cases=1
If AritmiTedavi="Three" Then Risk=1.0, #cases=1
If AritmiTedavi="Zero" Then Risk=0.08, #cases=75
If AritmiTedavi="Four" Then Risk=0.0, #cases=3

If PerkutenKronerSonHafta="Nine" Then Risk=0.12, #cases=25
If PerkutenKronerSonHafta="Zero" Then Risk=0.019007653, #cases=4051
If PerkutenKronerSonHafta="Two" Then Risk=0.01459854, #cases=137
If PerkutenKronerSonHafta="Eight" Then Risk=0.0, #cases=1
If PerkutenKronerSonHafta="One" Then Risk=0.0, #cases=39

If PerkutanKoroner="Two" Then Risk=0.11764706, #cases=34
If PerkutanKoroner="Zero" Then Risk=0.0882353, #cases=34
If PerkutanKoroner="One" Then Risk=0.0, #cases=1

If MISayisi="Three" Then Risk=0.22222222, #cases=9
If MISayisi="Two" Then Risk=0.024922118, #cases=321
If MISayisi="One" Then Risk=0.02125, #cases=1600
If MISayisi="Zero" Then Risk=0.017820425, #cases=2918

If MiyokardinfarktusZamani="One" Then Risk=0.09677419, #cases=62
If MiyokardinfarktusZamani="Zero" Then Risk=0.0754717, #cases=53
If MiyokardinfarktusZamani="Three" Then Risk=0.05882353, #cases=17
If MiyokardinfarktusZamani="Two" Then Risk=0.029411765, #cases=34
If MiyokardinfarktusZamani="Four" Then Risk=0.023952097, #cases=668
If MiyokardinfarktusZamani="Five" Then Risk=0.015555556, #cases=450
If MiyokardinfarktusZamani="Six" Then Risk=0.011764706, #cases=680

If PreopRespiratorGereksinimi="Yes" Then Risk=0.3, #cases=10
If PreopRespiratorGereksinimi="No" Then Risk=0.042105265, #cases=475

If PreopResustasyon="Yes" Then Risk=1.0, #cases=1
If PreopResustasyon="No" Then Risk=0.085365854, #cases=82

If SinusRitmi="No" Then Risk=0.038038038, #cases=999
If SinusRitmi="Yes" Then Risk=0.014836796, #cases=4044

If AF/flutter="Yes" Then Risk=0.04379562, #cases=274
If AF/flutter="No" Then Risk=0.01803313, #cases=4769

If AVbloktam="Yes" Then Risk=1.0, #cases=1
If AVbloktam="No" Then Risk=0.019238397, #cases=5042

If SistolikKanBasinci="NegInfinity..115.71429" Then Risk=0.10344828, #cases=29
If SistolikKanBasinci="115.71429 .. 121.12329" Then Risk=0.0952381, #cases=21
If SistolikKanBasinci="121.12329 .. PosInfinity" Then Risk=0.06666667, #cases=30

If DiyastolikKanBasinci="NegInfinity..68.57143" Then Risk=0.115384616, #cases=26
If DiyastolikKanBasinci="68.57143 .. 72.61644" Then Risk=0.09090909, #cases=22
If DiyastolikKanBasinci="72.61644 .. PosInfinity" Then Risk=0.0625, #cases=32

If OrtalamaKanBasinci="NegInfinity..74.57143" Then Risk=0.12903225, #cases=31
If OrtalamaKanBasinci="74.57143 .. 78.03278" Then Risk=0.1, #cases=10
If OrtalamaKanBasinci="78.03278 .. PosInfinity" Then Risk=0.074074075, #cases=27

If KarotisufurumuSag="No" Then Risk=0.042505592, #cases=447

If KarotisufurumuSag="Yes" Then Risk=0.027027028, #cases=74

If KarotisufurumuSol="No" Then Risk=0.042600896, #cases=446
If KarotisufurumuSol="Yes" Then Risk=0.027027028, #cases=74

If PulmonerRaller="Yes" Then Risk=0.33333334, #cases=15
If PulmonerRaller="No" Then Risk=0.046153847, #cases=65

