An integrated decision analytic framework of machine learning with multi-criteria decision making for patient prioritization in elective surgeries

Mémoire

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Résumé

Objectif: De nombreux centres de santé à travers le monde utilisent des critères d'évaluation des préférences cliniques (CPAC) pour donner la priorité aux patients pour accéder aux chirurgies électives. Le processus de priorisation clinique du patient utilise à cette fin les caractéristiques du patient et se compose généralement de critères cliniques, d'expériences de patients précédemment hospitalisés et de commentaires sur les réseaux sociaux. Le but de la hiérarchisation des patients est de déterminer un ordre précis pour les patients et de déterminer combien chaque patient bénéficiera de la chirurgie. En d'autres termes, la hiérarchisation des patients est un type de problème de prise de décision qui détermine l'ordre de ceux qui ont le plus bénéficié de la chirurgie. Cette étude vise à développer une méthodologie hybride en intégrant des algorithmes d'apprentissage automatique et des techniques de prise de décision multicritères (MCDM) afin de développer un nouveau modèle de priorisation des patients. L'hypothèse principale est de valider le fait que l'intégration d'algorithmes d'apprentissage automatique et d'outils MCDM est capable de mieux prioriser les patients en chirurgie élective et pourrait conduire à une plus grande précision.

Méthode: Cette étude vise à développer une méthodologie hybride en intégrant des algorithmes d'apprentissage automatique et des techniques de prise de décision multicritères (MCDM) afin de développer un modèle précis de priorisation des patients. Dans un premier temps, une revue de la littérature sera effectuée dans différentes bases de données pour identifier les méthodes récemment développées ainsi que les facteurs de risque / attributs les plus courants dans la hiérarchisation des patients. Ensuite, en utilisant différentes méthodes MCDM telles que la pondération additive simple (SAW), le processus de hiérarchie analytique (AHP) et VIKOR, l'étiquette appropriée pour chaque patient sera déterminée. Dans la troisième étape, plusieurs algorithmes d'apprentissage automatique seront appliqués pour deux raisons: d'abord la sélection des caractéristiques parmi les caractéristiques communes identifiées dans la littérature et ensuite pour prédire les classes de patients initialement déterminés. Enfin, les mesures détaillées des performances de prédiction des algorithmes pour chaque méthode seront déterminées.

Résultats: Les résultats montrent que l'approche proposée a atteint une précision de priorisation assez élevée (~70 %). Cette précision a été obtenue sur la base des données de 300 patients et elle pourrait être considérablement améliorée si nous avions accès à plus de données réelles à l'avenir. À notre connaissance, cette étude présente la première et la plus importante du genre à combiner efficacement les méthodes MCDM avec des algorithmes d'apprentissage automatique dans le problème de priorisation des patients en chirurgie élective.

Abstract

Objective: Many healthcare centers worldwide use Clinical Preference Assessment criteria (CPAC) to prioritize patients for accessing elective surgeries [44]. The patient's clinical prioritization process uses patient characteristics for this purpose and usually consists of clinical criteria, experiences of patients who have been previously hospitalized, and comments on social media. The sense of patient prioritization is to determine an accurate ordering for patients and how much each patient will benefit from the surgery. This research intends to build a hybrid approach for creating a new patient prioritizing model by combining machine learning algorithms with multi-criteria decision-making (MCDM) methodologies. The central hypothesis is to validate that the integration of machine learning algorithms and MCDM tools can better prioritize elective surgery patients and lead to higher accuracy.

Method: As a first step, a literature review was performed in different databases to identify the recently developed methods and the most common criteria in patient prioritization. Then, using various MCDM methods, including simple additive weighting (SAW), analytical hierarchy process (AHP), and VIKOR, the appropriate label for each patient was determined. As the third step, several machine learning algorithms were applied to predict each patient's classes. Finally, we established the algorithms' precise prediction performance metrics for each approach.

Results: The results show that the proposed approach has achieved relatively high prioritization accuracy (~70%). This accuracy has been obtained based on the data from 300 patients, and it could be significantly improved if we have access to more accurate data in the future. To the best of our knowledge, this research is the first of its type to demonstrate the effectiveness of combining MCDM methodologies with machine learning algorithms in patient prioritization problems in elective surgery.

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Analytic hierarchy process (AHP)

VIekriterijumsko KOmpromisno Rangiranje (VIKOR)

Simple Additive Weighting (SAW)

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Nima Jamshidi Shahvar

Introduction

Today, in many countries, patients who need surgery have to wait for a long time due to the lack of medical resources. This limitation may even lead to a significant risk to patients due to delayed surgery [1]. One of the problems of medical centers that leads to long-time waiting of patients is the imbalance between demand and access to scarce resources. Due to the high rate of patients and limited resources, hospitals cannot distribute resources among all patients. As a result, specialists don't have enough time to treat the patient due to the crowds. Also, the necessary equipment for surgery of all patients is not available in hospitals. Therefore, surgery and treatment of all patients at the same time is practically impossible.

On the other hand, due to high costs, anesthesiologists can't provide the necessary resources to treat all patients [2]. Therefore, to help patients and benefit from their services, a queue should be formed for patients to take into account factors such as the severity of the disease, the amount of pain, the benefit of surgery on the patient, patients' restrictions on daily activities, and so on [3]. In addition, medical centers and healthcare systems worldwide suffer from resource constraints, and therefore the need to prioritize elective surgeries has become necessary [4]. In some medical centers, traditional direct prioritization is still used, but the lack of attention to the essential factors and criteria between patients causes many differences in the prioritization of patients in different medical centers. Therefore, designing a general rule is for how to prioritize patients a challenging issue[1].

Chapter 1: Patient prioritization

1-1 Rational

"Prioritization is a complex multi-criteria decision-making process"[5]. Prioritization systems based on patient ranking can be used as a tool to guide surgeons in the right direction in decision-making for treatment and surgery of patients [5]. Patient prioritization systems were introduced in the 1990s. Still, the poor performance of these systems led to adverse outcomes and resulted in significant damage to a large number of patients who mistakenly prioritized the treatment process. Although the lack of precise prioritization systems, as a helpful tool in health care decisions, is felt, it is still not well developed due to limitations. The low accuracy of prioritization systems currently in use may indicate high priority patients for surgery with low priority, which affects the accuracy of the entire system. Inaccuracies in prioritization can also create problems in integrating decision criteria, and the interdependence between decision criteria for prioritization may not be considered. Therefore, increasing the accuracy of prioritization systems is the primary goal of research in this field.

Given the importance of prioritizing patients in medical and health care centers, there have been many recent attempts to create rankings based on statistical methods using artificial intelligence and machine learning techniques. Recently, artificial intelligence has significant performance in healthcare because it can optimize complex and complicated problems with enormous data sets distributed in various medical and control systems at the lowest cost. In order to control the condition of patients, healthcare systems need constant and efficient monitoring and follow-up in many stages of the disease. Each stage of the disease depends on many variables, and each of the variables may depend on several other stages [6]. Prioritization of patients who need surgery is an example of problems in which many variables are involved in its productivity, and to control and manage this issue requires an integrated management and control system to handle variables and data sets related to fundamental factors and continuously learn from the results of this process and use their experiences in the previous stages to improve the following stages and make the proper decision. Thus, the combination of artificial intelligence methods and multi-criteria decision-making techniques can achieve significant results.

1-2 Problem Statement

Prioritization of patients on waiting lists is a significant challenge for healthcare institutions since patients often experience adverse outcomes as a result of lengthy wait times[7-12]. Elective surgery is on the rise in the West, and waiting times are a severe concern in OECD countries [13, 14]. According to the Fraser Institute, wait times in Canada have climbed 95 percent since 1993 [15].

Russell et al. [16] claim that getting elective surgery for non-urgent operations is becoming more complex. This discrepancy forces some patients to wait longer than they should [16]. Extended wait times have a negative impact on the well-being of patients and the efficacy of their care. The long wait times may have a detrimental effect on medical outcomes, raise the likelihood of adverse events, and cause pain and misery [17, 18]. According to the Fraser Institute, between 1993 and 2009, 44,273 Canadian women died as a consequence of treatment delays. [20].

Although a lack of surgeons and nurses is the primary reason for the mismatch between demand and supply for elective surgery., appropriate patient prioritizing systems may make a significant difference in minimizing patient patients' injury or mortality.

This research aims to build a hybrid approach for developing a new patient prioritizing model by integrating machine learning algorithms and MCDM methodologies. As a first step, a literature review was conducted in different databases to identify the recently developed methods and the most common risk factors/criteria in patient prioritization. Then, the appropriate label for each patient was determined using different MCDM methods such as simple-additive weighting (SAW), analytical hierarchy process (AHP), and VIKOR. Next, various machine learning algorithms were used to predict patient classifications based on their initial determinations as a third step. Finally, precise prediction performance measures for each algorithm were obtained. The research's primary hypothesis is to demonstrate that machine learning algorithms are helpful to patient prioritizing concerns.

1-3 Research Motivation

The primary purpose of this study is to introduce the application of machine learning tools in elective surgery patients' prioritization in medical centers. As mentioned, current prioritization systems suffer from a lack of accuracy. On the other hand, the limitations of surgery and simultaneous treatment of patients reveal the urgent need for prioritization systems. Thus, to address the issues raised in this study, a hybrid strategy is provided that incorporates machine learning algorithms with multi-criteria decision-making methodologies to prepare a new patient prioritization model. The proposed method is expected to give a more accurate prioritization system by integrating the evolutionary ability of machine learning techniques with factors related to multiple criteria.

1-4 Research Objectives

1. Identifying the most common risk factors/features in patient prioritization
2. Developing the optimal classification model for new patient prediction and prioritizing.
3. The research's central hypothesis is to demonstrate that machine learning techniques are very suitable to challenges of patient prioritizing and could improve traditional patient prioritization methods using MCDM methods.
4. Developing a user-friendly prioritization system applicable in healthcare organizations (subject to time availability).

1-5 Research Questions

This study examines the following research questions: (a) Can machine learning and artificial intelligence methods help healthcare organizations in patients' prioritization process to enhance the efficacy and equity of health care access? And if so, b) How should it be developed to consider the issues confronting decision-makers in real-world healthcare settings?

1-6 Research Methods

This study aims to build a hybrid approach by integrating machine learning algorithms with MCDM techniques [21] to develop an accurate patient prioritization model. As a first step, a literature review was performed in different databases to identify the recently developed methods and the most common risk criteria in patient prioritization. Then, the appropriate label for each patient was determined using different MCDM methods such as simple additive weighting (SAW), analytical hierarchy process (AHP), and VIKOR. As the third step, multiple machine learning methods were used to forecast patient classifications based on their first determinations. Finally, precise prediction performance measures for each algorithm were obtained.

Given that multi-criteria methods have already been used widely, the use of neural networks to predict the priority of new patients for elective surgery is a unique contribution in the literature. In this thesis, based on the simple incremental weighting method, one weight is assigned to each patient according to the values of the criteria used and the obtained weights for the criteria by a random function. In the next stage, according to the effect of existing criteria on each other, the final weight of each patient is determined using the AHP method. In other words, we used the AHP method to investigate the effect that weights might have on each other to achieve a more accurate weight. Finally, using the VIKOR method, patients are classified into four priority classes. Due to the fact that the data on patients are not labeled, this data can't be directly trained in neural networks. Neural networks are one of the supervised learning methods and require data labeling before entering the neural network. Therefore, in the proposed method, we have to use the previously existing methods for labeling patients. After labeling patients, neural networks receive the necessary training on patient data based on each patient's priorities (tags). Based on this, a model for neural network learning is created. Neural networks based on this model can predict the priority of new patients without the need for SAW, AHP, and VIKOR methods. In other words, in patients who are new to the hospital and there is no information about the weight of their criteria and are not prioritized, the neural network will be able to predict the condition of patients. In fact, the role of machine learning in this study is to predict the priority of new patients.

1-7 Research Contribution

The main contribution of this research has expressed as follows:

- Using MCDM techniques to determine the essential factors of prioritizing patients to provide surgical services in medical centers.
- Using the simple additive weighting method to weigh the determining factors to prioritize patients in elective surgery.
- Using the AHP method to evaluate the impact of each factor on patient prioritization in elective surgery.
- Using machine learning techniques to learn the factors and the relationships between them to increase the accuracy of the patient prioritization system for elective surgery in medical centers and healthcare systems.

1-8 Organizing research

The rest of this thesis has organized as follows:

- Chapter 2 will review the research background.
- Chapter 3 will describe the methods and details of the proposed methods.
- Chapter 4 will model the proposed method on the collected data. Additionally, the suggested method's performance will be evaluated and compared to that of alternative prioritization systems.
- Chapter 5 will express the conclusions of the research and future work.

Chapter 2: Background

2-1 Introduction

As mentioned before, the imbalance between demand and access to medical resources and hospital equipment is a long-standing issue that has not been fundamentally resolved. As a result, patients who need treatment and surgery can't receive the desired services. Furthermore, due to the waiting list, the hospital's capacity is insufficient to address patient demands quickly. In addition, surgeons do not have enough time to treat and operate on patients due to patient imbalances. Therefore, one solution that seems necessary is to assign priority weight to patients so that patients with emergency conditions can be treated and operated on earlier than others. Prioritization is based on various criteria that the selection of each criterion according to the characteristics of patients can have different results. The evaluation of patients' priority criteria for treatment and surgery on the waiting list has been considered in many studies. Therefore, this chapter will review the background of patient prioritization and some of the research that has been conducted in this area.

2-2 Research background

In determining patients' priority for elective surgery, there are a variety of criteria for prioritizing and ranking the patient. Each of the criteria refers to a vital and biological aspect of the patient, and a combination of these criteria can create a different list of waiting patients. Each list can provide accurate results for the prioritization system in healthcare centers. The primary goal of this research is to develop criteria for selecting the most accurate list of patients to prioritize based on existing criteria. At the rest of this section, first, the classification of patient prioritization methods is presented, and then the evaluation criteria provided for patient prioritization will be reviewed.

2-2-1 Prioritization of patients

One of the most critical concerns in healthcare is how to prioritize patients on the waiting list. This challenging issue has resulted in several scientific breakthroughs, most notably in prioritizing inpatients or general surgery patients. In terms of approach, patient prioritizing is primarily categorized into two types.

The first category is concerned with patient scheduling and planning, with a particular emphasis on patient priority. In order to prioritize patients, Wang et al. [22] combined patient priority criteria with operating room scheduling for patients' surgery. The disadvantage of this method is that the priorities are determined only based on the patient's health status. Min and Yih [23] addressed the scheduling issue for elective surgery to prioritize patients and determine patient priority based on three clinical criteria: illness kind, pain intensity, and patient disorder. Azadeh et al. [24] prioritized the patient using operating room scheduling based on nurse triage information. The disadvantage of this work is that the work does not consider the health status of patients, and the ranking of patients is determined only based on waiting time for surgery. Finally, sung and Lee [25] used Mass Casualty Information (MCI) to prioritize patients for elective surgery. In this plan, priority is given to the accident victims, and their survival chances improve after surgery.

The establishment of a patient scoring system is another approach to prioritizing patients for elective surgery. Rodríguezmígue et al. [26] have established a scoring system for determining which patients should be prioritized for coronary artery surgery, which is based on several criteria in scoring patients. by considering the patient's condition and operating room schedule, this study has extracted the patient evaluation criteria, and the values of these criteria have been used to create a list of patients' priorities. Kuoppala et al. [27] have prepared 14 tests to prioritize patients. Patients' information has been collected from the results of these tests using a questionnaire, and priority criteria have been extracted from it. The study was conducted at New Zealand Medical Centers to identify people who benefit most from cataract surgery. Solans Domènech et al. [28] used nominal group approaches to obtain patient requirements for surgical prioritisation and created a two-level Delphi priority scoring system. The strength of this method was the focus on quantitative data, and its disadvantage is that it was not able to score accurately for quality criteria with incomplete and inaccurate information.

2-2-2 Patients' Prioritization Challenges

According to the previous section, by reviewing the publications, we can find ways to prioritize patients for elective surgery, but these methods still face shortcomings and challenges:

(1) For the first category, further research focuses on the patient's health status and operating room scheduling to bring the patient's prioritization of scheduling patterns closer to the actual situation. Prioritization of patients is the first stage in planning for the patients and reserving operating rooms. In these methods, patient planning is done as a simple segmentation to prioritize patients. Given that these methods focus solely on these two issues, patients' prioritization for elective surgery is crude. In this method, none of the sub-criteria that can harm the patient is considered to evaluate the prioritization.

(2) To prioritize patients for elective surgery in the second category, specialists and surgeons developed several criteria that focus on numerical or semi-quantitative values as a coefficient of the patient and operating room conditions. However, the majority of prioritizing techniques depend on a scoring system, which means that each

patient's score is determined by these criteria and the effect of each criterion's coefficients. The patient's preference for surgery is also assessed based on these criteria and their coefficients. However, such methods are not designed to determine the impact of criteria on each other. Therefore, patient prioritization based on these methods may not reflect all risks to the patient.

2-2-3 Patient Prioritization Criteria

The most critical phase in the prioritizing process is identifying and summarising the patients' prioritized criteria for elective surgery. Recently, [28] published a set of criteria for determining patient prioritizing. In this work, eight criteria for evaluating the prioritizing method are proposed, and each of the criteria is assigned a point value based on its influence on the ideal list. Additionally, [5] presents certain subsets of criteria in addition to the current ones, based on a group decision environment composed of many criteria and linkages between them. The following describes all criteria (C1-C8) and subgroups of criteria (C31-C36):

C1 - The severity of diseases. The severity of the condition is proportional to its impact on the patient's health or productivity. Accurately assessing the severity of the illness is a somewhat challenging undertaking, although clinical examination or biological testing may typically be used to evaluate the clinical severity of the condition.

C2 – Pain. Pain Is defined as the discomfort experienced by a patient due to a general or localized sickness. The patient may experience pain continuously or intermittently. The intensity of pain relates to the extent to which the patient's primary symptoms (type, severity, or frequency) interfere with everyday activities and quality of life.

C3 - Rate of disease progression. The progression of illness varies significantly amongst patients due to various variables such as the kind of disease, the patient's health status, the patient's age, and so on. In [29], the prioritization systems were examined in the treatment environment to evaluate patients and rank them and categorize the rate of disease progression into three overall categories: no progression, progression in the last three months, and rehabilitation based on previous treatment. However, in [5], the progression of the disease is examined in more detail, and based on this, six categories of main risks are presented as a subset of the main criteria, which are as follows:

C3-1- Risk of death. This criterion is related to the likelihood of dying while awaiting surgery and is one of the most critical sub-criteria for prioritizing patients for elective surgery. Due to the fact that patients waiting for surgery may face serious risks, this criterion shows the highest level of risk, so this criterion is used to ensure the selection of patients at higher risk [5].

C3-2- The risk of significant consequences, the development of complications, and the disease's aggravation. This criterion assesses the probability that a patient awaiting surgery will develop other illnesses related to the underlying disease or that there will be severe effects on their health status [5].

C3-3- Risk of reduced surgical effectiveness. Based on this criterion, the effect of surgical delay on the patient's recovery process is measured. Surgery may not be effective in some patients due to loss of time. For example, in the elderly, the effect of joint surgery decreases due to delay [5].

C3-4- Past complications. The health status of the deceased patient and the patient's complications before surgery may affect the outcome of the surgery and may even be a threat to the patient's health [5].

C3-5- Risk of disease spreading. This criterion captures the possibility of the disease increment and spreading to other organs involved with the disease. For example, patients who need urgent surgery may be more likely to develop the disease if it is delayed, and the disease can spread to other parts of the body that are directly affected near the limb [5].

C3-6 - Progression that may impact survival or modify the kind of surgery. Any delay in surgery affects the patient's chances of survival or causes physicians to correct the type of operation [5].

C4 - Difficulty carrying out daily tasks. Difficulty with activities refers to the patient's limits in doing everyday tasks he could perform before his disease. While there is a correlation between these criteria and illness severity, they should not be equated [28].

C5 - Probability and degree of improvement. This criterion evaluates the benefit of surgery and the rate of postoperative recovery, which affects the quality of life-related to the patient's health [28].

C6 - Time on the waiting list. The length of time it takes for a patient to undergo surgery is called waiting time, a critical component from a patient's perspective, and influences patients' views of the quality of services received [28].

C7 - Restrictions on the care of personal relatives. This criterion refers to the restrictions placed on the patient's companions to take responsibility for the care of relatives (i.e., children, older parents) [28].

C8 - Limitations on the ability to work/study/look for a job. This criterion indicates a restriction on the patient's social work (in paid or unpaid jobs). For example, patients may experience loss of education or educational and occupational activities due to complications from delayed surgery [28].

In [29], search results in scientific databases identified 17 criteria for patient prioritization. In addition, 12 works have been added to the entire criteria as a result of consultation with Chinese specialists and surgeons. These 29 criteria for prioritizing patients from the perspective of disease, hospital, patient, and community can be divided into five dimensions. These five dimensions include clinical and functional disorders (C1'), expected outcomes (C2'), social factors (C3'), core patient information (C4'), and subject value and research development (C5') as shown in Table 2-1.

As shown in Table 2-1, those criteria collected from scientific databases are referenced to their main source. The following is a brief explanation of each dimension of the criteria for evaluating patients' prioritization for elective surgery.

(1) Clinical and functional disorders (C1')

Each patient's clinical and functional disorders indicate the severity of the disease and the patient's need for medical services and operating room. This is an essential dimension of the criteria for patient prioritization for elective surgery, which is shown in the following four criteria:

Table 2-1. Patient Prioritization Evaluation Criteria [29]

Dimensions	Original criteria
Clinical and functional disorders (C_1')	Disease severity ($c1'$) Rate of disease progression ($c2'$) Pain level ($c3'$) Influence on physical function ($c4'$)
Expected outcomes ($C2'$)	Difficulty of treatment ($c5'$) Probability of postoperative improvement ($c6'$) The complication probability ($c7'$) Effect on patient's life quality ($c8'$)
Social factors ($C3'$)	Resource consumption during waiting periods ($c9'$) Loss of ability to support others ($c10'$) Limitations in doing activities of daily living ($c11'$) Social roles ($c12'$) Occupation of medical resources ($c13'$) Single disease cost ($c14'$)
Patient basic information ($C4'$)	Gender ($c15'$) Age ($c16'$) Waiting time under the same conditions ($c17'$) Medicare type ($c18'$) Medicare location ($c19'$) Patient's ability to pay ($c20'$) The patient's urgency for treatment ($c21'$) Patient region ($c22'$)
Subject value and research development ($C5'$)	Bidirectional referral cases ($c23'$) Research value contribution ($c24'$)

• Disease severity (c1')

• Rate of disease progression (c2')

• Pain level (c3')

• Influence on physical function (c4')

(2) Expected results (C2')

This criterion refers to the patient's recovery after treatment and surgery and the expected results for the effectiveness of postoperative therapy from the perspective of surgeons and experts. Medical and healthcare centers should evaluate the efficacy and success of surgery on patients. In similar cases, the right decisions can be made to save medical and hospital resources. On the other hand, hospital resources may be wasted in similar circumstances if these criteria do not meet the expected results. It does not mean that medical centers refuse to treat similar patients. Still, it does doubt that the hospital has the right to assess whether patients expect adverse effects after receiving treatment, such as mortality and severe consequences. In this regard, the following four criteria have been introduced [29]:

- The difficulty of treatment (c5 ')
- Postoperative improvement (c6')
- Complication probability (c7')
- Effect on patient's quality of life (c8 ').

(3) Social factors (C3 ')

Social factors in the patient, in addition to the patient himself, also pay attention to his side and try to minimize the existing restrictions for the well-being of the patient and his companions in the medical center and healthcare. When admitting patients, criteria based on the social welfare perspective should be considered to influence the patient's surgical prioritization. Therefore, social criteria are referred to as the following seven criteria [29]:

- Resource consumption during waiting periods (c9 ')
- Loss of ability to support others (c10 ')
- Limitations in doing activities of daily living (c11 ')
- Social roles (c12 ')
- Medical resources (c13 ')
- Single disease cost (c14 ')

(4) Basic patient information (C4 ')

Preliminary patient information is required for comprehensive registration and evaluation to prioritize surgery. According to the initial data, the waiting time for each patient can be estimated based on the relevant criteria. For example, suppose the other conditions of the two patients are the same. In that case, Chinese medical institutions prioritize out-of-province patients over in-province patients because the cost of waiting for the former is often more than the cost of waiting for the latter. The main information of the patient can be introduced as the following criteria [29]:

• Gender (c15 ')

• Age (c16 ')

• Waiting time under the same condition (c17 ')

• Medical type (c18 ')

• Medical location (c19 ')

• Patient's ability to pay (c20 ')

• Patient's urgency for treatment (c21 ')

• Patient's region (c22 ')

(5) subject value and research development (C5')

Patients on the waiting list should be classified according to "subject values and research development." A few studies have addressed this issue. But, since the process of patient admission and care continues, this criteria may be seen as a critical stage in patient screening, scientific study, and discipline advancement. This dimension reflects the position of medical centers and the primary responsibility of health care systems in providing high-level specialized services. This dimension is introduced in the following two criteria [29]:

• Bidirectional referral cases (c23 ')

• Research value contribution (c24 ')

Combining some of these criteria can help create a multi-criteria model for deciding patients' ranking in prioritizing surgery. In fact, in most research conducted in this field, all or some of these criteria are crucial in prioritizing patients for elective surgery. Therefore, in the continuation of this chapter, we will review the previous methods in prioritizing patients with different techniques.

Chapter 3: The proposed method

3.1 Introduction

The proposed method begins by determining the values associated with the patient prioritizing criteria stated in the preceding chapter. As mentioned before, in patient prioritization, 24 criteria related to patients are considered for accurate prioritization. The suggested approach takes the values of these priorities as input. The proposed methodology begins with the labeling of patients according to their assessment criterion values. In the proposed method, patients are divided into two groups of high and low priority patients. Patient labeling in the proposed method is based on an MCDM approach based on a combination of SAW and VIKOR. After labeling patients, this labeled data is used as input to estimated machine learning methods. Estimated machine learning methods include classification techniques such as decision tree, nearest neighbor, neural networks, Bayesian, support vector machine. Based on their performance, these methods can predict new samples and prioritize new patients. In the proposed method, neural networks are used to predict new examples and prioritize new patients. In the continuation of this chapter of the dissertation, the methods used in this dissertation are introduced. The proposed details will then be explained.

3.2 Multi-criteria prioritization

Prioritization of elective surgery patients is a critical decision in the health care system. The interaction between different criteria about the patient to achieve multiple goals in the research is considered. Research objectives may be conflicting and generally resource-constrained. In addition to the patient's health status, operating room status and other limitations in health care systems and hospitals are considered in prioritizing patients. In order to select patients for surgery, decision-makers usually consider the balance between the goals by evaluating the criteria related to the patient and the hospital conditions and according to the criteria associated with making general decisions and prioritizing patients. As previously stated, the proposed method employs five general criteria for clinical disorders and functionality, expected outcomes, social factors, initial patient information, and subject value and research development, each of which has its sub-criteria. To prioritize multiple criteria, a number of these criteria will naturally overlap. Therefore, multi-criteria methods will not be able to improve all the criteria related to the patient and the hospital environment. Thus, multi-criteria prioritization methods try to create a balance between these criteria as much as possible so that a list of the patient's exact priorities is obtained.

A combination of multi-criteria approach and machine learning method has been used in the proposed method to obtain patients' priority list for surgery. The multi-criteria technique used in the proposed method combines the simple additive weighting (SAW) method and hierarchical analytical processes (AHP) and VIKOR. The simple weighting method initially assigns a weight to each patient according to the patient's health status. Then, in the hierarchical-analytical method, each patient receives a more accurate weight according to the other criteria used and the other patients' weight. Finally, using the VIKOR approach, the label related to each patient is produced. This label indicates the patient's status for surgery and includes two categories of high priority and low priority. Finally, by determining the patient priority label, we will use neural networks to develop patterns that will allow us to predict the priority of incoming patients in the proposed method. In the continuation of this section, the function of simple weight gain methods, hierarchical analytic process, VIKOR, and neural networks in creating a patient prioritization framework for elective surgery will be explained.

3.2.1 Simple additive weighting method in patients' prioritization for surgery

Simple Additive Weighting (SAW), otherwise known as a weighted linear combination, is a straightforward multi-criteria decision-making technique employed in most multi-criteria decision-making applications. The average weights serve as the foundation for this strategy. Each of the problem's criteria is allocated an evaluation point using this procedure. The evaluation value is calculated by multiplying the replacement value for the criterion and the attribute associated with the criterion by the weight of the criterion's relative importance, which is chosen directly by the decision-maker while solving the multi-criteria problem [46]. In the proposed method, which is presented to solve the problem of patient prioritization, the values allocated by the hospital for the criteria mentioned in the previous chapter for patients and resources in the medical center, in the values of relative importance for each criterion by the specialists and the doctors at that treatment center provided, multiplied. Thus, a patient's initial priority is based on the sum of the criteria weights. Indeed, the initial priority allocated to each patient is established by expert opinion and the values assigned to each patient's criteria. In the proposed method, considering the use of five main criteria and sub-criteria related to these criteria, to determine the initial priority of each binary first, a value is assigned to each of the specified criteria. The values of the sub-criteria for each patient may be different, which is extracted based on the information entered in each patient's file. In the first step of the proposed method, each of the existing sub-criteria receives an initial score based on the simple incremental weighting method. Then the score of each of the general criteria is determined based on the weighted average of the relevant sub-criteria. Finally, each patient's initial priority is established based on the overall score for each patient's criteria.

The advantage of this method is that it creates a weight that is appropriate according to the characteristics and criteria set by the specialists and the patient's health condition. The disadvantage of this method is that the contrast of criteria is not considered in this method. Furthermore, due to the use of a multi-criteria method, some criteria may be contradictory in determining a patient's priority, and ignoring the conflict of these criteria can affect the performance of the entire prioritization system. Given the use of the multi-criteria method in the proposed method, the five criteria used are likely to conflict with each other, and the use of the simple incremental weighting method alone does not provide us with an accurate list of priorities. Therefore, in the proposed method, the hierarchical analytic method is used to investigate the effect of the criteria on each other. In this method, the effect of the criteria on each other is investigated in pairs, and the output result will be used to label patients. The process of simple incremental weighting method includes these steps:

Step 1:

1) Creating a square matrix: According to the criteria used in the proposed method, a square matrix with dimensions of 5×5 is created to compare pairs of criteria. In other words, in the proposed matrix method, each criterion's relative importance is determined by comparison to other criteria.

2) To find the relative importance of each criterion, we aggregate the values of the sub-criteria and obtain the relative importance of the existing criteria. We then compare these two criteria to other available criteria to determine which is more important and then assign a score indicating the greater importance of the desired criterion.

3) Each member of the comparison matrix is produced by the sum of its columns, and the priority vector is calculated by calculating the row averages [30].

4) By multiplying the comparison matrix and the priority vector, the sum matrix is produced.

5) The weighted sum matrix is separated into its constituent components by the corresponding priority vector element.

6) λ_{max} Is computed by taking the average of these values.

7) The following formula is used to determine the compatibility index, CI:

$$CI = \frac{\lambda_{max}-n}{n-1} \quad (3\text{-}1)$$

where n denotes the matrix's size

8) Compatibility rate, CR is also calculated as follows:

$$CR = \frac{CI}{RI} \quad (3\text{-}2)$$

9) Compatibility could be assessed by comparing the compatibility rate (CR of CI to the corresponding number in Table 3-1. If the compatibility rate is less than 0.12, it is acceptable). If this value is greater than 0.12, the evaluation matrix shows the discrepancy between the two criteria. To obtain a consistent matrix, the evaluation of Blain criteria should be reviewed and improved [31].

Table 3-1 Random compatibility values

Size of matrix	Random consistency
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

As shown in Table 3-1, Random adjustment values (RI) are different according to the size of the matrix, considering that in the proposed method, five criteria are used to prioritize patients in surgery, so the dimensions of the matrix are equal to 5 and the threshold value stochasticity follows 0.12.

Step 2:

After calculating the values of the criteria and the importance of each criterion, an m×n matrix is formed in which m is equal to the number of patients and n is equal to the number of criteria used for prioritization. Criteria that are not incompatible are calculated as follows:

$$n_{ij} = \frac{r_{ij}}{r_j^*} \qquad ,i = 1, \dots, m \quad ,j = 1, \dots, n \quad (3\text{-}3)$$

and we also have for incompatible criteria:

$$n_{ij} = \frac{r_j^{min}}{r_{ij}} \qquad ,i = 1, \dots, m \quad ,j = 1, \dots, n \quad (3\text{-}4)$$

In the above relation, r_{ij} is considered as the matrix data, and r_j^* is considered as the maximum value in each column.

Step 3:

The evaluation of each criterion is based on the following equation.

$$A_i = \sum w_j . x_{ij} \tag{3-5}$$

Where x_{ij} is the score assigned to the second option by the criterion of j, w_j is the weight given to the criteria [19].

The simple incremental weighting method is designed to select and consider multiple criteria consisting of the patient's health status and the conditions of the hospital and medical staff in the treatment center, respectively. If the consistency of the criteria used in the proposed method is greater than the specified threshold, a two-by-two comparison of the criteria should be reconsidered. Therefore, this method continues until the level of compatibility reaches below the threshold. Once the CR is below the threshold, it indicates sufficient compatibility. At that time, we use the simple incremental weighting method for the initial ranking of patients. Then, the output results of this method are used as input to the hierarchical analytic process method. Figure 3-1 of the flowchart shows a simple incremental weighting method.

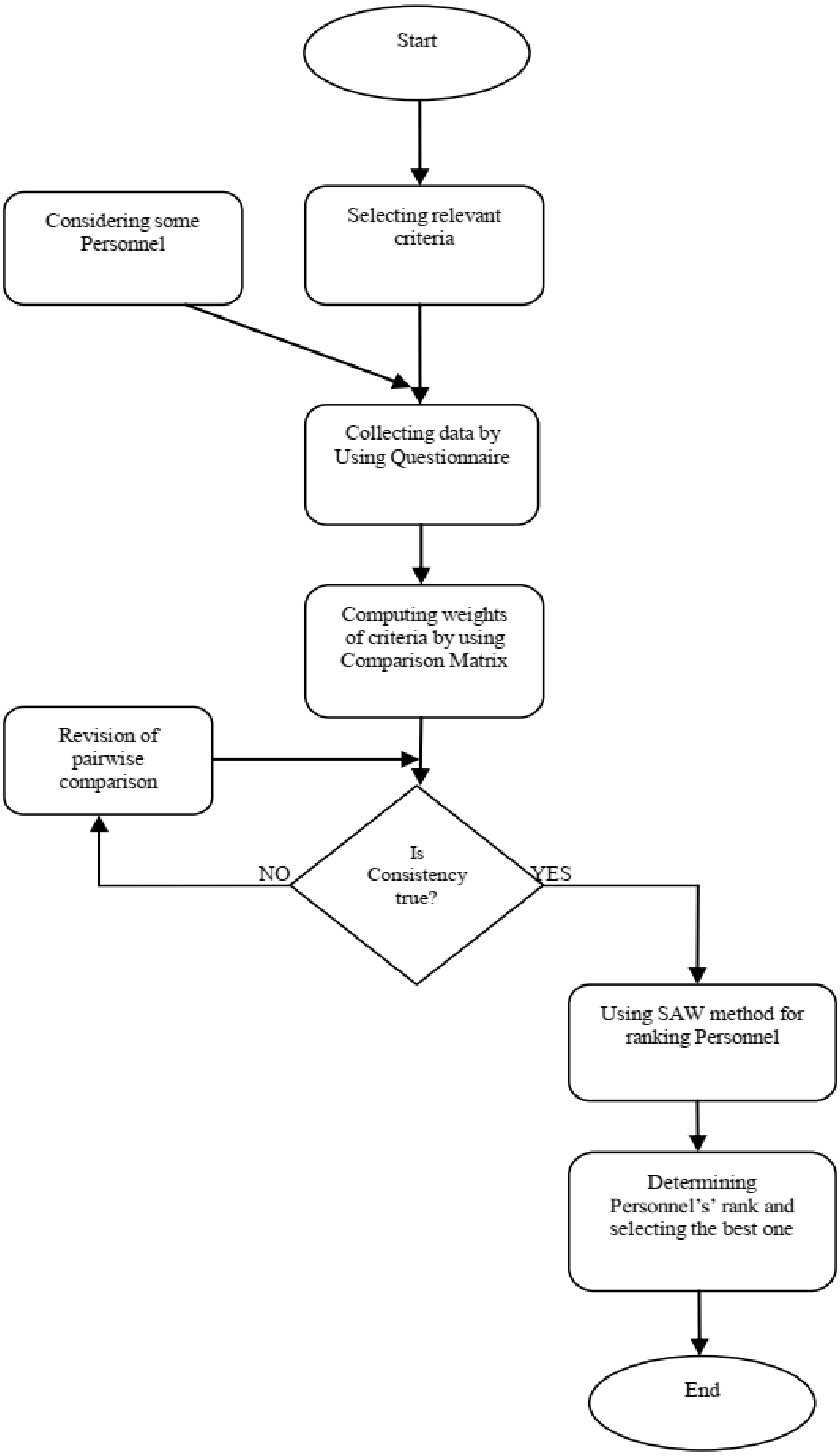

Figure 3-1 Flowchart Simple incremental weighting method.

3.2.2 Hierarchical Analytical Process (AHP)

The hierarchical analytical process is a tool for multi-criteria decision-making. This tool is a special value approach for comparing criteria pairs. It also provides a method for calibrating the numerical scale to measure quantitative as well as qualitative performance. AHP helps to combine group consensus. In general, this includes the method of a questionnaire to compare each element and the mean to reach a final solution.

AHP is a model and technique for relative measuring in general. We are not concerned with correctly measuring specific values in relative measurement but rather with their relationship. Relative measurement theory is particularly well-suited for situations in which the best alternative should be selected. Indeed, in many circumstances, we are less concerned with the precise scores of the options than their relative measures, which suffice to determine which option is the best. Additionally, when the attributes of the alternatives are conceptual, it is challenging to create a measuring scale, and the analysis is simplified by using relative measures. The ideal goal of AHP is to construct a ranking of alternatives using binary comparisons between them as input, in accordance with the principle of relative measurement [32].

According to the authors, the AHP should be at the crossroads of decision analysis and operational research. Based on the initial definitions, the decision analysis is presented as follows:

"Decision analysis theory is designed to assist the individual in selecting a set of predetermined options" [32].

As a result, it seems that AHP research is concerned with decision analysis as long as it is employed to assist in decision making.

Some of the basic steps in this method include the following:

1. State the problem.

2. Expand the objectives of the issue by considering the goals and results

3- Identifying criteria that affect behavior.

4- Forming a hierarchical structure of different levels of objectives, criteria, and sub-criteria.

5- Compare each criterion at the relevant level and calculate the priority weight on a numerical scale. They will be easily comparable to other elements.

6- To find the maximum specific value, the CI compatibility index, CR compatibility ratio, and normalized values for each criterion are performed.

7. If the specified maximum particular values, CI and CR, are acceptable, decisions can be made using normal values. Alternatively, the method is repeated until the appropriate range of values is achieved [33].