If Pulmonerwheezing="Yes" Then Risk=0.2857143, #cases=14
If Pulmonerwheezing="No" Then Risk=0.060606062, #cases=66

If Toraksdeformitesi="Yes" Then Risk=0.5, #cases=4
If Toraksdeformitesi="No" Then Risk=0.08108108, #cases=74

If Mitraldiastolikrulman="Yes" Then Risk=0.125, #cases=8
If Mitraldiastolikrulman="No" Then Risk=0.08450704, #cases=71

If Mitralsistolikufurum="Five" Then Risk=0.5, #cases=2
If Mitralsistolikufurum="Two" Then Risk=0.2857143, #cases=7
If Mitralsistolikufurum="Three" Then Risk=0.18181819, #cases=11
If Mitralsistolikufurum="Zero" Then Risk=0.03508772, #cases=57
If Mitralsistolikufurum="Six" Then Risk=0.0, #cases=1
If Mitralsistolikufurum="Four" Then Risk=0.0, #cases=1

If Aortdiastolikufurum="Yes" Then Risk=0.2857143, #cases=7
If Aortdiastolikufurum="No" Then Risk=0.072463766, #cases=69

If Aortsistolikufurum="One" Then Risk=1.0, #cases=1
If Aortsistolikufurum="Zero" Then Risk=0.08695652, #cases=69
If Aortsistolikufurum="Three" Then Risk=0.0, #cases=3
If Aortsistolikufurum="Six" Then Risk=0.0, #cases=1
If Aortsistolikufurum="Five" Then Risk=0.0, #cases=2
If Aortsistolikufurum="Four" Then Risk=0.0, #cases=1

If Aortsistolikufurum="Two" Then Risk=0.0, #cases=1

If PulmonerArterSistolik="One" Then Risk=1.0, #cases=1
If PulmonerArterSistolik="Zero" Then Risk=0.077922076, #cases=77

If Hepatomegali="Yes" Then Risk=0.25, #cases=4
If Hepatomegali="No" Then Risk=0.097222224, #cases=72

If VarisSag="Yes" Then Risk=0.2857143, #cases=7
If VarisSag="No" Then Risk=0.0882353, #cases=68

If VarisSol="Yes" Then Risk=0.14285715, #cases=7
If VarisSol="No" Then Risk=0.10144927, #cases=69

If FemoralArterSag="Yes" Then Risk=0.101265825, #cases=79

If FemoralArterSol="Yes" Then Risk=0.1, #cases=80

If PoplitealArterSag="Yes" Then Risk=0.1, #cases=80

If PoplitealArterSol="Yes" Then Risk=0.102564104, #cases=78

If DorsalisPedisSag="Yes" Then Risk=0.09090909, #cases=77
If DorsalisPedisSag="No" Then Risk=0.0, #cases=1

If TibialisPosteriorSag="No" Then Risk=1.0, #cases=1
If TibialisPosteriorSag="Yes" Then Risk=0.09090909, #cases=77

If DorsalisPedisSol="No" Then Risk=0.5, #cases=2
If DorsalisPedisSol="Yes" Then Risk=0.0945946, #cases=74

If TibialisPosteriorSol="No" Then Risk=1.0, #cases=1
If TibialisPosteriorSol="Yes" Then Risk=0.093333334, #cases=75

If RadialisSag="Yes" Then Risk=0.09589041, #cases=73

If RadialisSol="Yes" Then Risk=0.08974359, #cases=78

If DominantEl="Zero" Then Risk=0.1, #cases=70

If DominantKoronerArter="One" Then Risk=0.12765957, #cases=47
If DominantKoronerArter="Zero" Then Risk=0.1, #cases=20

If KoronerArterSayisi="Zero" Then Risk=0.03664122, #cases=655
If KoronerArterSayisi="Three" Then Risk=0.018488085, #cases=2434
If KoronerArterSayisi="One" Then Risk=0.016706444, #cases=419
If KoronerArterSayisi="Two" Then Risk=0.01192843, #cases=1006

If LMCAHastaligi="No" Then Risk=0.043902438, #cases=410
If LMCAHastaligi="Yes" Then Risk=0.029850746, #cases=201

If LeftAnteriorDescending="No" Then Risk=0.13043478, #cases=23
If LeftAnteriorDescending="Yes" Then Risk=0.0877193, #cases=57

If Circumflex="No" Then Risk=0.15384616, #cases=39
If Circumflex="Yes" Then Risk=0.051282052, #cases=39

If SagKoronerArter="Yes" Then Risk=0.13157895, #cases=38
If SagKoronerArter="No" Then Risk=0.075, #cases=40

If SolVentrikulEjeksiyonFraksiyonu="Three" Then Risk=0.067307696, #cases=208
If SolVentrikulEjeksiyonFraksiyonu="Zero" Then Risk=0.05179283, #cases=251
If SolVentrikulEjeksiyonFraksiyonu="Two" Then Risk=0.0220234, #cases=1453
If SolVentrikulEjeksiyonFraksiyonu="One" Then Risk=0.0115644075, #cases=3113

If EjeksiyonFraksiyonuDegeri="NegInfinity..54.545456" Then Risk=0.07042254,

#cases=71
If EjeksiyonFraksiyonuDegeri="54.545456 .. 62.35168" Then Risk=0.03076923, #cases=65
If EjeksiyonFraksiyonuDegeri="62.35168 .. PosInfinity" Then Risk=0.01980198, #cases=202

If SistolikPulmonerArterDegeri="53.185184 .. 60.23077" Then Risk=0.2173913, #cases=23
If SistolikPulmonerArterDegeri="60.23077 .. PosInfinity" Then Risk=0.09090909, #cases=55
If SistolikPulmonerArterDegeri="NegInfinity..53.185184" Then Risk=0.030927835, #cases=97

If LVESDdeger="5.5443597 .. 9.509999" Then Risk=0.5, #cases=2
If LVESDdeger="9.509999 .. PosInfinity" Then Risk=0.041666668, #cases=24
If LVESDdeger="NegInfinity..5.5443597" Then Risk=0.02846975, #cases=281

If LVEDDdeger="9.940001 .. PosInfinity" Then Risk=0.04, #cases=25
If LVEDDdeger="NegInfinity..8.690032" Then Risk=0.031468533, #cases=286

If AortStenozuPeakGradient="NegInfinity..59.5" Then Risk=0.0952381, #cases=21
If AortStenozuPeakGradient="59.5 .. 75.05173" Then Risk=0.071428575, #cases=14
If AortStenozuPeakGradient="75.05173 .. PosInfinity" Then Risk=0.037037037, #cases=27

If AortYetmezlik="Two" Then Risk=0.16666667, #cases=6
If AortYetmezlik="Three" Then Risk=0.0952381, #cases=21
If AortYetmezlik="Zero" Then Risk=0.06557377, #cases=61
If AortYetmezlik="Four" Then Risk=0.05076142, #cases=197
If AortYetmezlik="One" Then Risk=0.0, #cases=14

If KalsifiyeAort="One" Then Risk=0.33333334, #cases=6

If KalsifiyeAort="Two" Then Risk=0.25, #cases=4
If KalsifiyeAort="Zero" Then Risk=0.0625, #cases=64

If MitralYetmezlik="Three" Then Risk=0.15789473, #cases=19
If MitralYetmezlik="Two" Then Risk=0.11111111, #cases=9
If MitralYetmezlik="Four" Then Risk=0.0777027, #cases=296
If MitralYetmezlik="Zero" Then Risk=0.04347826, #cases=46
If MitralYetmezlik="One" Then Risk=0.0, #cases=17

If MitralYetmezlikKlas0="Yes" Then Risk=0.2, #cases=10
If MitralYetmezlikKlas0="No" Then Risk=0.01907411, #cases=5033

If MitralYetmezlikKlas1="Yes" Then Risk=0.11111111, #cases=9
If MitralYetmezlikKlas1="No" Then Risk=0.019268971, #cases=5034