The main objective of applying AHP in addition to SAW in this study is to increase the accuracy of prioritized data by SAW. The SAW method does not consider the effect of criteria on each other, and by applying the AHP method, we try to overcome this shortcoming.

3-2-2-1 Priority vector in AHP

The generation of a priority vector for each pairwise comparison matrix is a critical step in AHP [32]. In the proposed method, the AHP method is employed to extract the exact relationship between the criteria in patient prioritization. Since in the proposed method, the simple incremental weighting method is used to extract the initial weight of patients' criteria, the output normalized weight matrix of the SAW method is used as the AHP input. Therefore, each element of the input matrix to AHP in the form of a_{ij} indicates the ratio between the two weights w_i and w_j, which i and j are the criteria for patients. Therefore, all columns A are proportional to each other, and as a result, the weight vector is equivalent to each normalized column A. Thus, in this scenario, the data in matrix A may be integrated with w, and there is no data loss.

Given that the AHP method is based on the premise that "a single decision-maker is quite rational and can accurately express his preferences for all pairs of independent options and criteria using positive real numbers" [32], therefore, in the proposed method, it is assumed that the values of the required criteria are expressed by specialists and medical staff based on the medical record and the condition of the patient and the medical staff as real positive values. On the other hand, based on the use of the multi-criteria method, there may be contradictions between criteria. Therefore, in the AHP method, due to the use of several criteria to obtain patients' priority for general surgery, inconsistencies between the criteria in this method should also be investigated.

3-2-2-2 Compatibility calculation in AHP

Using the proposed method, specialists and physicians should correctly describe the relationship between the two criteria as a logical decision-maker, for example, $a_{ij} = w_i / w_j, \forall i, j$. Furthermore, the SAW method In the proposed method is used to avoid ambiguity of the criteria weight. Therefore, the following two conditions must be met to check the compatibility of the criteria in the AHP method:

1) All inputs to the normal matrix should be based on a pairwise comparison of criteria, which implies that each directly a_{ik} comparison is validated precisely by all indirectly $a_{ij}\, a_j\, k_j$ comparisons.

2) Formally, a decision-maker who can make perfectly consistent pair comparisons.

A matrix that has these transferability conditions is called compatible. Therefore, in the proposed output method, the hierarchical analysis process will be used as an accurate prioritization based on multiple criteria by examining the interaction of criteria as the input of the VIKOR method for labeling.

3-2-3 VIKOR method for labeling patients

Different multi-criteria methods often produce different results for patient prioritization for elective surgery from decision options. As a result, in multi-criteria techniques, the notion of a compromise solution is crucial. After identifying the criteria for patients and treatment centers in a patient prioritization application, the full version of VIKOR that has been suggested may be utilized to determine optimum priorities. The VIKOR approach was created for optimizing complicated systems using several criteria and has gained widespread acceptance. It is concerned with ranking and prioritizing possibilities based on criteria that are in contradiction. Compromise ranking is accomplished using the VIKOR technique by assessing the degree of proximity to the ideal option, and a compromise is reached using reciprocal weights for various patient criteria. The main steps of the VIKOR method in the proposed multi-criteria combined method are presented:

1) Determining the values of interest for the criteria related to patients in the proposed method.

T= { T_1, T_2, T_3, ..., T_j, . . ., T_n}= { The most desired element (r_{ij}) or criteria j goal value}

In which r_{ij} is the data related to the proposed method's output decision matrix of the AHP method.

2) S_i and R_i values are based on the following equation:

$$S_i = \sum_{j=1}^{n} w_j \left(1 - e^{\frac{|r_{ij}-T_j|}{-A_j}}\right), R_i = \max_j \left[w_j \left(1 - e^{\frac{|r_{ij}-T_j|}{-A_j}}\right)\right] \tag{3-6}$$

Where A_j is equal to 1 if the standard values of j are normalized between 0 and 1, otherwise it is equal: $\max\{r_j^{max}, T_j\} - \min\{r_j^{min}, T_j\}$

r_j^{max} and r_j^{min} are equal to the highest and lowest values inside the criterion j, and W_j is equal to the criterion j's weight.

3) Calculate the Q_i index, which is defined as follows:

$$Q_i = \begin{cases} \left[\frac{R_i - R^-}{R^+ - R^-}\right] & if S^+ = S^- \\ \left[\frac{S_i - S^-}{S^+ - S^-}\right] & if R^+ = R^- \\ \left[\frac{S_i - S^-}{S^+ - S^-}\right] \nu + \left[\frac{R_i - R^-}{R^+ - R^-}\right](1-\nu) & otherwisw \end{cases} \tag{3-7}$$

Where $S^{-} = \min S_i$ ، $S^{+} = \max S_i$ ، $R^{-} = \min R_i$ و $R^{+} = \max R_i$. We define ν to be a weight for the majority approach (use by the majority group) so that $1 - \nu$ is considered as the weight of the minority group. The value of ν is between 0 and 1, which is compared with a threshold of 0.5 [34].

4) The results are sorted in descending order S and Q, respectively.

5) According to the obtained values, patients can be categorized as high priority patients given the results of the criteria in list Q and as low priority patients based on the findings of the criteria in list S.

3-2-4 Neural networks

A set of neural connections functioning with "neural networks," which are artificial neural networks, is a popular term that originated when it was discovered that the human brain does computations differently than digital computers. The human brain is a very sophisticated, parallel, and nonlinear computer (information processing system). The brain can coordinate its structural components, known as neurons (basic processing elements), execute specific tasks several times quicker than today's greatest digital computers, such as pattern classification, perception, and motor control. The brain at birth has a massive structure that can produce its own rules through what we call "experience." In fact, experience is gained over time [35].

A neural network is generally a machine in which the function of the brain is modeled when it performs a particular task. It is, therefore, a broadly distributed parallel-processing neural network consisting of basic processing elements that are innately capable of storing information gained from experiences and preparing them for use. The network receives information as a result of a learning process from its environment, and the intensity of the connections between neurons, known as synaptic weights (free parameters), are used to store the information received. These networks have shown very high efficiency for estimation and approximation [36].

A learning algorithm is a mechanism used to perform the learning process in which the synaptic network weights are modified step by step to achieve the desired design goal. Synaptic weight correction is an old way of designing neural networks. In addition, the neural network can modify its topology.

It is clear that the neural network's processing strength is derived mostly from its broad parallel structure and secondarily from its capacity to learn and generalize. The term "generalization property" refers to the ability of the neural network to provide acceptable outputs for inputs that were not observed during training. The neural network can respond to complex, large-scale problems that have been unexplored due to these two information-processing skills. However, neural networks cannot resolve all issues in practice but must be combined with a sustainable system engineering method [37].

Beginning in the late 1990s, research into building scalable systems to measure the dynamic properties of distributed environments, such as the Meteorological Studies Network, began. The Meteorological Studies Network examines network resources and predicts future resource efficiency with statistical technology. Application-level timers can use forecasting to achieve better performance [38].

A predictive analytical algorithm's objective is to simulate the relationship between two variables: input and output. The neural network approach overcomes this obstacle by building a mathematical model that is very close to the biological operation of a neuron. Even though the researchers of this approach utilized several biological terms to describe the internal dynamics of the neural network modeling process, it is based on a straightforward mathematical concept. For example, consider the simple linear mathematical model as follows:

$$Y = 1 + 2X_1 + 3X_2 + 4X_3 \tag{3-8}$$

Where y is the output value and X1, X2, and X3 are the input properties. 1 implies interception, whereas 2, 3, and 4 indicate coefficients for the input of X1, X2, and X3 variables. As illustrated in Figure 2-3, this simple linear model can be presented topologically.[39].

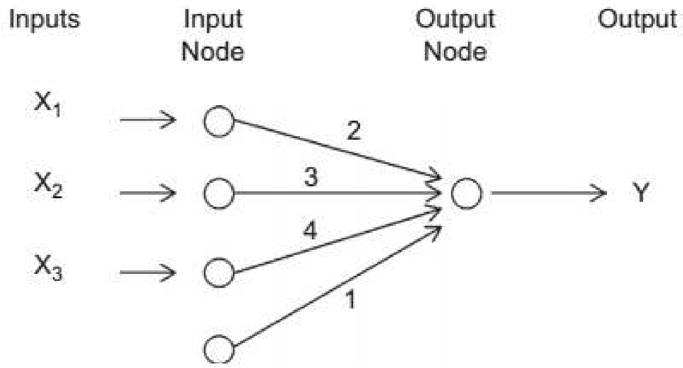

Figure 3-2 Topology model [39]

X1 is the input value in this topology, and it goes via a node marked by a circle. Then double the value of X1 by its weight, which is 2. All additional variables (X2, X3) are likewise sent through a node and its weight. The last node is a specific case that has no input variable and is used exclusively for interception. As a final step, all connection values are totaled together to provide the output prediction Y. Simple linear model Y = 1 + 2X1 + 3X2 + 4X3 is depicted in Figure 3-2, with the topology indicated. The topology also resembles a very primitive artificial neural network, which is another feature (ANN). This is a basic structure for an artificial neural network (ANN). With more complicated nonlinear interactions than data, the neural network model may learn to adjust node weights. Inspired by the human nervous system, artificial neural networks (ANN) are computer and mathematical models, and many terms used in this context have biological roots.

In the context of a neural network, nodes are referred to as "units." The node layer closest to the input is referred to as the "input node," while the node's last layer is referred to as the "output node." In the output layer, aggregation and transition functions can be implemented. The transfer function range is specified here. In addition to aggregation and transmission, the output layer also performs an activation function. Figure 3-2 depicts a perceptron, the simplest artificial neural network, with just one input and one output layer. Due to the fact that the input is unidirectional, the perceptron is referred to as a forward transmission neural network, which is described below as multi-layer perceptron (MLP) networks.

3-2-4-1 Multilayer Perceptron Network (MLP)

Three layers comprise this network: an input layer, one or more hidden layers, and an output layer. This neural network is typically trained using the broadcast algorithm, abbreviated as BP. The BP learning approach trains MLP networks by conducting calculations between the network's input and output and then broadcasting the derived error values to the preceding layers. At first, the output is computed layer by layer, with each layer's output serving as the input for the subsequent layer. As the first step in post-diffusion mode, the output layers are adjusted, as each of the output layer neurons has a good value, and weights may be altered using these values and update rules. There are various issues with error propagation that the approach cannot resolve despite its great results, due to long or unclear learning time, improper selection of learning coefficient, or random distribution of initial weights. In some instances, a local minimum impairs the learning process since the response is positioned in the smooth regions of the threshold functions. This algorithm's training phases are as follows: (A) - Each link is assigned a randomly generated weight matrix (B) - Optimal vector selection for input and output (C) - Calculating the output of each layer, and hence the output of the output layer (D) - By comparing the actual output to what the network anticipates, network error propagation is utilized to calculate weight updates. (E) Before returning to c or completing training, evaluate the network's performance against a set of specified performance criteria, such as the square root of the mean square error (MSE). The MLP neural network for prediction is shown in Figure 3-3 [39].

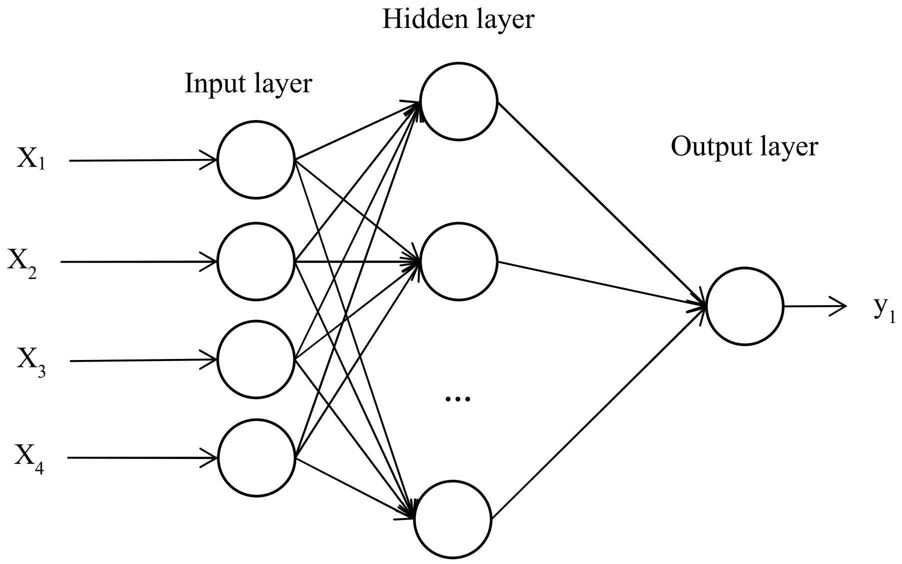

Figure 3-3- MLP neural networks structure for prediction [39]

3-2-4-2 Modeling of Artificial Neural Networks

Artificial neural networks strive to find underlying correlations between data by learning from data, trying to map between the input layer and the output layer utilizing processors called neurons. Output layers receive data from hidden layers that process and analyze the input layer's data. It is only through obtaining instances that a network may be trained. Eventually, as a result of the training phase, learning occurs. When the discrepancy between the predicted and calculated values is considered reasonable, a change in the communication weights across layers is termed network learning. After these requirements are fulfilled, the learning process is complete, and the weights show how much information the network has stored. It is possible to apply trained neural networks to anticipate outputs that are acceptable for a new data set. The main properties of artificial neural networks are their high processing speed, pattern learning capability, capacity to generalize information after learning, adaptability to undesirable errors, and lack of significant disruption in the event of problems with specific links related to the network weight distribution.

An artificial neural network is often used to model complicated nonlinear interactions between input and output variables. Thus, the topology may be constructed with more than one layer in addition to the input and output layer, known as the hidden layer. This layer of nodes connects the inputs from the previous levels to an active function in the current layer which output is computed by using a more complicated set of input values [39].

The active function, which comprises an aggregate function, a routine summary, and a transfer function, is applied in the output node. Transfer functions may take on a variety of shapes, including normal, sigmoid, hyperbolic, logistic, and linear curves.

The transfer function and multiple hidden layers make it possible to express or estimate any continuous mathematical connection between the input and output variables. As a consequence, a multilayer artificial neural network performs the function of a generic estimator. But, by including various user preferences such as topology, transfer function, and the number of hidden layers to search for, a very time-consuming optimal solution would arise [39].

Post-diffusion is a technique that artificial neural networks employ to establish a connection between input properties and output class labeling. Weighting the connections is a fundamental component of training for any network structure and activation function. There are some parallels between neural networks and human neurons in terms of information transport. The predicted output error is calculated by comparing each training record to the actual output value. The model then employs the error to modify the weights and reduce the error in subsequent training records, which is continued until the error is decreased to a reasonable threshold. The correction rate from one step to another must be properly managed. The following steps describe how to construct an artificial neural network using training data.

Step 1: Define the Activation Function and Topology.

Suppose there is a data set with three numerical properties (X1, X2, and X3) and a numerical output (Y). As depicted in Figure 3-4, a two-layer topology and a basic aggregate active function are employed as components of a relational model. This example makes no use of a transfer function:

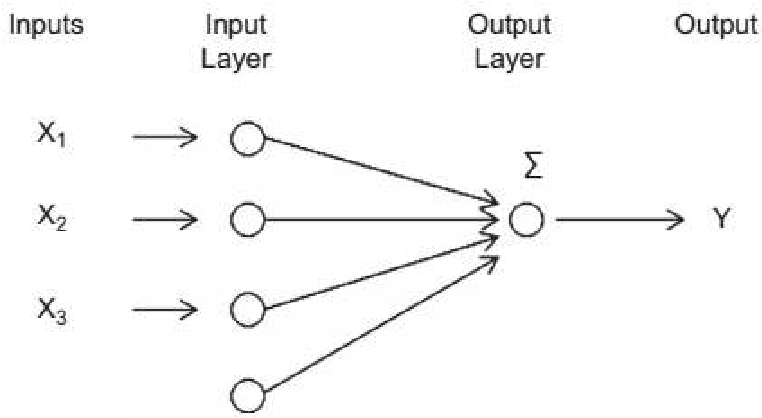

Figure 3-4 Two-layer topology and an active simple aggregation function [39]

Step 2: Initialize

Assume that the four linkages are initially weighted as 1, 2, 3, and 4. Consider the following model and test record, including all known input values of 1 and known output values of 15. As a consequence, x1=x2=x3=1 and the output value y = 15 is obtained. Figure 3-5 illustrates an instance of an initialization training record:

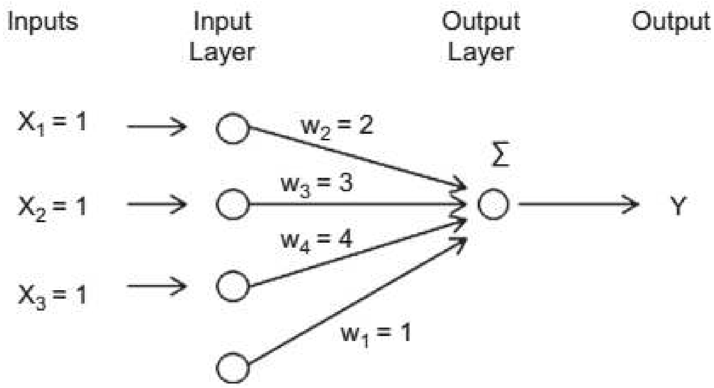

Figure 3-5 Initialization and first record [39]

Step 3: Calculate the error

Record output can be calculated from Figure 3-5. This is a forward-looking trend by passing the input parameters and computing the output. As per the present model, the estimated output y is equal to:

$$1 + 1 * 2 + 1 * 3 + 1 * 4 = 10$$

In this case, the difference between the actual output of the training record and the anticipated output of the error is equal to:

$$E = Y - \bar{Y} \tag{3-9}$$

This training record has an error rate of 15-10 = 5.

Step 4: Adjust the weight

Weight control training is crucial for an artificial neural network. The error associated with this step is returned in a reverse way to each other node in the network. With a fraction of the error, the weight of links is adjusted from their previous values. The learning rate is defined as the fraction of the error that is applied. The value is between 0 and 1. Values close to 1 indicate a significant change in the model for each training record, while results close to 0 indicate minor changes and fewer adjustments. The new link weight (W) is calculated by adding the previous link weights (W') and the result of the learning rate and error ratio (λ* E).

$$W = W' + \lambda * E \tag{3-10}$$

Selecting λ can be difficult in implementing an ANN. It is common for some models to begin with λ near 1, but as training progresses, the value of λ drops in each cycle. Thus, each consecutive record and error during the training cycle will not affect the connection between the model layers. Figure 3-6 demonstrates the propagation of an error inside the topology.

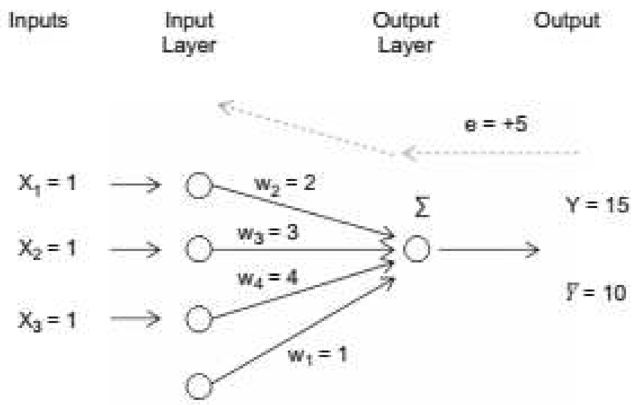

Figure 3-6 Neural networks with error propagation [39]

W2 = 2 is the current weight of the first connection. With a 0.5 learning rate, the new weight will be :

W2 = 2 + 0.5 *5/ 3 = 2.83.