If MitralYetmezlikKlas3="Yes" Then Risk=1.0, #cases=1
If MitralYetmezlikKlas3="No" Then Risk=0.019238397, #cases=5042

If MitralScallop0="Yes" Then Risk=0.2, #cases=10
If MitralScallop0="No" Then Risk=0.01907411, #cases=5033

If MitralScallop5="Yes" Then Risk=0.25, #cases=4
If MitralScallop5="No" Then Risk=0.01924985, #cases=5039

If TrikuspidYetmezlik="Three" Then Risk=0.22222222, #cases=9
If TrikuspidYetmezlik="One" Then Risk=0.11764706, #cases=17
If TrikuspidYetmezlik="Zero" Then Risk=0.0754717, #cases=53
If TrikuspidYetmezlik="Four" Then Risk=0.0625, #cases=64
If TrikuspidYetmezlik="Two" Then Risk=0.0, #cases=2

If Onceligi="Three" Then Risk=0.14285715, #cases=35
If Onceligi="Two" Then Risk=0.067010306, #cases=194
If Onceligi="One" Then Risk=0.05105105, #cases=333

If Onceligi="Zero" Then Risk=0.014059362, #cases=4481

If AciliyetNedeni="Six" Then Risk=0.6666667, #cases=3
If AciliyetNedeni="Eight" Then Risk=0.5, #cases=2
If AciliyetNedeni="Two" Then Risk=0.33333334, #cases=3
If AciliyetNedeni="Ten" Then Risk=0.25, #cases=4
If AciliyetNedeni="Four" Then Risk=0.2, #cases=5
If AciliyetNedeni="One" Then Risk=0.083333336, #cases=36
If AciliyetNedeni="Five" Then Risk=0.083333336, #cases=12
If AciliyetNedeni="Zero" Then Risk=0.029411765, #cases=34
If AciliyetNedeni="Three" Then Risk=0.027777778, #cases=36
If AciliyetNedeni="Seven" Then Risk=0.0, #cases=5
If AciliyetNedeni="Nine" Then Risk=0.0, #cases=1

If Insidans="Three" Then Risk=0.09859155, #cases=71
If Insidans="Two" Then Risk=0.078947365, #cases=152
If Insidans="One" Then Risk=0.01629413, #cases=4787
If Insidans="Four" Then Risk=0.0, #cases=13
If Insidans="Five" Then Risk=0.0, #cases=1

If GecirilmisKoronerArterBaypas="Yes" Then Risk=0.101123594, #cases=89
If GecirilmisKoronerArterBaypas="No" Then Risk=0.017965281, #cases=4954

If GecirilmisKapakOperasyonu="Yes" Then Risk=0.09195402, #cases=87
If GecirilmisKapakOperasyonu="No" Then Risk=0.018159807, #cases=4956

If GecirilmisDigerOperasyon="No" Then Risk=0.021189895, #cases=3681
If GecirilmisDigerOperasyon="Yes" Then Risk=0.014684288, #cases=1362

If KoronerCerrahisi="No" Then Risk=0.031105991, #cases=868
If KoronerCerrahisi="Yes" Then Risk=0.017005987, #cases=4175

If KapakCerrahisi="Yes" Then Risk=0.049071617, #cases=754

If KapakCerrahisi="No" Then Risk=0.014222429, #cases=4289

If KarotisCerrahisi="Yes" Then Risk=0.125, #cases=32
If KarotisCerrahisi="No" Then Risk=0.018758731, #cases=5011

If PeriferikdamarCerrahisi="Yes" Then Risk=0.09375, #cases=32
If PeriferikdamarCerrahisi="No" Then Risk=0.018958291, #cases=5011

If KardiakProsedur1="Yes" Then Risk=0.042857144, #cases=70
If KardiakProsedur1="No" Then Risk=0.019103156, #cases=4973

If KardiakProsedur6="Yes" Then Risk=0.11111111, #cases=9
If KardiakProsedur6="No" Then Risk=0.019268971, #cases=5034

If KardiakProsedur9="Yes" Then Risk=0.060606062, #cases=66
If KardiakProsedur9="No" Then Risk=0.01888688, #cases=4977