Where 2 denotes the current weight, 0.5 signifies the learning rate, 5 represents the sum of the current and past weights, and 3 indicates the number of links. Because the error is multiplied by three links from the output node, it is divided by three. Likewise, all links' weights will be adjustable. The following cycle will generate a new error for the next training record. This cycle is repeated until the iteration cycle has processed all training records. The same training instances may be used again as long as the error rate is below a certain threshold. In this subsection, an artificial neural network in its simplest form was investigated. in reality, each nominal class value will be represented by several hidden layers and output linkages. Because of the numerical calculations required, the ANN model works well with numerical inputs and outputs. Nominal attributes included in inputs must be preprocessed into several numeric attributes (one for each value), a procedure analogous to creating a fictional variable. This additional processing increases the number of links to the neural network representing the nominal attributes and hence the computer resources needed. As a result, an ANN is better suited to attributes with a single kind of numerical data.. [39]. Figure 3-7 shows the proposed method flowchart:

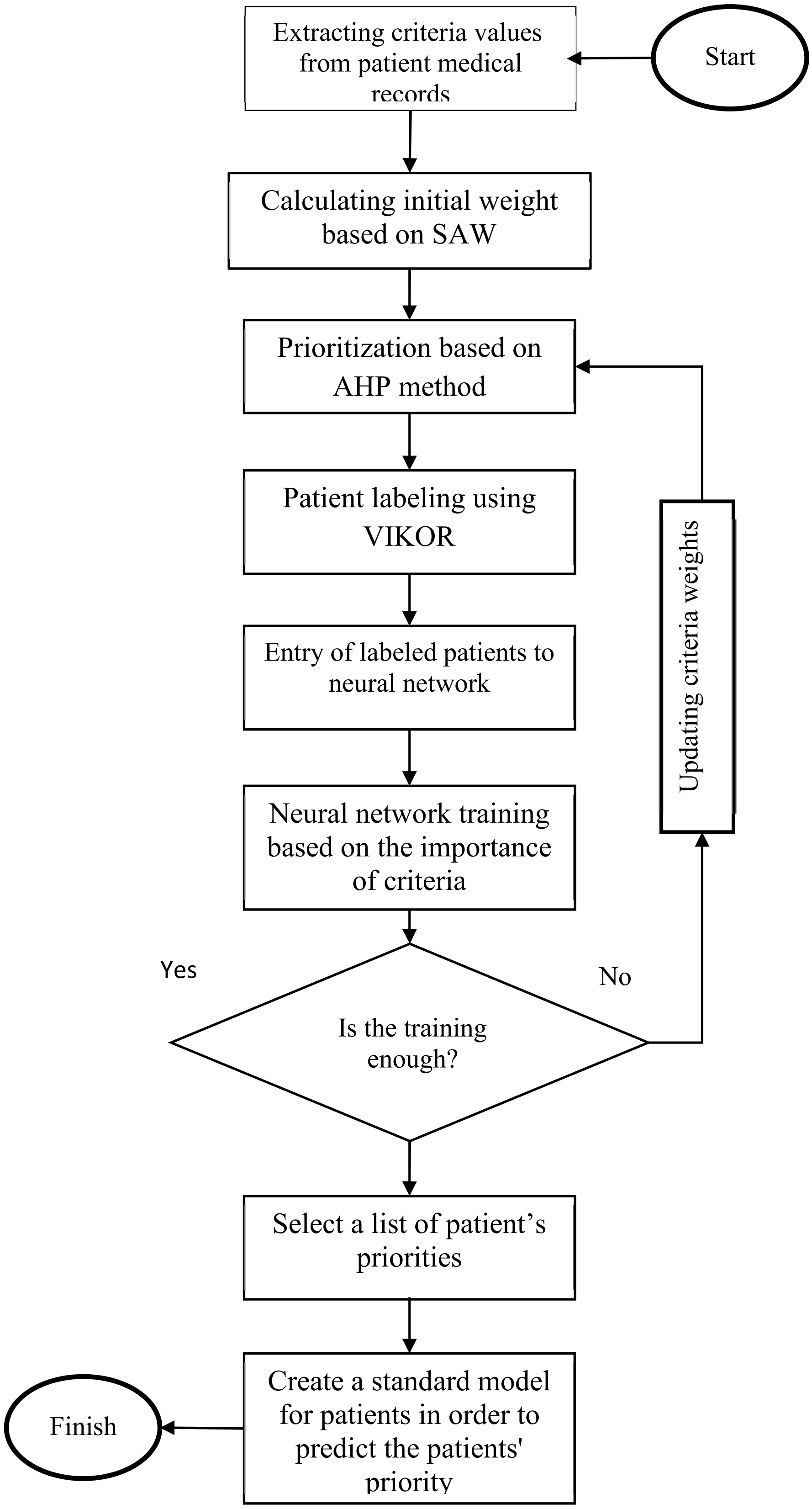

Figure 3-7 proposed method flowchart

Chapter4: Implementation of the proposed method

4-1 Introduction

Today, health care systems and treatment centers try to provide high-quality services to all patients. Hospitals try to distribute the available resources fairly among patients to facilitate the process of treating patients. Therefore, caring for all patients is one of the main duties of hospitals to provide medical services. On the other hand, the lack of medical facilities and equipment has made not all patients have access to the required tools and services at the same time. Therefore, patients who are not in good physical and other critical conditions should prioritize treatment to prevent irreparable damage. Thus, prioritization of patients in medical centers is one of the requirements of health care systems, which has been more focused on today. Therefore, in this study, we tried to prioritize patients for elective surgery in health care systems and medical centers using a combination of simple incremental weighting methods, hierarchical analysis process, and VIKOR for initial prioritization and neural networks for training and final weighting has been used for patients. In the rest of this chapter and the dissertation, we will implement the proposed method.

4-2 Implementation of the proposed method

As noted before, the proposed method examined the patient's condition using various criteria. Input criteria in the proposed method include 12 main criteria obtained from patients' records in the hospital environment. The database contains information on 299 patients admitted to the hospital for heart surgery[1]. Table 4-1 shows an example of patient data used in this study.

Table 4-1 An example of the data set used

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	75	55	65	50	65
Anaemia	0	0	0	1	1
Creatinine_ phosphokinase	582	7861	146	111	160
Diabetes	0	0	0	0	1
Ejection_fraction	20	38	20	20	20
High_blood_pressure	1	0	0	0	0
Platelets	265000	263358	162000	210000	327000
Serum_creatinine	1.9	1.1	1.3	1.9	2.7
Serum_sodium	130	136	129	137	116
Gender	1	1	1	1	0
Smoking	0	0	1	0	0
Time	4	6	7	7	8

[1] https://www.kaggle.com/andrewmvd/heart-failure-clinical-data

As shown in Table 4.1, the data set in the Makhnev Learning Database collected data on hospitalized cardiac patients and provided them to researchers for research. On the other hand, considering that the proposed method uses a multi-criteria approach, the opinions of specialist physicians on each of the criteria should also be considered in methods of weighting and prioritization of patients. In order to determine the status of patients, they must first assess the patient's condition based on the values of the criteria and then achieve a general prioritization based on the concurrence of the criteria. In this respect, to determine the importance of each of the criteria, physicians specializing in this field should express their opinions and determine the importance of each criterion used. Table 4-2 shows the weighting of specialists for each of the criteria.

Table 4-2 Weighting criteria used for patients by experts

Criteria	Experts' opinion
Age	0.109
Anemia	0.105
Creatinine_ phosphokinase	0.101
Diabetes	0.097
Ejection_fraction	0.094
High_blood_pressure	0.094
Platelets	0.094
Serum_creatinine	0.093
Serum_sodium	0.088
Gender	0.071
Smoking	0.078
Time	0.083

As seen in Table 4-2, due to the pandemic and limited access to hospital resources, the weighting criteria for patients are computed using random functions implemented in Matlab [42], as illustrated in Appendix B. The combination of the obtained weight with the values of the criteria can determine the initial condition of the patient using the simple incremental weighting method. In the continuation of this chapter, the implementation of the proposed method, which consists of four methods, will be performed using the current data set and the values of weights for the criteria.

4-2-1 Implementation a simple incremental weighting method

Simple incremental weighting is a technique for resolving multi-criteria decision-making issues. In the proposed method, according to the explanations of the previous chapter and based on the present data set, values related to multiple criteria for patients hospitalized in the cardiac intensive care unit who are waiting for surgery have been collected. The proposed method is a multi-criteria method according to the criteria related to heart patients, which can be generalized to other data sets and hospital wards. The main benefit of the incremental weighting method is the simple finding of the number of weight performance scores for each option in all criteria and sub-criteria for each patient.

As stated in the preceding chapter and shown in the previous section in Table 4-1, the data sets used in this study have different values, and the so-called data are not normal. Given that data values per criteria can negatively affect the results, there is a need to normalize the data first. Normalization of data by mapping the values related to the criteria in the interval [0,1] reduces the negative effect of criteria with larger values on the criteria with smaller values and increases the accuracy of statistical methods. Because there are different methods for normalization in publications [40, 41], in the proposed method, five methods of normalization have been used to observe the changes and results related to different methods of normalization. The purpose of using different normalization methods in the proposed method is to navigate between the methods and select more probable results for the initial prioritization on which the final prioritization should be based. The more accurate the normalization and selection of the initial priority based on patient characteristics and expert opinions, the more accurate the final result will be. Therefore, in the proposed method, five different normalization methods have been used to determine the optimal normalization. Table 3-4 shows the values related to normalization by the MAX method.

Table 4-3 Data normalized by MAX method

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	0.7895	0.5789	0.6842	0.5263	0.6842
Anemia	0	0	0	1	1
Creatinine_ phosphokinase	0.0740	1	0.0186	0.0141	0.0204
Diabetes	0	0	0	0	1
Ejection_fraction	0.2500	0.4750	0.2500	0.2500	0.2500
High_blood_pressure	1	0	0	0	0
Platelets	0.3118	0.3098	0.1906	0.2471	0.3847
Serum_creatinine	0.2021	0.1170	0.1383	0.2021	0.2872
Serum_sodium	0.8784	0.9189	0.8716	0.9257	0.7838
Gender	1	1	1	1	0
Smoking	0	0	1	0	0
Time	0.0140	0.0211	0.0246	0.0246	0.0281

As shown in Table 4-3, all values for the five patients listed in Table 4-1 as a sample of their criteria values were normalized according to the criteria values of all patients and, in the interval [0, 1], is mapped. Tables 4-4 to 4-7 show the Sum, Vector, MAX-MIN, and DEA normalization methods, respectively.

Table 4-4 Data normalized by Sum method

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	0.0041	0.0030	0.0036	0.00027	0.0036
Anemia	0	0	0	0.0078	0.0078
Creatinine_ phosphokinase	0.0033	0.0452	0.00083	0.00063	0.00091
Diabetes	0	0	0	0	0.0080
Ejection_fraction	0.0018	0.0033	0.0018	0.0018	0.0018
High_blood_pressure	0.0095	0	0	0	0
Platelets	0.0034	0.0033	0.0021	0.0027	0.0042
Serum_creatinine	0.0046	0.0026	0.0031	0.0046	0.0065
Serum_sodium	0.0032	0.0033	0.0032	0.0034	0.0028
Gender	0.0052	0.0052	0.0052	0.0052	0
Smoking	0	0	0.0104	0	0
Time	0.00010	0.00015	0.00017	0.00017	0.00020

Table 4-5 Normalized data by Vector method

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	0.0700	0.0513	0.0606	0.0467	0.0606
Anemia	0	0	0	0.0880	0.0880
Creatinine_ phosphokinase	0.0298	0.04023	0.0075	0.0057	0.0082
Diabetes	0	0	0	0	0.0894
Ejection_fraction	0.0290	0.0551	0.0290	0.0290	0.0290
High_blood_pressure	0.0976	0	0	0	0
Platelets	0.0546	0.0542	0.0334	0.0432	0.0673
Serum_creatinine	0.0633	0.0367	0.0433	0.0633	0.0900
Serum_sodium	0.0550	0.0575	0.0546	0.0580	0.0491
Gender	0.0718	0.0718	0.0718	0.0718	0
Smoking	0	0	0.1021	0	0
Time	0.0015	0.0023	0.0027	0.0027	0.0031

Table 4-6 Data normalized by MAX-MIN method

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	0.6364	0.02727	0.04545	0.01818	0.04545
Anaemia	0	0	0	1	1
Creatinine_ phosphokinase	0.0713	1	0.0157	0.0112	0.0175
Diabetes	0	0	0	0	1
Ejection_fraction	0.0909	0.3636	0.0909	0.0909	0.0909
High_blood_pressure	1	0	0	0	0
Platelets	0.2908	0.2888	0.1660	0.241	0.3660
Serum_creatinine	0.1573	0.0674	0.0899	0.1573	0.2472
Serum_sodium	0.4857	0.6571	0.4571	0.6857	0.0857
Gender	1	1	1	1	0
Smoking	0	0	1	0	0
Time	0	0.0071	0.0107	0.0107	0.0142

Table 4-7 Data normalized by DEA method

Criteria	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Age	0.9980	0.9961	0.9971	0.9956	0.9971
Anemia	0.09941	0.09941	0.09941	1	1
Creatinine_ phosphokinase	0.9967	1	0.9965	0.9964	0.9965
Diabetes	0.9943	0.9943	0.9943	0.9943	1
Ejection_fraction	0.9952	0.9966	0.9952	0.9952	0.9952
High_blood_pressure	1	0.9948	0.9948	0.9948	0.9948
Platelets	0.9967	0.9967	0.9961	0.9964	0.9970
Serum_creatinine	0.9969	0.9965	0.9966	0.9969	0.9972
Serum_sodium	0.9947	0.9965	0.9944	0.9968	0.9906
Gender	1	1	1	1	0.9905
Smoking	0.9951	0.9951	1	0.9951	0.9951
Time	0.9939	0.9940	0.9940	0.9940	0.9940

As shown in Tables 4-3 to 4-7, the values of patient criteria vary according to different normalization methods. We will now use this normalized data to generate the initial ranking by the incremental weighting method.

The simple incremental weighting method is a multi-attribute method based on the concept of a weighted set from a normalized data set. This method deals with the initial weighting of patients according to the features and criteria used in the proposed method. This method seeks to summarize the weight to rank the performance of each patient according to all the criteria in the data set. In other words, the simple incremental weighting method tries to determine the initial condition of the patient at a glance according to the values of the characteristics in each patient. In other words, according to the patient's condition and the list of criteria related to each patient, this method assigns weight to each of the criteria pertaining to patients, which based on the total weight of these criteria, patients are given initial priority. The disease with the highest score will be the best option and is recommended for prioritization in higher categories. Table 4-8 shows the values related to patient weighting. The simple incremental weighting method is based on expert opinions and different normalization methods.

Table 4-8 Weighting Criteria for patients in a simple incremental weighting method

SAW & Normalization	SAW-MAX	SAW-Sum	SAW-Vector	SAW-MAX-MIN	SAW-DEA
Patient 1	1.3760	0.0145	0.1858	1.3087	1.8402
Patient 2	1.1916	0.0095	0.1413	1.1231	1.8356
Patient 3	1.3392	0.0154	0.1846	1.2616	1.8403
Patient 4	1.3536	0.144	0.1840	1.2780	1.8405
Patient 5	1.3867	0.0148	0.1877	1.2850	1.8397
Patient 6	1.5876	0.0165	0.2071	1.5409	1.8417
Patient 7	1.3634	0.0144	0.1847	1.3074	1.8407
Patient 8	1.6065	0.0166	0.2119	1.5393	1.8419
Patient 9	1.2485	0.0137	0.1784	1.1987	1.8397
Patient 10	1.5158	0.0149	0.1865	1.4581	1.8392

As shown in Table 4-8, the values for the criteria of the simple incremental weighting method were calculated according to the different normalization methods for each patient. According to the values in Table 4-8, it can be seen that different normalization methods have obtained different values for each patient. Therefore, it may affect the final outcome and patient prioritization. As mentioned, the simple incremental weighting method is used in the proposed method to determine the initial priority of patients. Therefore, in this step, we will determine the initial priority of patients based on different normalization methods to select the exact initial prioritization to continue the steps. Table 4-9 shows an example of patients' initial prioritization based on simple incremental weighting method according to different normalization methods.

Table 4-9 Initial prioritization of patients based on simple incremental weighting method

SAW & Normalization	SAW-MAX	SAW-Sum	SAW-Vector	SAW-MAX-MIN	SAW-DEA
Patient 1	8	8	8	6	8
Patient 2	6	6	6	8	6
Patient 3	11	23	23	11	23
Patient 4	23	28	28	23	28
Patient 5	28	11	11	28	37
Patient 6	10	79	48	38	14
Patient 7	38	48	79	10	17
Patient 8	43	22	38	43	12
Patient 9	79	43	22	37	35
Patient 10	48	54	14	79	43

Table 4-9 shows, different prioritization for patients has been achieved according to different normalization methods. As noted above, the standard MCDM tool [42] was employed in the proposed method to implement the SAW method, which included five normalization methods. Data normalization is the process of mapping data in the range [0,1]. According to Table 4-8, each normalization technique has mapped the patient's criterion values in this range based on their policies. The SAW technique was then used to weigh these values. Logically, the ideal weight for the patients' criterion is in the range [0,1], and the initial prioritizing of patients will be done more appropriately based on this. Table 4-8 shows that only the combination of the VECTOR normalizing method and the SAW method obtained the desired value in the range. The results of the MAX, MIN-MAX, and DEA normalization procedures are out of range. The SUM method has also yielded near-zero numbers, which may not appropriately prioritize patients. As a result, we choose the prioritization of the Vector normalization method for initial prioritization based on the simple incremental weighting method. In this regard, in the second step of the proposed method, based on the values of different criteria in the data set and the initial prioritization obtained from the simple weighting method, we determine the final priority of patients in the hierarchical analysis process method.

4-2-2 Implementation of Hierarchical Analysis

AHP method is one of the multi-criteria decision-making methods in which different criteria are collected on the subject. Criteria selection, the first part of the hierarchical analysis process, is where a number of criteria that are relevant to the topic are selected. In the next step, the effect of each of the criteria on each other is measured and based on that, the final weight of each factor is determined. The hierarchical analysis approach is one of the most extensively used techniques for ranking and assessing the relevance of elements. It prioritizes factors by performing pairwise comparisons of options to each of the criteria. The goal of the AHP approach is to identify the best option based on various criteria using pairwise comparisons. Additionally, this approach is used to weigh the criterion. This approach has been used to identify the priority of heart surgery patients admitted to the cardiac unit in the proposed method. The suggested method tries to determine the weight of the patient and determine the patients' priority for the selected surgery by examining the effect of the selection criteria on each other. Depending on the health status, the medical staff, and the condition of the hospital, the values are determined for each patient waiting in line for surgery, which can be used to determine the patient's weight and prioritize them. Table 4-10 shows a part of patients' weighting based on the hierarchical analysis method.

Table 4-10 Weighting of criteria related to patients in the hierarchical analysis method

Patients	AHP	Patients	AHP	Patients	AHP
Patient 1	2.7099	Patient 11	3.1141	Patient 21	3.5918
Patient 2	1.4340	Patient 12	3.6956	Patient 22	3.5009
Patient 3	3.2319	Patient 13	2.2101	Patient 23	3.8132
Patient 4	3.1896	Patient 14	3.9708	Patient 24	3.5183
Patient 5	3.0529	Patient 15	4.0803	Patient 25	2.2127
Patient 6	4.1049	Patient 16	3.0152	Patient 26	2.7221
Patient 7	3.2173	Patient 17	3.6109	Patient 27	3.4165
Patient 8	4.3793	Patient 18	2.4075	Patient 28	3.4321
Patient 9	2.9816	Patient 19	3.6463	Patient 29	1.3821
Patient 10	2.0438	Patient 20	2.4535	Patient 30	3.1114

As shown in Table 4-10 weighting of patients has been calculated using the AHP method and considering the cross interaction of criteria with each other. In this method, the cross-correlation of criteria to each other is obtained using the AHP method and is used to determine the final weight. As mentioned, due to the differences in normalization methods, the Vector normalization approach has been used, based on which the effect of criteria on each other in the AHP method has been calculated, and the weight values of patients based on this effect of criteria on each other has been shown in Table 4-10. Now, based on the new weight values of patients, we will finalize the patients based on the proposed method. In the final prioritization of patients, in addition to considering the health status of patients, the effect of criteria on each other and the opinions of experts are also considered. Thus, since the suggested technique is presented as a multi-criteria approach, the final priority of patients may be determined using the hierarchical analysis process. Table 4-11 shows some of the final prioritization of patients based on existing criteria .