If KardiakProsedur13="Yes" Then Risk=1.0, #cases=1
If KardiakProsedur13="No" Then Risk=0.019238397, #cases=5042

If KardiakProsedur20="Yes" Then Risk=0.072, #cases=250
If KardiakProsedur20="No" Then Risk=0.016691009, #cases=4793

If KardiakProsedur24="Yes" Then Risk=0.03448276, #cases=29
If KardiakProsedur24="No" Then Risk=0.019345831, #cases=5014

If MImekanik="Yes" Then Risk=0.2, #cases=10
If MImekanik="No" Then Risk=0.051685393, #cases=445

E.3 Best rules learned

Rules learned:
If Yas="65.4 .. PosInfinity" Then Risk=0.036285363, #cases=1626
If Yas="59.1083 .. 65.4" Then Risk=0.015625, #cases=1024
If Yas="NegInfinity..59.1083" Then Risk=0.008385744, #cases=2385

If Agirlik="NegInfinity..63.39796" Then Risk=0.034418605, #cases=1075
If Agirlik="63.39796 .. 71.584175" Then Risk=0.02017291, #cases=1041
If Agirlik="71.584175 .. PosInfinity" Then Risk=0.013679891, #cases=2924

If BMI="33.022263 .. PosInfinity" Then Risk=0.2857143, #cases=7
If BMI="NegInfinity..27.636835" Then Risk=0.11627907, #cases=43
If BMI="27.636835 .. 33.022263" Then Risk=0.033333335, #cases=30

If AmeliyatOncesiAnjinaPektoris="Zero" Then Risk=0.060240965, #cases=83
If AmeliyatOncesiAnjinaPektoris="Four" Then Risk=0.038674034, #cases=543
If AmeliyatOncesiAnjinaPektoris="One" Then Risk=0.025996534, #cases=1154
If AmeliyatOncesiAnjinaPektoris="Three" Then Risk=0.019812305, #cases=959
If AmeliyatOncesiAnjinaPektoris="Two" Then Risk=0.009713229, #cases=2162

If UnstablAnjina="Four" Then Risk=1.0, #cases=1
If UnstablAnjina="Two" Then Risk=0.5, #cases=2
If UnstablAnjina="Zero" Then Risk=0.07575758, #cases=66
If UnstablAnjina="One" Then Risk=0.0, #cases=6
If UnstablAnjina="Three" Then Risk=0.0, #cases=1

If KardiyakPrezantasyon="Four" Then Risk=1.0, #cases=1
If KardiyakPrezantasyon="Zero" Then Risk=0.0882353, #cases=34
If KardiyakPrezantasyon="Two" Then Risk=0.05263158, #cases=19
If KardiyakPrezantasyon="Three" Then Risk=0.0, #cases=5
If KardiyakPrezantasyon="One" Then Risk=0.0, #cases=1
If KardiyakPrezantasyon="Five" Then Risk=0.0, #cases=1

If AmeliyatOncesiDispne="Four" Then Risk=0.14166667, #cases=120
If AmeliyatOncesiDispne="Three" Then Risk=0.049152542, #cases=590
If AmeliyatOncesiDispne="Two" Then Risk=0.015881708, #cases=1826
If AmeliyatOncesiDispne="One" Then Risk=0.009716941, #cases=2367

If KojestifKalpYetmezligi="One" Then Risk=0.14438502, #cases=187
If KojestifKalpYetmezligi="Zero" Then Risk=0.015040825, #cases=4654

If HipertansiyonHikayesi="Zero" Then Risk=0.14285715, #cases=28
If HipertansiyonHikayesi="One" Then Risk=0.11764706, #cases=34
If HipertansiyonHikayesi="Two" Then Risk=0.022123894, #cases=2260
If HipertansiyonHikayesi="Three" Then Risk=0.01472754, #cases=2716

If SigaraKullanimi="Two" Then Risk=0.1, #cases=10
If SigaraKullanimi="One" Then Risk=0.022564102, #cases=1950
If SigaraKullanimi="Four" Then Risk=0.021558871, #cases=1206
If SigaraKullanimi="Three" Then Risk=0.012419007, #cases=1852