Table 4-11 Prioritization of patients in the hierarchical analysis method

Priorities	AHP	Priorities	AHP	Priorities	AHP
Patient 1	298	Patient 11	73	Patient 21	201
Patient 2	281	Patient 12	188	Patient 22	283
Patient 3	296	Patient 13	276	Patient 23	289
Patient 4	172	Patient 14	53	Patient 24	165
Patient 5	247	Patient 15	297	Patient 25	200
Patient 6	135	Patient 16	209	Patient 26	277
Patient 7	228	Patient 17	218	Patient 27	279
Patient 8	251	Patient 18	61	Patient 28	221
Patient 9	104	Patient 19	282	Patient 29	292
Patient 10	284	Patient 20	229	Patient 30	244

As shown in Table 4-11, the final prioritization of patients is based on the patients' health status, the effect of the criteria on each other, and the opinion of the experts. In the next step of the proposed method, we will label patients using the VIKOR method. At this step of the proposed method, patients are labeled to transmit the criterion values to neural networks and train patients about their condition using these labels.

4-2-3 Implementation of VIKOR

Multi-criteria approaches give an appropriate platform for comparing criteria based on the examination of many contradictory criteria. The VIKOR technique was designed as a multi-criteria method for solving problems with conflicting or incomparable criteria. As previously stated, in the proposed method, criteria related to patients 'health status and experts' opinions on the relative importance of the criteria were determined by the method of the hierarchical analysis process. Contradictory and conflicting criteria were identified in the hierarchical analysis process method, and patients were prioritized accordingly. In this step, to combine the VIKOR method with the hierarchical analysis process, we will rank patients into four priority categories. Patients with lower priority rankings need faster attention and are selected for surgery at the earliest opportunity. Table 4-12 shows part of the ranking of patients based on the VIKOR method.

Table 4-12 Ranking of patients using VIKOR method

Patients	VIKOR Rank	Patients	VIKOR Rank	Patients	VIKOR Rank
Patient 1	4	Patient 11	2	Patient 21	2
Patient 2	2	Patient 12	2	Patient 22	2
Patient 3	3	Patient 13	1	Patient 23	1
Patient 4	2	Patient 14	1	Patient 24	1
Patient 5	2	Patient 15	2	Patient 25	2
Patient 6	1	Patient 16	1	Patient 26	1
Patient 7	2	Patient 17	1	Patient 27	2
Patient 8	2	Patient 18	2	Patient 28	1
Patient 9	2	Patient 19	1	Patient 29	2
Patient 10	1	Patient 20	1	Patient 30	1

As shown in Table 4-12, in the VIKOR method, patients admitted to the cardiac ward awaiting surgery are ranked. Figure 4-1 shows a histogram of patient ranking .

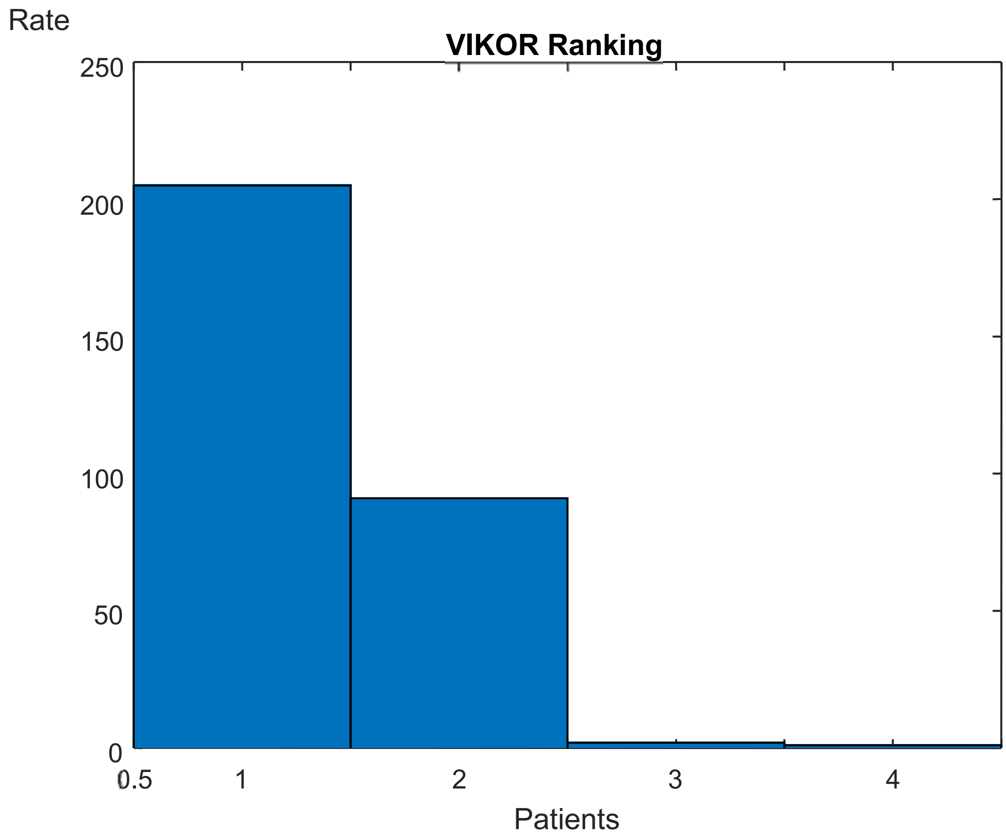

Figure 4-1 Patient ranking histogram

As shown in Figure 4-1, 205 patients have priority for surgery, 91 patients have second priority, two patients have third priority, and only one patient has a fourth priority. Therefore, according to the patient's condition and experts' opinions, these patients are labeled so that each of the criteria can be trained to patients through neural networks. Criteria training for patients can provide a model for prioritizing new patients coming to the hospital.

4-2-4 Implementation of neural networks

As mentioned in the previous section, the purpose of using neural networks in this study is to train criteria to patients whose information is in the data set. Training in these criteria can be used for similar patients who go to the hospital and lead to accurate prioritization. The neural network has three layers, as previously stated: input, middle, and output. Input data includes criteria for patients to apply to the input layer of the neural network. The neural network in the middle layer conducts the required processing to train the model on the input criteria obtained from the input layer and presents the results to the output layer. The middle layer is composed of many hidden layers that are adjusted in accordance with the number of input criteria. According to the publications [39], in the proposed method, the number of hidden inner layers equal to 15 has been selected, as shown in figure 4-2.

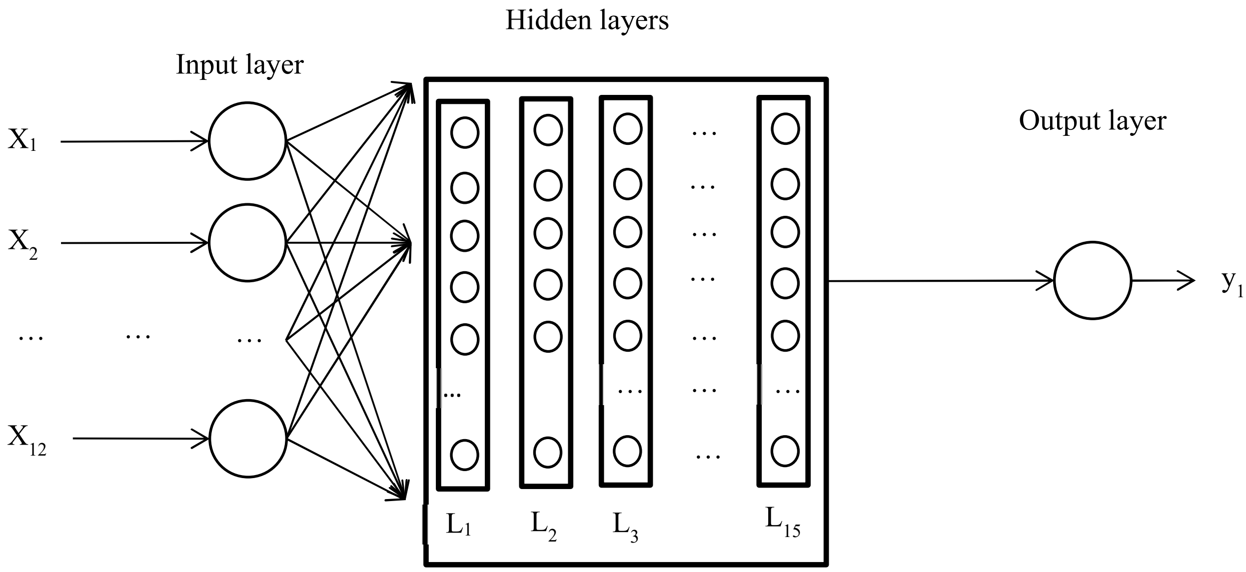

Figure 4-2 Proposed Neural Network

We employed the MATLAB simulator's "Neural Network Start" toolbox [42]. Three functions were employed to adjust weights in the neural network structure used in this research: trainscg, trainbr, and trainlm. All three functions included an error propagation function. The trainscg function is a network training function that uses the scaled conjugate gradient approach to update the weight and bias values. The trainbr function is a network training function that uses Levenberg-Marquardt optimization to update the weight and bias values. It finds the best combination of squared errors and weights to construct a well-generalized network. trainlm is a network training function that uses Levenberg-Marquardt optimization to update weight and bias values [43]. Although the trainlm function is often the fastest backpropagation method in the toolbox, it is strongly recommended as a first-choice supervised approach, despite consuming more memory than other algorithms. This is referred to as Bayesian regularisation. We utilized these functions to develop the optimal function for learning the weights of criteria and estimating a patient's priority level. The trainscg function is seen in Figure 4-3.

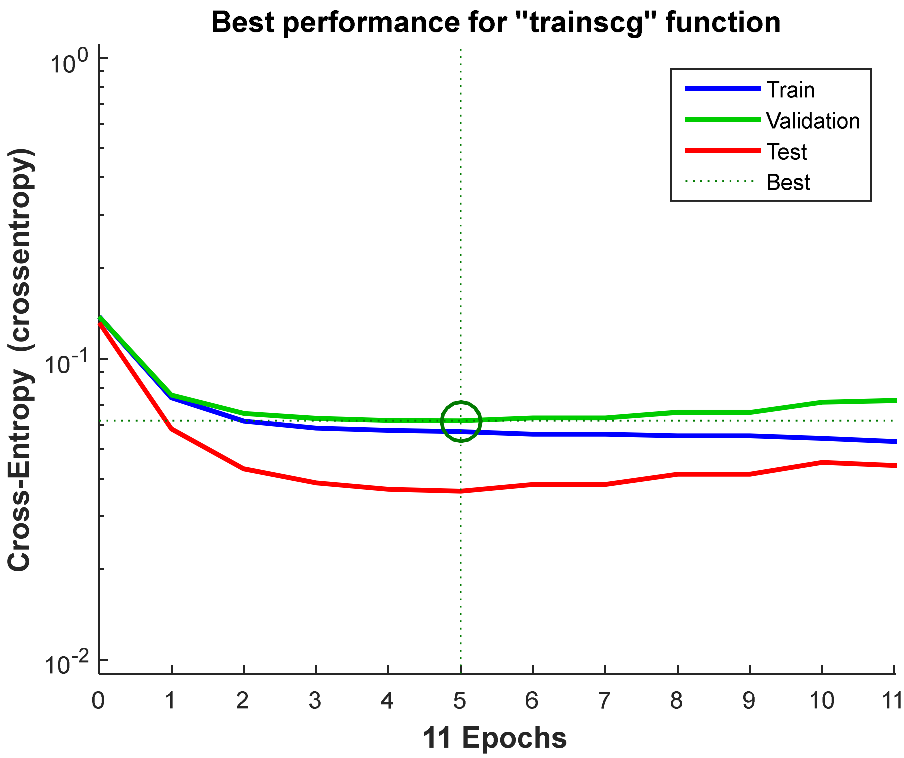

Figure 4-3 Performance curve of the trainscg function

The performance curve for the trainscg training function in the neural network is illustrated in Figures 4-3. The training performance diagram depicts the performance of the training model for training, validation, and testing data. Four lines are drawn in the figure, as illustrated in Figure 4-3. The dotted line represents the best performance in each iteration, the blue line represents the developed model's performance on training data, the green line represents the developed model's performance on validation data, and the red line represents the produced model's performance on test data. The green line, as seen, is incredibly near to the dotted line. This indicates that the suggested model performs optimally in the trainscg training function for validation data and that any line is near to the validation line, showing that the provided model performs optimally. As seen in Figure 4-3, the proposed model's trainscg function performs better on training data than on test data. After five iterations, the performance of neural networks utilizing the trainscg function tends to be optimal in the training, validation, and test stages (dotted lines). The performance curve for the trainbr training function is seen in Figure 4-4.

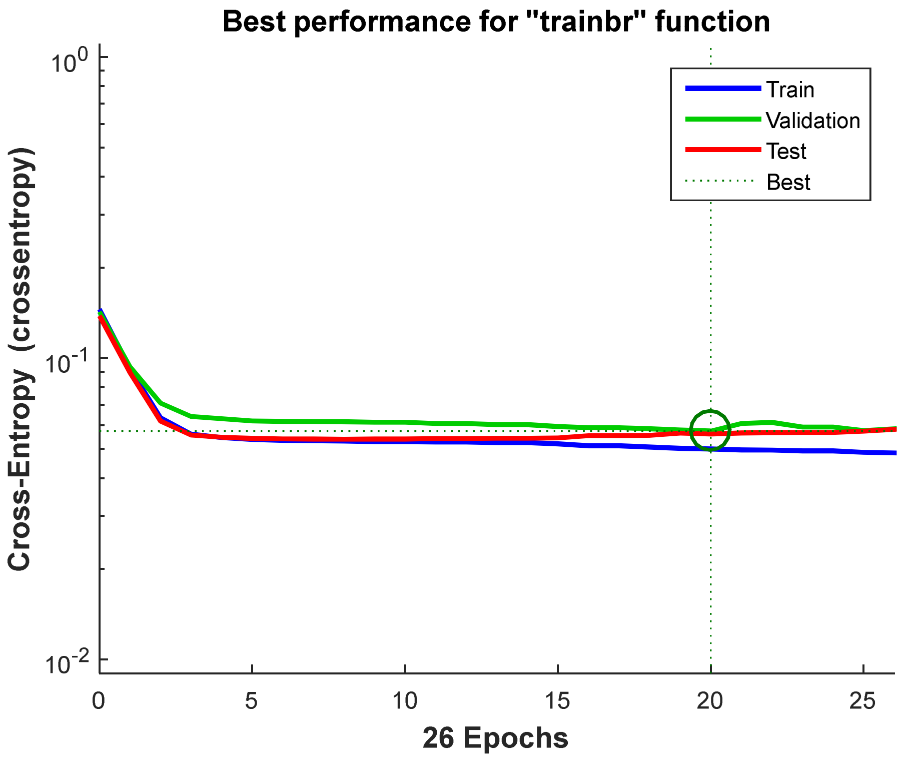

Figure 4-4 Performance curve of the trainbr function

As shown in Figures 4-4, the performance curve of the trainbr training function in the neural network is plotted. As can be seen, the green line diagram tends to be a dotted line. It means that the performance of the proposed model in the trainbr training function is also optimal for validation data. Therefore, the closer the line to the dotted line and the line related to the model performance per validation data, the better the performance of the developed model. Figure 4-4 shows that the performance of the trainbr function in the proposed model for test data is better than its performance for training data. Neural network performance using the trainbr function after 20 iterations of training, validation, and test phases tends to be the best possible performance. Figure 4-5 shows the performance curve for the trainlm training function.

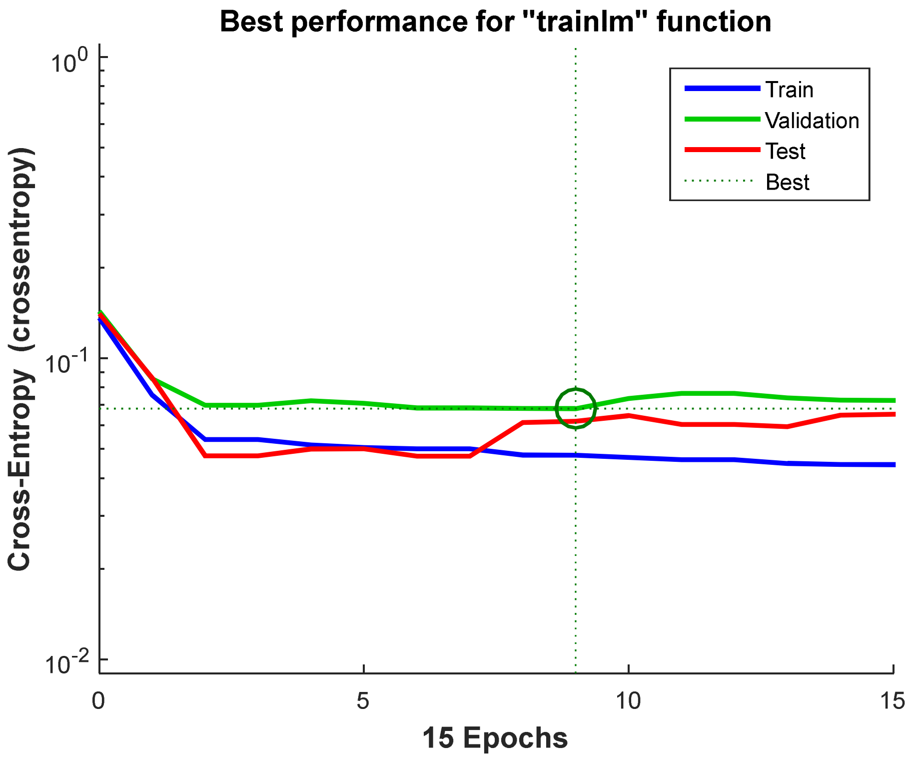

Figure 4-5 Performance curve of the trainlm function

As shown in Figure 4-5, the performance curve of the trainlm training function in the neural network is plotted. As can be seen from Figure 4-5, the green line diagram is closer to the dotted line than the other lines. It means that the performance of the proposed model in the trainlm training function, like other training functions for validation data, is the best. Therefore, the condition for optimal performance of the training function is close to the training lines and the test to the dotted line. Figure 4-5 shows that the performance of the trainlm function, like the trainbr function in the proposed model for test data, is better than training data. Neural network performance using the trainlm function after nine iterations in the training, validation, and test phases tends to the best possible performance. Based on this, it can be realized that the neural networks used in the proposed method using the trainscg function can perform optimal training in less time. Neural networks can also predict test samples more accurately using the trainbr function. In this regard, figure 4-6 shows the training status in the proposed neural network with respect to the trainscg function.