If KOAH="Three" Then Risk=1.0, #cases=2
If KOAH="Two" Then Risk=0.375, #cases=8
If KOAH="One" Then Risk=0.05263158, #cases=19
If KOAH="Four" Then Risk=0.04144385, #cases=748
If KOAH="Zero" Then Risk=0.013653484, #cases=4248
If KOAH="Five" Then Risk=0.0, #cases=1

If SonPreopKreatinin="Three" Then Risk=0.13461539, #cases=52
If SonPreopKreatinin="One" Then Risk=0.083333336, #cases=12
If SonPreopKreatinin="Zero" Then Risk=0.06451613, #cases=62
If SonPreopKreatinin="Two" Then Risk=0.04488778, #cases=401

If SerebrovaskulerHastalik="Six" Then Risk=0.22222222, #cases=9
If SerebrovaskulerHastalik="Three" Then Risk=0.0882353, #cases=34

If SerebrovaskulerHastalik="Two" Then Risk=0.04761905, #cases=273
If SerebrovaskulerHastalik="Zero" Then Risk=0.016999574, #cases=4706
If SerebrovaskulerHastalik="One" Then Risk=0.0, #cases=13
If SerebrovaskulerHastalik="Five" Then Risk=0.0, #cases=2
If SerebrovaskulerHastalik="Four" Then Risk=0.0, #cases=5

If Endokardit="Four" Then Risk=1.0, #cases=1
If Endokardit="Two" Then Risk=0.5, #cases=2
If Endokardit="Zero" Then Risk=0.07594936, #cases=79

If MaligniteHikayesi="Yes" Then Risk=0.5, #cases=2
If MaligniteHikayesi="No" Then Risk=0.07692308, #cases=78

If AritmiHikayesi="One" Then Risk=1.0, #cases=1
If AritmiHikayesi="Four" Then Risk=0.125, #cases=8
If AritmiHikayesi="Zero" Then Risk=0.08928572, #cases=56
If AritmiHikayesi="Three" Then Risk=0.0, #cases=1

If AritmiTedavi="Two" Then Risk=1.0, #cases=1
If AritmiTedavi="Three" Then Risk=1.0, #cases=1
If AritmiTedavi="Zero" Then Risk=0.08, #cases=75
If AritmiTedavi="Four" Then Risk=0.0, #cases=3

If MiyokardinfarktusZamani="One" Then Risk=0.09677419, #cases=62
If MiyokardinfarktusZamani="Zero" Then Risk=0.0754717, #cases=53
If MiyokardinfarktusZamani="Three" Then Risk=0.05882353, #cases=17
If MiyokardinfarktusZamani="Two" Then Risk=0.029411765, #cases=34
If MiyokardinfarktusZamani="Four" Then Risk=0.023952097, #cases=668
If MiyokardinfarktusZamani="Five" Then Risk=0.015555556, #cases=450
If MiyokardinfarktusZamani="Six" Then Risk=0.011764706, #cases=680

If PreopResustasyon="Yes" Then Risk=1.0, #cases=1
If PreopResustasyon="No" Then Risk=0.085365854, #cases=82

If SinusRitmi="No" Then Risk=0.038038038, #cases=999
If SinusRitmi="Yes" Then Risk=0.014836796, #cases=4044

If DiyastolikKanBasinci="NegInfinity..68.57143" Then Risk=0.115384616, #cases=26
If DiyastolikKanBasinci="68.57143 .. 72.61644" Then Risk=0.09090909, #cases=22
If DiyastolikKanBasinci="72.61644 .. PosInfinity" Then Risk=0.0625, #cases=32

If OrtalamaKanBasinci="NegInfinity..74.57143" Then Risk=0.12903225, #cases=31
If OrtalamaKanBasinci="74.57143 .. 78.03278" Then Risk=0.1, #cases=10
If OrtalamaKanBasinci="78.03278 .. PosInfinity" Then Risk=0.074074075, #cases=27

If PulmonerRaller="Yes" Then Risk=0.33333334, #cases=15
If PulmonerRaller="No" Then Risk=0.046153847, #cases=65

If Pulmonerwheezing="Yes" Then Risk=0.2857143, #cases=14
If Pulmonerwheezing="No" Then Risk=0.060606062, #cases=66

If Toraksdeformitesi="Yes" Then Risk=0.5, #cases=4
If Toraksdeformitesi="No" Then Risk=0.08108108, #cases=74

If Mitralsistolikufurum="Five" Then Risk=0.5, #cases=2
If Mitralsistolikufurum="Two" Then Risk=0.2857143, #cases=7
If Mitralsistolikufurum="Three" Then Risk=0.18181819, #cases=11
If Mitralsistolikufurum="Zero" Then Risk=0.03508772, #cases=57
If Mitralsistolikufurum="Six" Then Risk=0.0, #cases=1
If Mitralsistolikufurum="Four" Then Risk=0.0, #cases=1

If Aortdiastolikufurum="Yes" Then Risk=0.2857143, #cases=7
If Aortdiastolikufurum="No" Then Risk=0.072463766, #cases=69

If Aortsistolikufurum="One" Then Risk=1.0, #cases=1
If Aortsistolikufurum="Zero" Then Risk=0.08695652, #cases=69
If Aortsistolikufurum="Three" Then Risk=0.0, #cases=3
If Aortsistolikufurum="Six" Then Risk=0.0, #cases=1
If Aortsistolikufurum="Five" Then Risk=0.0, #cases=2
If Aortsistolikufurum="Four" Then Risk=0.0, #cases=1
If Aortsistolikufurum="Two" Then Risk=0.0, #cases=1

If PulmonerArterSistolik="One" Then Risk=1.0, #cases=1
If PulmonerArterSistolik="Zero" Then Risk=0.077922076, #cases=77

If VarisSag="Yes" Then Risk=0.2857143, #cases=7
If VarisSag="No" Then Risk=0.0882353, #cases=68

If TibialisPosteriorSag="No" Then Risk=1.0, #cases=1
If TibialisPosteriorSag="Yes" Then Risk=0.09090909, #cases=77

If TibialisPosteriorSol="No" Then Risk=1.0, #cases=1
If TibialisPosteriorSol="Yes" Then Risk=0.093333334, #cases=75

If KoronerArterSayisi="Zero" Then Risk=0.03664122, #cases=655
If KoronerArterSayisi="Three" Then Risk=0.018488085, #cases=2434
If KoronerArterSayisi="One" Then Risk=0.016706444, #cases=419
If KoronerArterSayisi="Two" Then Risk=0.01192843, #cases=1006

If Circumflex="No" Then Risk=0.15384616, #cases=39
If Circumflex="Yes" Then Risk=0.051282052, #cases=39

If SagKoronerArter="Yes" Then Risk=0.13157895, #cases=38
If SagKoronerArter="No" Then Risk=0.075, #cases=40

If SolVentrikulEjeksiyonFraksiyonu="Three" Then Risk=0.067307696, #cases=208

If SolVentrikulEjeksiyonFraksiyonu=”Zero” Then Risk=0.05179283, #cases=251
If SolVentrikulEjeksiyonFraksiyonu=”Two” Then Risk=0.0220234, #cases=1453
If SolVentrikulEjeksiyonFraksiyonu=”One” Then Risk=0.0115644075, #cases=3113

If EjeksiyonFraksiyonuDegeri=”NegInfinity..54.545456” Then Risk=0.07042254, #cases=71
If EjeksiyonFraksiyonuDegeri=”54.545456 .. 62.35168” Then Risk=0.03076923, #cases=65
If EjeksiyonFraksiyonuDegeri=”62.35168 .. PosInfinity” Then Risk=0.01980198, #cases=202

If SistolikPulmonerArterDegeri=”53.185184 .. 60.23077” Then Risk=0.2173913, #cases=23
If SistolikPulmonerArterDegeri=”60.23077 .. PosInfinity” Then Risk=0.09090909, #cases=55
If SistolikPulmonerArterDegeri=”NegInfinity..53.185184” Then Risk=0.030927835, #cases=97