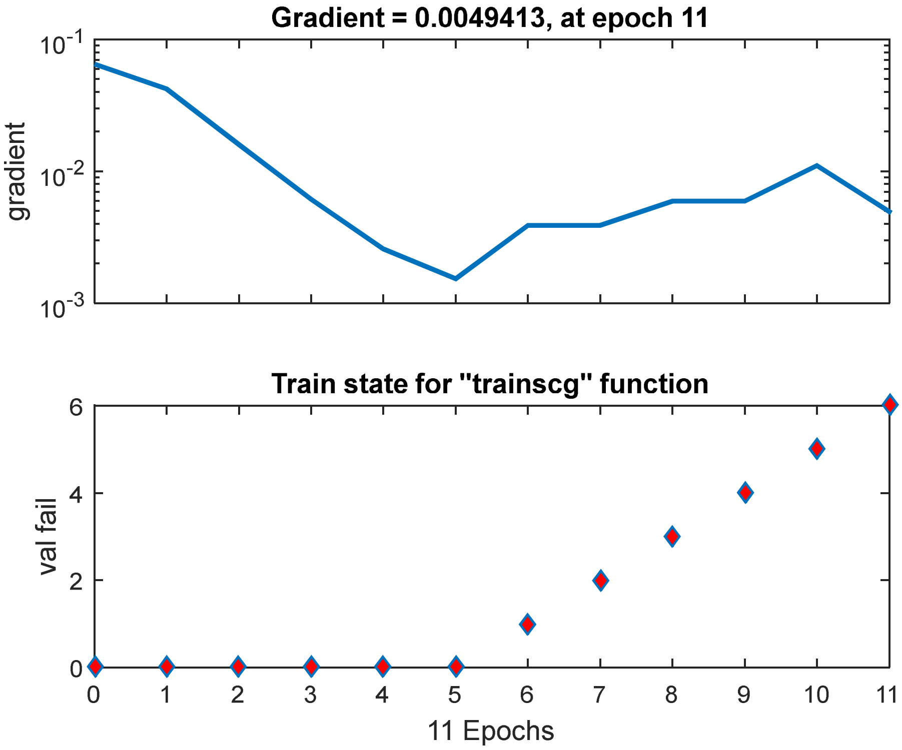

Figure 4-6 Network training process based on the trainscg function

As shown in Figure 4-6, the training process is shown in the trainscg function. Due to the fact that the training function is a type of descending gradient, the lower the value of this function, the less the error of prioritizing patients in the data set and the more optimal the education. Figure 4-6 shows that the trainscg training function achieved its lowest error value of 0.0049413 in the fifth iteration. Also, Figure 4-6 shows that overfitting has occurred after the fifth to the eleventh iterations, and the amount of training error has increased. In overfitting, the model focuses on training data, and the model's accuracy for predicting test samples will be reduced. Figure 4-7 shows the training process of the trainbr function.

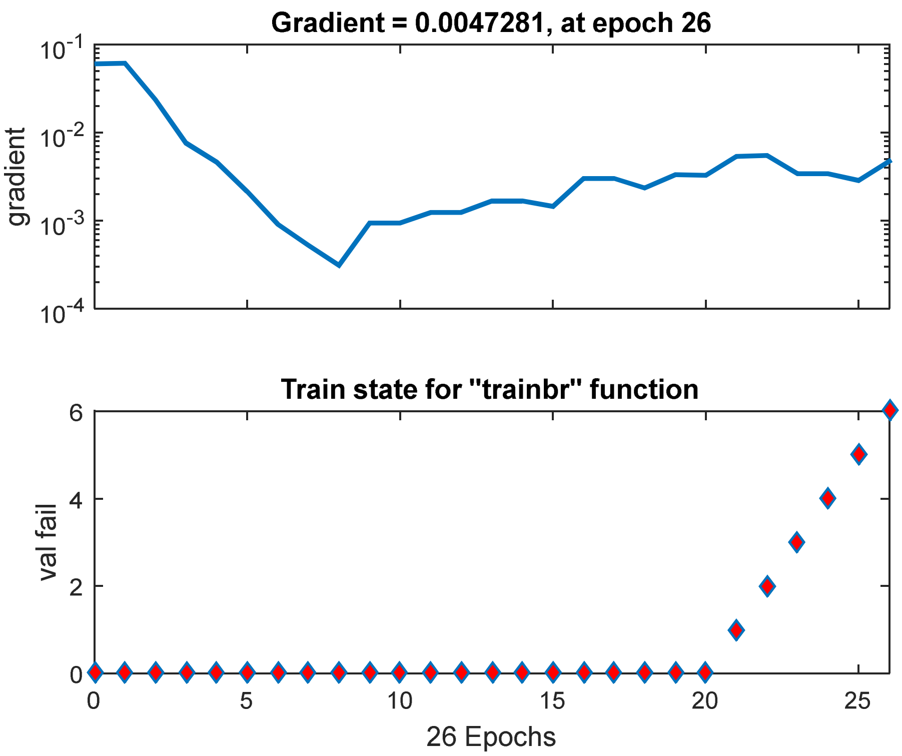

Figure 4-7 Network training process based on the trainbr function

As shown in Figure 4-7, the training process is shown in the trainbr function. According to 4-7, it can be seen that the trainbr function has reached its lowest error value equal to 0.0047281 by reducing the value of the gradient in the twentieth iteration. This error value in the trainbr function is less than the error value of the trainscg function, and we can expect the overall performance of the trainbr function to be more optimal than the trainscg function. Also, in Figure 4-7, it can be seen that after the twentieth iteration, overfitting occurred, and the amount of training error increased. However, the amount of overfitting error in the trainbr function is less than the trainscg function. Figure 4-8 shows the training process of the trainlm function.

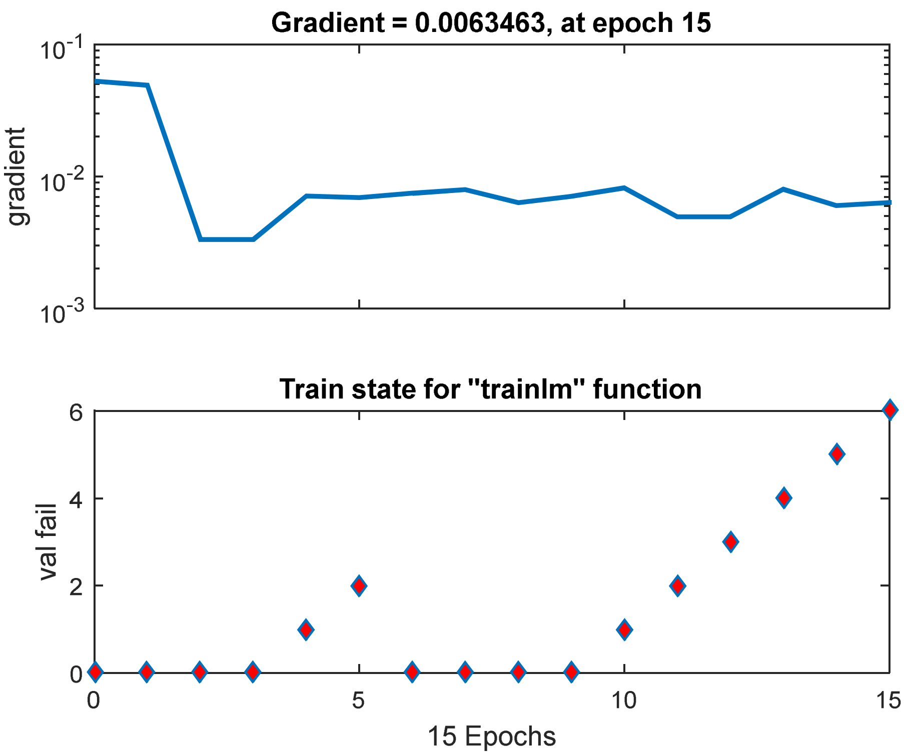

Figure 4-8 Network training process based on trainlm function

As shown in Figure 4-8, the training process is shown in the trainlm function. According to 4-7, it can be seen 8that the trainlm function has reached its lowest error value equal to 0.0063463 by reducing the gradient value in the ninth iteration. This error value in trainlm function is more than the error value of trainscg and trainbr functions, and it can be expected that the accuracy of prioritizing patients by trainlm function is less than other functions. Also, in Figure 4-8, it can be seen that overfitting has occurred after the ninth, and the amount of training error has increased. Also, in Figures 4-9, 4-10, and 4-11, the diagrams of the errors in the patient training process show the criteria related to the patients, both in the model training phase and in the data testing phase, for the trainscg, trainbr and trainlm functions .

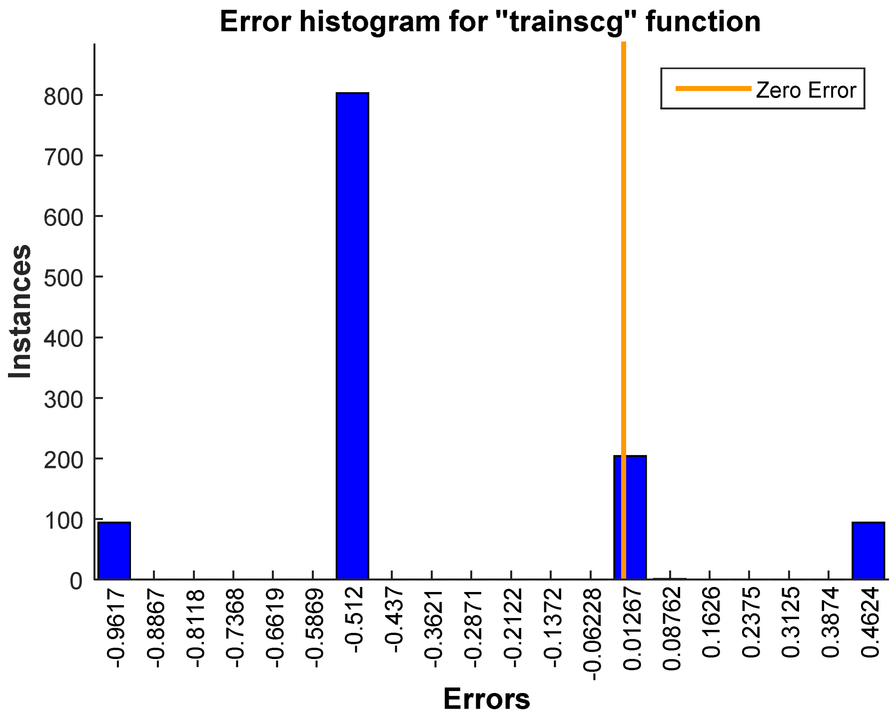

Figure 4-9 Graph of error rates in the trainscg function

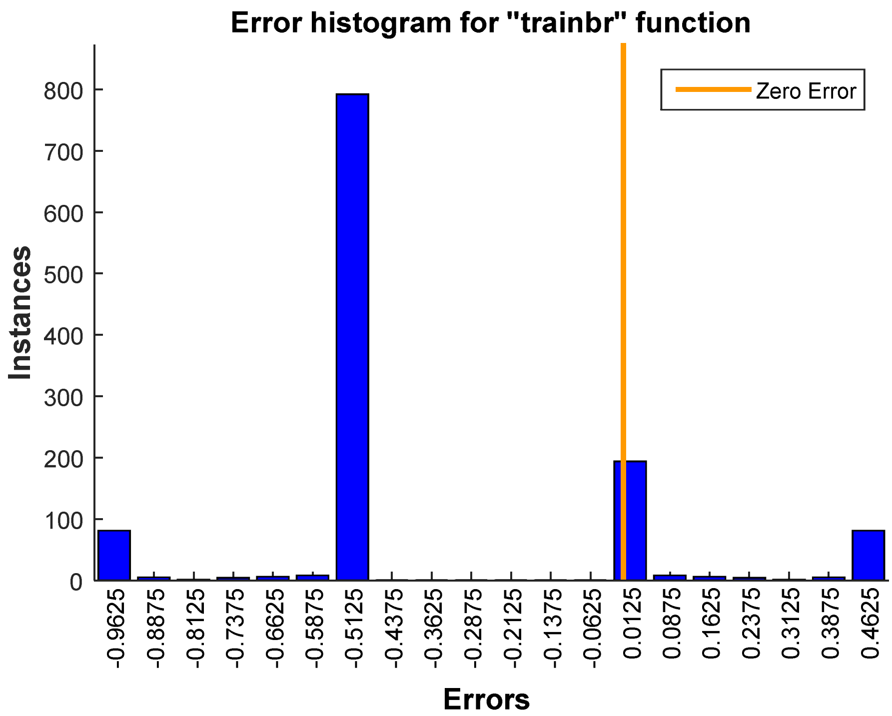

Figure 4-10 Graph of error frequency in the trainbr function

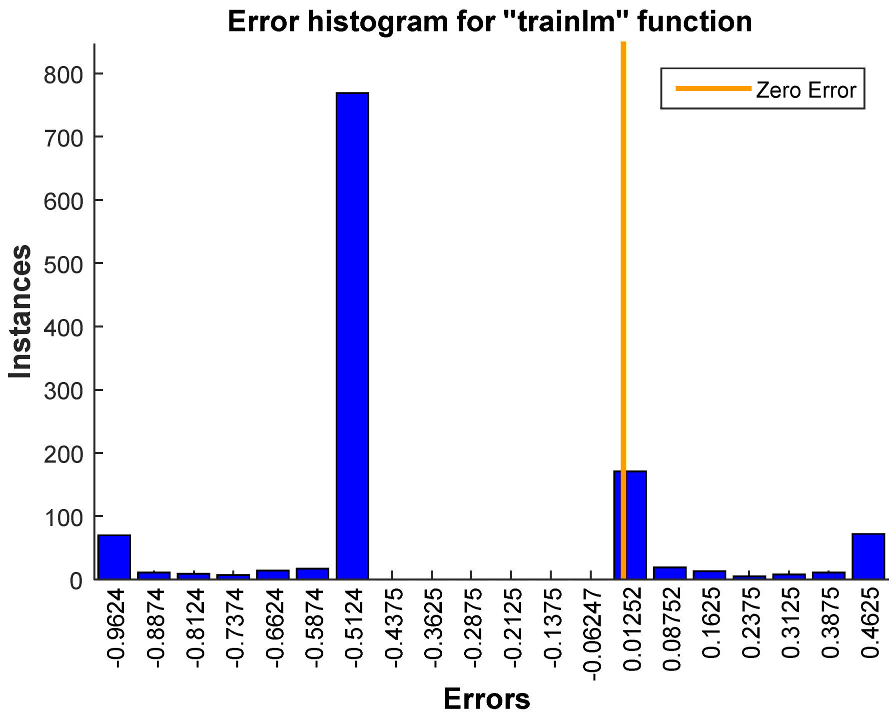

Figure 4-11 Graph of error frequency in trainlm function

As shown in Figures 4-9, 4-10, and 4-11, the number of errors at the beginning of the training process is not large, but with increasing the number of repetition steps, this value increases, and with the completion of the training process, the number of errors for Training samples and test samples tends to zero. The model also has a zero error to a threshold, which gradually increases with the number of repetitions in the neural network.

4-3 Evaluation of neural networks

Finally, the accurate training rate of the criteria in the model training stages on the training data, validation, and testing stages of the model repetition is utilized to determine the accuracy of the proposed model in this research. For this purpose, a diagram called Confusion is drawn. The number of correctly trained patients versus the number of incorrectly trained patients in the training, validation, and testing of data is determined. In this research, due to the result of VIKOR that has divided the patients into four groups of priority, we have used four labels related to them. So, in the confusion matrix of the proposed neural network, four classes have been considered. Figure 4-12 shows the confusion matrix for the proposed model for the trainscg, function.

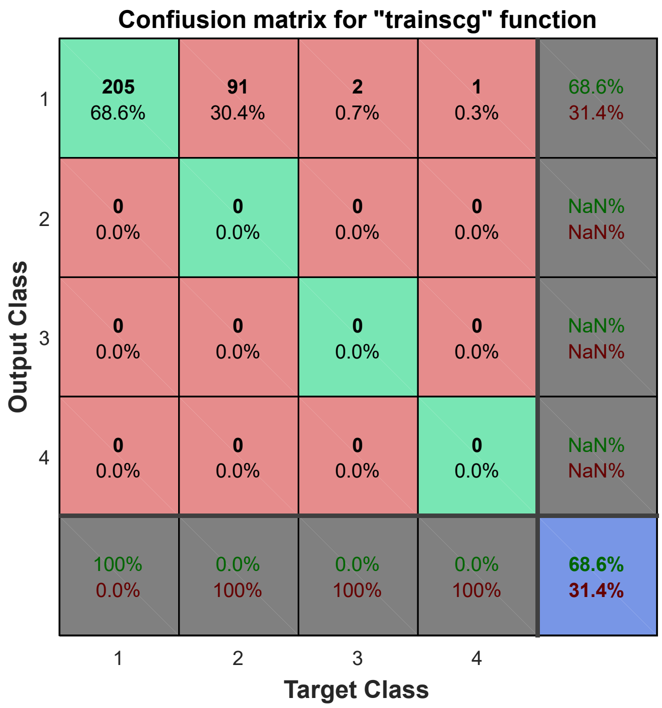

Figure 4-12 Confusion diagram of the proposed model for the trainscg function

Figure 4-12 shows that the neural network model proposed in this study in the training phase using the trainscg function correctly trained and tested the criteria for 68.6% of patients. According to Figure 4-12, it can be seen that the trainscg function has detected all patients related to priority class 1 but has not been able to detect patients related to other classes. Figure 4-13 shows the confusion matrix of the trainbr training function.

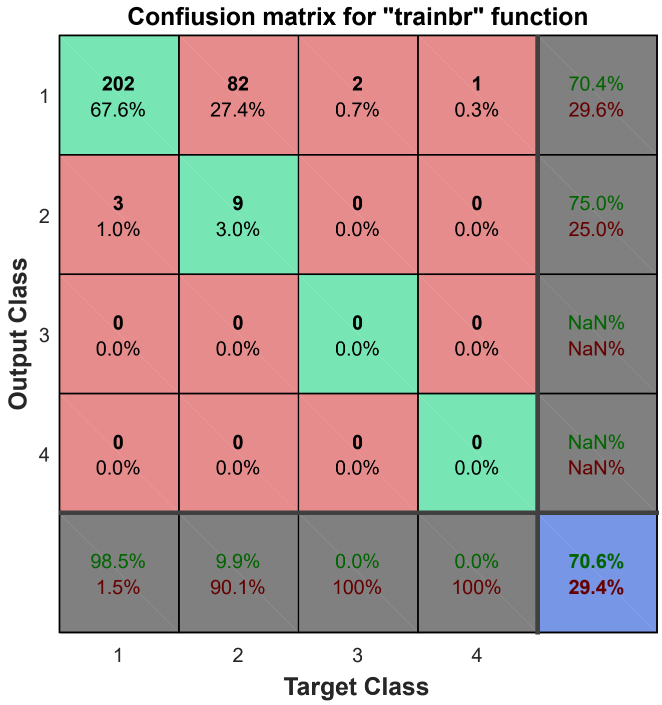

Figure 4-13 Confusion diagram of the proposed model for the trainbr function

Figure 4-13 shows that the neural network model proposed in this study in the training phase using the trainbr function correctly trained the criteria for 70.6% of patients and predicted the test patients. According to Figure 4-13, it can be seen that the trainbr function has detected 202 patients from priority class 1, and 3 patients could not be detected in this class. It also detected nine patients from priority class 2 and failed to prioritize 82 patients. It has also not been able to identify patients from other classes. Figure 4-13 shows the confusion matrix of the trainlm training function.