If LVESDdeger=”5.5443597 .. 9.509999” Then Risk=0.5, #cases=2
If LVESDdeger=”9.509999 .. PosInfinity” Then Risk=0.041666668, #cases=24
If LVESDdeger=”NegInfinity..5.5443597” Then Risk=0.02846975, #cases=281

If AortStenozuPeakGradient=”NegInfinity..59.5” Then Risk=0.0952381, #cases=21
If AortStenozuPeakGradient=”59.5 .. 75.05173” Then Risk=0.071428575, #cases=14
If AortStenozuPeakGradient=”75.05173 .. PosInfinity” Then Risk=0.037037037, #cases=27

If AortYetmezlik=”Two” Then Risk=0.16666667, #cases=6
If AortYetmezlik=”Three” Then Risk=0.0952381, #cases=21
If AortYetmezlik=”Zero” Then Risk=0.06557377, #cases=61
If AortYetmezlik=”Four” Then Risk=0.05076142, #cases=197
If AortYetmezlik=”One” Then Risk=0.0, #cases=14

If KalsifiyeAort="One" Then Risk=0.33333334, #cases=6
If KalsifiyeAort="Two" Then Risk=0.25, #cases=4
If KalsifiyeAort="Zero" Then Risk=0.0625, #cases=64

If MitralYetmezlik="Three" Then Risk=0.15789473, #cases=19
If MitralYetmezlik="Two" Then Risk=0.11111111, #cases=9
If MitralYetmezlik="Four" Then Risk=0.0777027, #cases=296
If MitralYetmezlik="Zero" Then Risk=0.04347826, #cases=46
If MitralYetmezlik="One" Then Risk=0.0, #cases=17

If TrikuspidYetmezlik="Three" Then Risk=0.22222222, #cases=9
If TrikuspidYetmezlik="One" Then Risk=0.11764706, #cases=17
If TrikuspidYetmezlik="Zero" Then Risk=0.0754717, #cases=53
If TrikuspidYetmezlik="Four" Then Risk=0.0625, #cases=64
If TrikuspidYetmezlik="Two" Then Risk=0.0, #cases=2

If Onceligi="Three" Then Risk=0.14285715, #cases=35
If Onceligi="Two" Then Risk=0.067010306, #cases=194
If Onceligi="One" Then Risk=0.05105105, #cases=333
If Onceligi="Zero" Then Risk=0.014059362, #cases=4481

If AciliyetNedeni="Six" Then Risk=0.6666667, #cases=3
If AciliyetNedeni="Eight" Then Risk=0.5, #cases=2
If AciliyetNedeni="Two" Then Risk=0.33333334, #cases=3
If AciliyetNedeni="Ten" Then Risk=0.25, #cases=4
If AciliyetNedeni="Four" Then Risk=0.2, #cases=5
If AciliyetNedeni="One" Then Risk=0.083333336, #cases=36
If AciliyetNedeni="Five" Then Risk=0.083333336, #cases=12
If AciliyetNedeni="Zero" Then Risk=0.029411765, #cases=34
If AciliyetNedeni="Three" Then Risk=0.027777778, #cases=36
If AciliyetNedeni="Seven" Then Risk=0.0, #cases=5
If AciliyetNedeni="Nine" Then Risk=0.0, #cases=1

If Insidans="Three" Then Risk=0.09859155, #cases=71
If Insidans="Two" Then Risk=0.078947365, #cases=152
If Insidans="One" Then Risk=0.01629413, #cases=4787
If Insidans="Four" Then Risk=0.0, #cases=13
If Insidans="Five" Then Risk=0.0, #cases=1

If KapakCerrahisi="Yes" Then Risk=0.049071617, #cases=754
If KapakCerrahisi="No" Then Risk=0.014222429, #cases=4289

If KardiakProsedur20="Yes" Then Risk=0.072, #cases=250
If KardiakProsedur20="No" Then Risk=0.016691009, #cases=4793