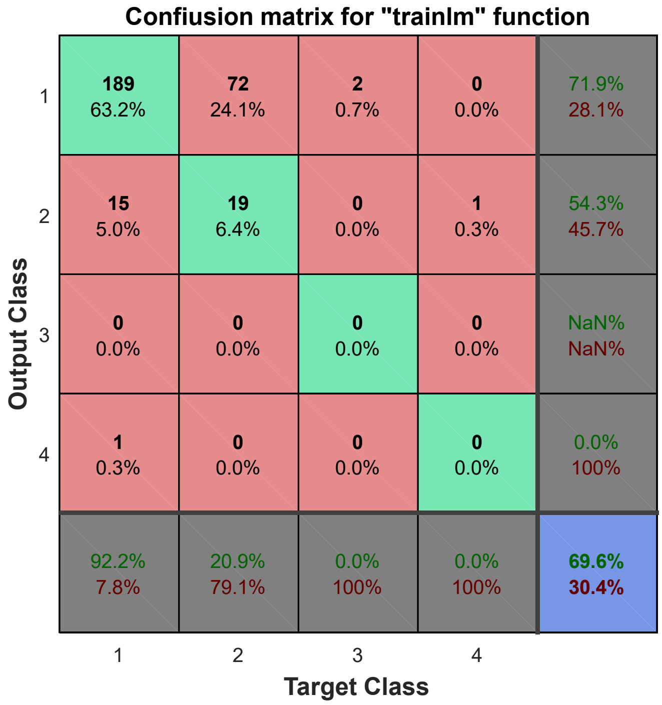

Figure 4- 14 Confusion diagram of the proposed model for the trainlm function

Figure 4-14 shows that the proposed neural network model in the training phase using the trainlm function correctly trained and tested the criteria for 69.6% of patients. Therefore, the average total accuracy of the proposed neural network model for learning patient-related criteria is 69.6%. According to Figure 4-14, it can be seen that the trainlm function has detected 189 patients from priority class 1. It also noticed 19 patients from priority class 2 and failed to prioritize 72 patients. It has also not been able to detect patients from other classes. Therefore, it can be said that the trainbr function has higher detection and prediction accuracy, among other functions.

In addition, another criterion used to measure the accuracy of the proposed method in neural network training is the ROC diagram. ROC diagram is one of the well-known criteria that has been used in various researches to measure the accuracy of machine learning methods. In this criterion, the area below the diagram enclosed between the midline and the accuracy diagram shows the performance of the proposed method. In the proposed method, according to the ranking of patients in 4 priority categories, the accuracy of the proposed method for each of the four categories is checked separately and plotted in the ROC curve. The ROC curve measures True Positive Rate (TPR) versus False Positive Rate (FPR). This curve shows the number of correctly prioritized patients compared to the number of patients who were incorrectly prioritized. This curve is drawn for all classes in the research. In this curve, a diagonal line is drawn, and the matching of the curve of each class on this diagonal line shows the high quality of learning in that class. In other words, the closer a class's ROC curve is to the diagonal line, the better the class's learning and classification processes are. Figure 4-14 shows the ROC diagrams for the trainscg function.

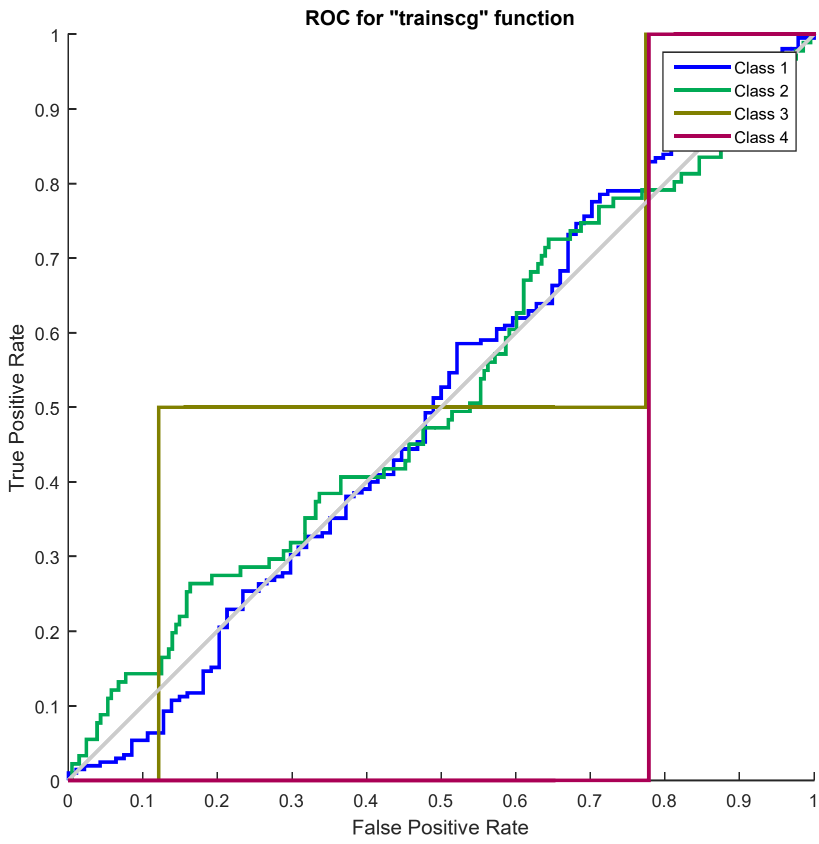

Figure 4- 15 ROC diagrams for the trainscg function

Figure 4-15 ROC diagram is drawn for the trainscg training function in neural networks. The ROC diagram is the contrast between patients who are correctly prioritized and patients who are incorrectly prioritized. The vertical axis in this diagram includes the True Positive Rate (TPR), which in the proposed method refers to the proportion of patients who have been prioritized by the VIKOR method, and the neural network predicted their priority correctly according to the criteria related to patients. The horizontal axis in the ROC diagram includes the False Positive Rate (FPR), which in the proposed method refers to the proportion of patients who have been prioritized by the VIKOR method, but the neural network has not been able to predict their priority correctly according to the criteria. The VIKOR method has identified four priority categories, so the ROC diagram has been drawn for all four classes. Each of these classes is closer to the center diagonal line, indicating the proper model performance for that class. Figure 4-15 shows that the trainscg training function performed well for classes 1 and 2, which have a larger number of instances. However, due to the lack of data related to classes 3 and 4, this function cannot predict patients associated with these classes. Figure 4-16 shows the ROC diagram for the trainbr training function.

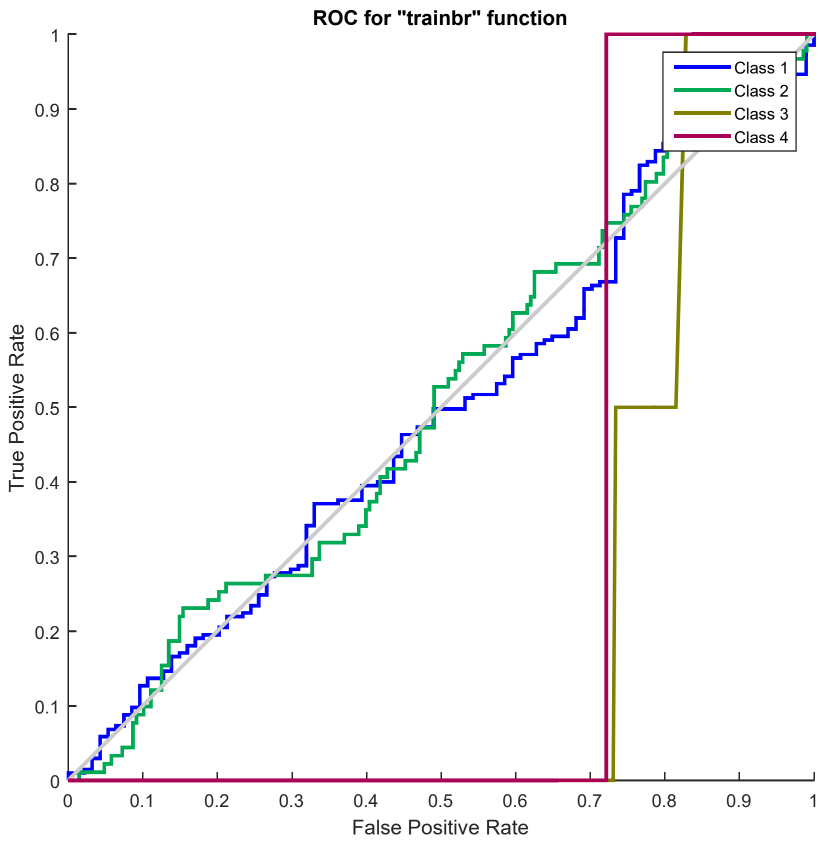

Figure 4- 16 ROC diagrams for the trainbr function

Figure 4-16 ROC diagram is drawn for the trainbr training function in neural networks. The trainbr training function worked well for grades 1 and 2, which have more instances. However, due to the lack of data related to classes 3 and 4, this function does not have the ability to predict patients related to these classes. Figure 4-17 shows the ROC diagram for the trainlm training function.

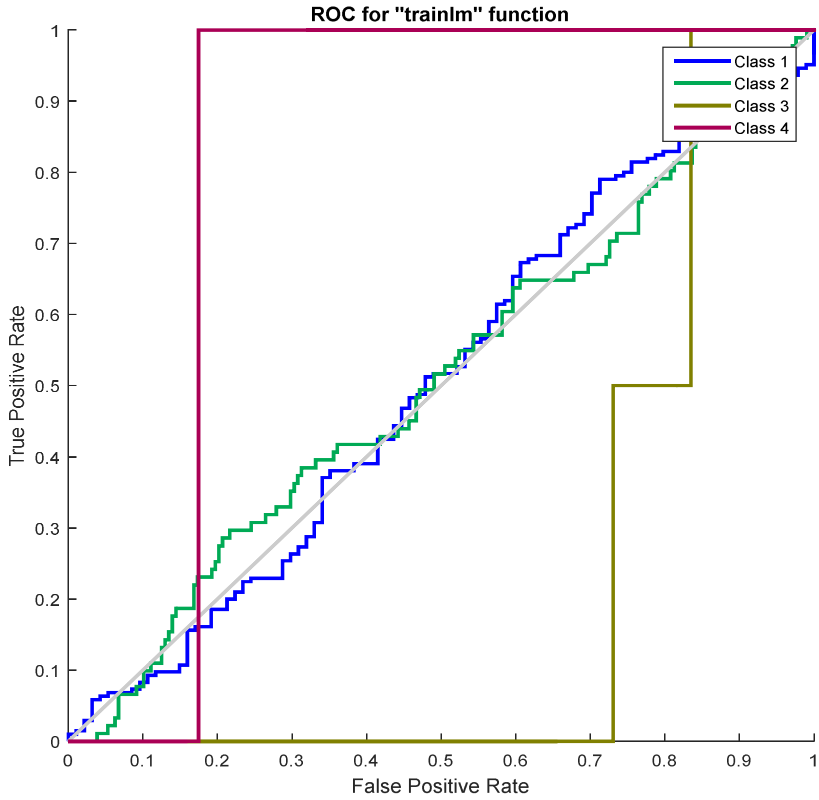

Figure 4- 17 ROC diagrams for the trainlm function

Figure 4-17 shows plotted ROC diagram for the trainlm training function in neural networks. The trainlm training function worked well for grades 1 and 2, which have more instances. Due to the lack of data related to classes 3 and 4, this function cannot predict patients related to these classes.

The functions used to learn the proposed method, given that the number of patients in priority categories 1 and 2 are higher and more information about these patients is available in the neural network are more accurate than other categories. The lack of data for categories 3 and 4 has reduced the accuracy of the proposed method for these two categories. Naturally, the proposed method will increase the accuracy of patient criteria training by increasing the volume of samples.

In fact, a questionnaire should have been prepared according to Chapter 2, and information should have been collected from some experts; however, due to the pandemic issues in hospitals, real patients' data collection was not possible, we needed to use an existing dataset and criteria, and in order to apply them to our machine learning-based prioritizing model, we had to weight criteria using a random function. One of the major problems in this field is the lack of sufficient records for the classification learning model. This has led to low accuracy in neural network-based learning methods. If it is possible to collect data on many patients, the accuracy of the learning model can certainly be improved.

Conclusion

As mentioned, health care systems and treatment centers try to address the condition of patients according to the patient's health condition and other effective criteria in the treatment process. Elective surgery is one of the most successful therapies available to individuals who visit medical clinics with various ailments. However, due to the variety of patients' conditions, it may not be possible to accurately diagnose which patient urgently needs medical care, especially surgery, which will cause irreparable damage to the patient. Furthermore, procrastination in caring for elective surgery patients and endangering the patient himself will create a negative record for the medical staff. Therefore, creating a waiting list for patients according to their health status and other factors in the healthcare centers and hospitals seems necessary. To address this challenge, patients can be prioritized using multi-criteria methods and machine learning tools based on different patient criteria. The proposed model in this study used an integrated method for developing a new machine learning-based patient prioritizing model by combining machine learning algorithms with MCDM tools. The research's main hypothesis was to confirm that machine learning algorithms are useful for patient prioritization problems. Based on the results of the proposed method, it can be said that the combination of multi-criteria method consisting of simple weight gain (SAW), hierarchical analytic process (AHP), and VIKOR with machine learning method has been able to extract patients' priorities with fairly high accuracy (~ 70%). However, as a limitation of this study, we can point out the lack of real patient data as it could affect the accuracy of the developed prediction model to some extent.

Regarding the validation of the proposed method in practice, considering that a standard MATILAB toolbox [42] has been used to implement the SAW, AHP, and VIKOR methods, the validity of these methods is provable because other researchers have already used this toolbox and the validity of this toolbox has been verified. On the other hand, in previous methods, the combination of neural networks with statistical algorithms has not been used. Also, each related work in this field has used a different data set. Therefore, we were not able to compare the proposed method with other methods applied in the literature. So, we had to train neural networks based on different training functions to compare the results. According to the results obtained from different training functions, it can be seen that the accuracy values in prioritizing new patients based on different functions are almost the same, and there is not much difference between the accuracy values of different training functions. Consequently, the validation of the proposed approach was verified on the test data, and the validation of the whole proposed method was approved.

In order to make suggestions for improving the accuracy of the proposed method, the following could be considered:

- Use of multi-criteria approaches with bagging classification methods to increase accuracy in determining patients' preferences for elective surgery.
- Using a combination of multi-objective approaches and meta-heuristics search methods to determine important criteria in determining patients' preferences for elective surgery.

- Using a combination of multi-criteria and classification methods based on feature selection and meta-heuristics search algorithms.
- Using advanced machine learning approaches with hyperparameter tuning and grid search for obtaining optimal values for each parameter.

Appendix A (dataset)

Age	Anaemia	Creatinine_Phosphokinase	Diabetes	Ejection_Fraction	High_Blood_Pressure	Platelets	Serum_Creatinine	Serum_Sodium	Sex	Smoking	Time	Death_Event
75	0	582	0	20	1	265000	1.9	130	1	0	4	1
55	0	7861	0	38	0	263358.03	1.1	136	1	0	6	1
65	0	146	0	20	0	162000	1.3	129	1	1	7	1
50	1	111	0	20	0	210000	1.9	137	1	0	7	1
65	1	160	1	20	0	327000	2.7	116	0	0	8	1
90	1	47	0	40	1	204000	2.1	132	1	1	8	1
75	1	246	0	15	0	127000	1.2	137	1	0	10	1
60	1	315	1	60	0	454000	1.1	131	1	1	10	1
65	0	157	0	65	0	263358.03	1.5	138	0	0	10	1
80	1	123	0	35	1	388000	9.4	133	1	1	10	1
75	1	81	0	38	1	368000	4	131	1	1	10	1
62	0	231	0	25	1	253000	0.9	140	1	1	10	1
45	1	981	0	30	0	136000	1.1	137	1	0	11	1
50	1	168	0	38	1	276000	1.1	137	1	0	11	1
49	1	80	0	30	1	427000	1	138	0	0	12	0
82	1	379	0	50	0	47000	1.3	136	1	0	13	1
87	1	149	0	38	0	262000	0.9	140	1	0	14	1
45	0	582	0	14	0	166000	0.8	127	1	0	14	1
70	1	125	0	25	1	237000	1	140	0	0	15	1
48	1	582	1	55	0	87000	1.9	121	0	0	15	1
65	1	52	0	25	1	276000	1.3	137	0	0	16	0
65	1	128	1	30	1	297000	1.6	136	0	0	20	1
68	1	220	0	35	1	289000	0.9	140	1	1	20	1
53	0	63	1	60	0	368000	0.8	135	1	0	22	0
75	0	582	1	30	1	263358.03	1.83	134	0	0	23	1
80	0	148	1	38	0	149000	1.9	144	1	1	23	1
95	1	112	0	40	1	196000	1	138	0	0	24	1
70	0	122	1	45	1	284000	1.3	136	1	1	26	1
58	1	60	0	38	0	153000	5.8	134	1	0	26	1
82	0	70	1	30	0	200000	1.2	132	1	1	26	1
94	0	582	1	38	1	263358.03	1.83	134	1	0	27	1
85	0	23	0	45	0	360000	3	132	1	0	28	1
50	1	249	1	35	1	319000	1	128	0	0	28	1

50	1	159	1	30	0	302000	1.2	138	0	0	29	0
65	0	94	1	50	1	188000	1	140	1	0	29	1
69	0	582	1	35	0	228000	3.5	134	1	0	30	1
90	1	60	1	50	0	226000	1	134	1	0	30	1
82	1	855	1	50	1	321000	1	145	0	0	30	1
60	0	2656	1	30	0	305000	2.3	137	1	0	30	0
60	0	235	1	38	0	329000	3	142	0	0	30	1
70	0	582	0	20	1	263358.03	1.83	134	1	1	31	1
50	0	124	1	30	1	153000	1.2	136	0	1	32	1
70	0	571	1	45	1	185000	1.2	139	1	1	33	1
72	0	127	1	50	1	218000	1	134	1	0	33	0
60	1	588	1	60	0	194000	1.1	142	0	0	33	1
50	0	582	1	38	0	310000	1.9	135	1	1	35	1
51	0	1380	0	25	1	271000	0.9	130	1	0	38	1
60	0	582	1	38	1	451000	0.6	138	1	1	40	1
80	1	553	0	20	1	140000	4.4	133	1	0	41	1
57	1	129	0	30	0	395000	1	140	0	0	42	1
68	1	577	0	25	1	166000	1	138	1	0	43	1
53	1	91	0	20	1	418000	1.4	139	0	0	43	1
60	0	3964	1	62	0	263358.03	6.8	146	0	0	43	1
70	1	69	1	50	1	351000	1	134	0	0	44	1
60	1	260	1	38	0	255000	2.2	132	0	1	45	1
95	1	371	0	30	0	461000	2	132	1	0	50	1
70	1	75	0	35	0	223000	2.7	138	1	1	54	0
60	1	607	0	40	0	216000	0.6	138	1	1	54	0
49	0	789	0	20	1	319000	1.1	136	1	1	55	1
72	0	364	1	20	1	254000	1.3	136	1	1	59	1
45	0	7702	1	25	1	390000	1	139	1	0	60	1
50	0	318	0	40	1	216000	2.3	131	0	0	60	1
55	0	109	0	35	0	254000	1.1	139	1	1	60	0
45	0	582	0	35	0	385000	1	145	1	0	61	1
45	0	582	0	80	0	263358.03	1.18	137	0	0	63	0
60	0	68	0	20	0	119000	2.9	127	1	1	64	1
42	1	250	1	15	0	213000	1.3	136	0	0	65	1
72	1	110	0	25	0	274000	1	140	1	1	65	1
70	0	161	0	25	0	244000	1.2	142	0	0	66	1
65	0	113	1	25	0	497000	1.83	135	1	0	67	1
41	0	148	0	40	0	374000	0.8	140	1	1	68	0
58	0	582	1	35	0	122000	0.9	139	1	1	71	0
85	0	5882	0	35	0	243000	1	132	1	1	72	1
65	0	224	1	50	0	149000	1.3	137	1	1	72	0
69	0	582	0	20	0	266000	1.2	134	1	1	73	1
60	1	47	0	20	0	204000	0.7	139	1	1	73	1
70	0	92	0	60	1	317000	0.8	140	0	1	74	0

42	0	102	1	40	0	237000	1.2	140	1	0	74	0
75	1	203	1	38	1	283000	0.6	131	1	1	74	0
55	0	336	0	45	1	324000	0.9	140	0	0	74	0
70	0	69	0	40	0	293000	1.7	136	0	0	75	0
67	0	582	0	50	0	263358.03	1.18	137	1	1	76	0
60	1	76	1	25	0	196000	2.5	132	0	0	77	1
79	1	55	0	50	1	172000	1.8	133	1	0	78	0
59	1	280	1	25	1	302000	1	141	0	0	78	1
51	0	78	0	50	0	406000	0.7	140	1	0	79	0
55	0	47	0	35	1	173000	1.1	137	1	0	79	0
65	1	68	1	60	1	304000	0.8	140	1	0	79	0
44	0	84	1	40	1	235000	0.7	139	1	0	79	0
57	1	115	0	25	1	181000	1.1	144	1	0	79	0
70	0	66	1	45	0	249000	0.8	136	1	1	80	0
60	0	897	1	45	0	297000	1	133	1	0	80	0
42	0	582	0	60	0	263358.03	1.18	137	0	0	82	0
60	1	154	0	25	0	210000	1.7	135	1	0	82	1
58	0	144	1	38	1	327000	0.7	142	0	0	83	0
58	1	133	0	60	1	219000	1	141	1	0	83	0
63	1	514	1	25	1	254000	1.3	134	1	0	83	0
70	1	59	0	60	0	255000	1.1	136	0	0	85	0
60	1	156	1	25	1	318000	1.2	137	0	0	85	0
63	1	61	1	40	0	221000	1.1	140	0	0	86	0
65	1	305	0	25	0	298000	1.1	141	1	0	87	0
75	0	582	0	45	1	263358.03	1.18	137	1	0	87	0
80	0	898	0	25	0	149000	1.1	144	1	1	87	0
42	0	5209	0	30	0	226000	1	140	1	1	87	0
60	0	53	0	50	1	286000	2.3	143	0	0	87	0
72	1	328	0	30	1	621000	1.7	138	0	1	88	1
55	0	748	0	45	0	263000	1.3	137	1	0	88	0
45	1	1876	1	35	0	226000	0.9	138	1	0	88	0
63	0	936	0	38	0	304000	1.1	133	1	1	88	0
45	0	292	1	35	0	850000	1.3	142	1	1	88	0
85	0	129	0	60	0	306000	1.2	132	1	1	90	1
55	0	60	0	35	0	228000	1.2	135	1	1	90	0
50	0	369	1	25	0	252000	1.6	136	1	0	90	0
70	1	143	0	60	0	351000	1.3	137	0	0	90	1
60	1	754	1	40	1	328000	1.2	126	1	0	91	0
58	1	400	0	40	0	164000	1	139	0	0	91	0
60	1	96	1	60	1	271000	0.7	136	0	0	94	0
85	1	102	0	60	0	507000	3.2	138	0	0	94	0
65	1	113	1	60	1	203000	0.9	140	0	0	94	0
86	0	582	0	38	0	263358.03	1.83	134	0	0	95	1
60	1	737	0	60	1	210000	1.5	135	1	1	95	0

66	1	68	1	38	1	162000	1	136	0	0	95	0
60	0	96	1	38	0	228000	0.75	140	0	0	95	0
60	1	582	0	30	1	127000	0.9	145	0	0	95	0
60	0	582	0	40	0	217000	3.7	134	1	0	96	1
43	1	358	0	50	0	237000	1.3	135	0	0	97	0
46	0	168	1	17	1	271000	2.1	124	0	0	100	1
58	1	200	1	60	0	300000	0.8	137	0	0	104	0
61	0	248	0	30	1	267000	0.7	136	1	1	104	0
53	1	270	1	35	0	227000	3.4	145	1	0	105	0
53	1	1808	0	60	1	249000	0.7	138	1	1	106	0
60	1	1082	1	45	0	250000	6.1	131	1	0	107	0
46	0	719	0	40	1	263358.03	1.18	137	0	0	107	0
63	0	193	0	60	1	295000	1.3	145	1	1	107	0
81	0	4540	0	35	0	231000	1.18	137	1	1	107	0
75	0	582	0	40	0	263358.03	1.18	137	1	0	107	0
65	1	59	1	60	0	172000	0.9	137	0	0	107	0
68	1	646	0	25	0	305000	2.1	130	1	0	108	0
62	0	281	1	35	0	221000	1	136	0	0	108	0
50	0	1548	0	30	1	211000	0.8	138	1	0	108	0
80	0	805	0	38	0	263358.03	1.1	134	1	0	109	1
46	1	291	0	35	0	348000	0.9	140	0	0	109	0
50	0	482	1	30	0	329000	0.9	132	0	0	109	0
61	1	84	0	40	1	229000	0.9	141	0	0	110	0
72	1	943	0	25	1	338000	1.7	139	1	1	111	1
50	0	185	0	30	0	266000	0.7	141	1	1	112	0
52	0	132	0	30	0	218000	0.7	136	1	1	112	0
64	0	1610	0	60	0	242000	1	137	1	0	113	0
75	1	582	0	30	0	225000	1.83	134	1	0	113	1
60	0	2261	0	35	1	228000	0.9	136	1	0	115	0
72	0	233	0	45	1	235000	2.5	135	0	0	115	1
62	0	30	1	60	1	244000	0.9	139	1	0	117	0
50	0	115	0	45	1	184000	0.9	134	1	1	118	0
50	0	1846	1	35	0	263358.03	1.18	137	1	1	119	0
65	1	335	0	35	1	235000	0.8	136	0	0	120	0
60	1	231	1	25	0	194000	1.7	140	1	0	120	0
52	1	58	0	35	0	277000	1.4	136	0	0	120	0
50	0	250	0	25	0	262000	1	136	1	1	120	0
85	1	910	0	50	0	235000	1.3	134	1	0	121	0
59	1	129	0	45	1	362000	1.1	139	1	1	121	0
66	1	72	0	40	1	242000	1.2	134	1	0	121	0
45	1	130	0	35	0	174000	0.8	139	1	1	121	0
63	1	582	0	40	0	448000	0.9	137	1	1	123	0
50	1	2334	1	35	0	75000	0.9	142	0	0	126	1
45	0	2442	1	30	0	334000	1.1	139	1	0	129	1

80	0	776	1	38	1	192000	1.3	135	0	0	130	1
53	0	196	0	60	0	220000	0.7	133	1	1	134	0
59	0	66	1	20	0	70000	2.4	134	1	0	135	1
65	0	582	1	40	0	270000	1	138	0	0	140	0
70	0	835	0	35	1	305000	0.8	133	0	0	145	0
51	1	582	1	35	0	263358.03	1.5	136	1	1	145	0
52	0	3966	0	40	0	325000	0.9	140	1	1	146	0
70	1	171	0	60	1	176000	1.1	145	1	1	146	0
50	1	115	0	20	0	189000	0.8	139	1	0	146	0
65	0	198	1	35	1	281000	0.9	137	1	1	146	0
60	1	95	0	60	0	337000	1	138	1	1	146	0
69	0	1419	0	40	0	105000	1	135	1	1	147	0
49	1	69	0	50	0	132000	1	140	0	0	147	0
63	1	122	1	60	0	267000	1.2	145	1	0	147	0
55	0	835	0	40	0	279000	0.7	140	1	1	147	0
40	0	478	1	30	0	303000	0.9	136	1	0	148	0
59	1	176	1	25	0	221000	1	136	1	1	150	1
65	0	395	1	25	0	265000	1.2	136	1	1	154	1
75	0	99	0	38	1	224000	2.5	134	1	0	162	1
58	1	145	0	25	0	219000	1.2	137	1	1	170	1
60.667	1	104	1	30	0	389000	1.5	136	1	0	171	1
50	0	582	0	50	0	153000	0.6	134	0	0	172	1
60	0	1896	1	25	0	365000	2.1	144	0	0	172	1
60.667	1	151	1	40	1	201000	1	136	0	0	172	0
40	0	244	0	45	1	275000	0.9	140	0	0	174	0
80	0	582	1	35	0	350000	2.1	134	1	0	174	0
64	1	62	0	60	0	309000	1.5	135	0	0	174	0
50	1	121	1	40	0	260000	0.7	130	1	0	175	0
73	1	231	1	30	0	160000	1.18	142	1	1	180	0
45	0	582	0	20	1	126000	1.6	135	1	0	180	1
77	1	418	0	45	0	223000	1.8	145	1	0	180	1
45	0	582	1	38	1	263358.03	1.18	137	0	0	185	0
65	0	167	0	30	0	259000	0.8	138	0	0	186	0
50	1	582	1	20	1	279000	1	134	0	0	186	0
60	0	1211	1	35	0	263358.03	1.8	113	1	1	186	0
63	1	1767	0	45	0	73000	0.7	137	1	0	186	0
45	0	308	1	60	1	377000	1	136	1	0	186	0
70	0	97	0	60	1	220000	0.9	138	1	0	186	0
60	0	59	0	25	1	212000	3.5	136	1	1	187	0
78	1	64	0	40	0	277000	0.7	137	1	1	187	0
50	1	167	1	45	0	362000	1	136	0	0	187	0
40	1	101	0	40	0	226000	0.8	141	0	0	187	0
85	0	212	0	38	0	186000	0.9	136	1	0	187	0
60	1	2281	1	40	0	283000	1	141	0	0	187	0

49	0	972	1	35	1	268000	0.8	130	0	0	187	0
70	0	212	1	17	1	389000	1	136	1	1	188	0
50	0	582	0	62	1	147000	0.8	140	1	1	192	0
78	0	224	0	50	0	481000	1.4	138	1	1	192	0
48	1	131	1	30	1	244000	1.6	130	0	0	193	1
65	1	135	0	35	1	290000	0.8	134	1	0	194	0
73	0	582	0	35	1	203000	1.3	134	1	0	195	0
70	0	1202	0	50	1	358000	0.9	141	0	0	196	0
54	1	427	0	70	1	151000	9	137	0	0	196	1
68	1	1021	1	35	0	271000	1.1	134	1	0	197	0
55	0	582	1	35	1	371000	0.7	140	0	0	197	0
73	0	582	0	20	0	263358.03	1.83	134	1	0	198	1
65	0	118	0	50	0	194000	1.1	145	1	1	200	0
42	1	86	0	35	0	365000	1.1	139	1	1	201	0
47	0	582	0	25	0	130000	0.8	134	1	0	201	0
58	0	582	1	25	0	504000	1	138	1	0	205	0
75	0	675	1	60	0	265000	1.4	125	0	0	205	0
58	1	57	0	25	0	189000	1.3	132	1	1	205	0
55	1	2794	0	35	1	141000	1	140	1	0	206	0
65	0	56	0	25	0	237000	5	130	0	0	207	0
72	0	211	0	25	0	274000	1.2	134	0	0	207	0
60	0	166	0	30	0	62000	1.7	127	0	0	207	1
70	0	93	0	35	0	185000	1.1	134	1	1	208	0
40	1	129	0	35	0	255000	0.9	137	1	0	209	0
53	1	707	0	38	0	330000	1.4	137	1	1	209	0
53	1	582	0	45	0	305000	1.1	137	1	1	209	0
77	1	109	0	50	1	406000	1.1	137	1	0	209	0
75	0	119	0	50	1	248000	1.1	148	1	0	209	0
70	0	232	0	30	0	173000	1.2	132	1	0	210	0
65	1	720	1	40	0	257000	1	136	0	0	210	0
55	1	180	0	45	0	263358.03	1.18	137	1	1	211	0
70	0	81	1	35	1	533000	1.3	139	0	0	212	0
65	0	582	1	30	0	249000	1.3	136	1	1	212	0
40	0	90	0	35	0	255000	1.1	136	1	1	212	0
73	1	1185	0	40	1	220000	0.9	141	0	0	213	0
54	0	582	1	38	0	264000	1.8	134	1	0	213	0
61	1	80	1	38	0	282000	1.4	137	1	0	213	0
55	0	2017	0	25	0	314000	1.1	138	1	0	214	1
64	0	143	0	25	0	246000	2.4	135	1	0	214	0
40	0	624	0	35	0	301000	1	142	1	1	214	0
53	0	207	1	40	0	223000	1.2	130	0	0	214	0
50	0	2522	0	30	1	404000	0.5	139	0	0	214	0
55	0	572	1	35	0	231000	0.8	143	0	0	215	0
50	0	245	0	45	1	274000	1	133	1	0	215	0

70	0	88	1	35	1	236000	1.2	132	0	0	215	0
53	1	446	0	60	1	263358.03	1	139	1	0	215	0
52	1	191	1	30	1	334000	1	142	1	1	216	0
65	0	326	0	38	0	294000	1.7	139	0	0	220	0
58	0	132	1	38	1	253000	1	139	1	0	230	0
45	1	66	1	25	0	233000	0.8	135	1	0	230	0
53	0	56	0	50	0	308000	0.7	135	1	1	231	0
55	0	66	0	40	0	203000	1	138	1	0	233	0
62	1	655	0	40	0	283000	0.7	133	0	0	233	0
65	1	258	1	25	0	198000	1.4	129	1	0	235	1
68	1	157	1	60	0	208000	1	140	0	0	237	0
61	0	582	1	38	0	147000	1.2	141	1	0	237	0
50	1	298	0	35	0	362000	0.9	140	1	1	240	0
55	0	1199	0	20	0	263358.03	1.83	134	1	1	241	1
56	1	135	1	38	0	133000	1.7	140	1	0	244	0
45	0	582	1	38	0	302000	0.9	140	0	0	244	0
40	0	582	1	35	0	222000	1	132	1	0	244	0
44	0	582	1	30	1	263358.03	1.6	130	1	1	244	0
51	0	582	1	40	0	221000	0.9	134	0	0	244	0
67	0	213	0	38	0	215000	1.2	133	0	0	245	0
42	0	64	0	40	0	189000	0.7	140	1	0	245	0
60	1	257	1	30	0	150000	1	137	1	1	245	0
45	0	582	0	38	1	422000	0.8	137	0	0	245	0
70	0	618	0	35	0	327000	1.1	142	0	0	245	0
70	0	582	1	38	0	25100	1.1	140	1	0	246	0
50	1	1051	1	30	0	232000	0.7	136	0	0	246	0
55	0	84	1	38	0	451000	1.3	136	0	0	246	0
70	0	2695	1	40	0	241000	1	137	1	0	247	0
70	0	582	0	40	0	51000	2.7	136	1	1	250	0
42	0	64	0	30	0	215000	3.8	128	1	1	250	0
65	0	1688	0	38	0	263358.03	1.1	138	1	1	250	0
50	1	54	0	40	0	279000	0.8	141	1	0	250	0
55	1	170	1	40	0	336000	1.2	135	1	0	250	0
60	0	253	0	35	0	279000	1.7	140	1	0	250	0
45	0	582	1	55	0	543000	1	132	0	0	250	0
65	0	892	1	35	0	263358.03	1.1	142	0	0	256	0
90	1	337	0	38	0	390000	0.9	144	0	0	256	0
45	0	615	1	55	0	222000	0.8	141	0	0	257	0
60	0	320	0	35	0	133000	1.4	139	1	0	258	0
52	0	190	1	38	0	382000	1	140	1	1	258	0
63	1	103	1	35	0	179000	0.9	136	1	1	270	0
62	0	61	1	38	1	155000	1.1	143	1	1	270	0
55	0	1820	0	38	0	270000	1.2	139	0	0	271	0
45	0	2060	1	60	0	742000	0.8	138	0	0	278	0

45	0	2413	0	38	0	140000	1.4	140	1	1	280	0
50	0	196	0	45	0	395000	1.6	136	1	1	285	0

Appendix B (MATLAB codes)

```
clear
clc
close all
load Dataset

%%
tm = clock;

iN=5;   %-- Number of Example (Project) 1 2 3 ...5 ...
%%
'************************************************************************';

if iN==5
   T_Name='Test for 15 alternatives '%A1-A15  C1-C11
   Tx={'Test'};
D=data;%(1:15,1:11);


    w=sort(rand(1,12), 'descend ');
   MM=[1 1 -1 1 1 1 1 -1 1 1 1 -1];
end

[m,n]=size(D);

nM=2;  % -- metods
Metods={'SAW' 'AHP' 'VIKOR'};

 %---  A1, A2 ... Am
 Alter= cell(1,m);
 for i=1:m
     Alter(i)={ ['A' num2str(i,'%d')] };
 end
%%

' ------------- Normalization  of decision matrix DM -------------';

 %    p=1- Max method; 2- Sum method; 3- Vector method; 4- Rng method;
 %    p=5- Max-Min method; 6- Dea; 7- Max.d; 10- Max2; 11-Log

 V1 =Fun_DMnorm(m,n,D,1);         % Max
 iV1=Fun_ReS(m, n, V1, MM,3);    %  invers Cost
 V2 =Fun_DMnorm(m,n,D,2);         % Sum
 iV2=Fun_ReS(m, n, V2, MM,3);    %  invers Cost
 V3 =Fun_DMnorm(m,n,D,3);         % Vec
 iV3=Fun_ReS(m, n, V3, MM,3);    %  invers Cost
 V4 =Fun_DMnorm(m,n,D,5);         % Max-Min
 iV4=Fun_ReS(m, n, V4, MM,3);    %  invers Cost
 V5 =Fun_DMnorm(m,n,D,6);         % Dea
 iV5=Invers(m,n, V5, MM, 6);      %  iDea
%%
 %  IZ1=0; IZ2=0; par=0;
 %  [iV6]=Fun_IZ(m,n,V1,MM,IZ1,IZ2,par);   % IZ, ReS
 %  iV7=Fun_MS(m,n,V1,MM,1,0);             % MS+, ReS
```

```
i1=0; iJ=0;
for num_Method=1:nM

    Metods(num_Method)

       % Norm: C1- Max; C2- Sum; C3-Vector; C4- Max-Min; C5- Dea;

       if  num_Method==1  %--- SAW
          C1=iV1*w';
          C2=iV2*w';
          C3=iV3*w';
          C4=iV4*w';
          C5=iV5*w';
       end
       if  num_Method==2  %--- AHP
          u=0.02;
          C1=Fun_CODAS(m,n,iV1,w,MM,u,0);
          C2=Fun_CODAS(m,n,iV2,w,MM,u,0);
          C3=abs(Fun_CODAS(m,n,iV3,w,MM,u,0));
          C4=Fun_CODAS(m,n,iV4,w,MM,u,0);
          C5=Fun_CODAS(m,n,iV5,w,MM,u,0);
       end
       if num_Method==3  %--- 'VIKOR'
          v=0.5;
         [S R C1 Rank IX]=Fun_VIKOR(m,n,D,w,MM,v, 0 );

         %--- TOPSIS with D
         C2=Fun_TOPSIS(m,n,D,w,MM,1, 0);
         C3=Fun_TOPSIS(m,n,D,w,MM,2, 0);
         C4=Fun_TOPSIS(m,n,D,w,MM,Inf, 0);
       end
       %---------------------------------------------------------------


       %-------- rank

      [Q1 R1]=sort(C1,'descend');
      [Q2 R2]=sort(C2,'descend');
      [Q3 R3]=sort(C3,'descend');
      [Q4 R4]=sort(C4,'descend');
      [Q5 R5]=sort(C5,'descend');


      if num_Method==2   % ORESTE
         [Q1 R1]=sort(C1);
         [Q2 R2]=sort(C2);
         [Q3 R3]=sort(C3);
         [Q4 R4]=sort(C4);
         minQ1=min(Q1); maxQ1=max(Q1); % ReS inversion
         Q1=-Q1+minQ1+maxQ1;
         minQ2=min(Q2); maxQ2=max(Q2);
         Q2=-Q2+minQ2+maxQ2;
         minQ3=min(Q3); maxQ3=max(Q3);
         Q3=-Q3+minQ3+maxQ3;
         minQ4=min(Q4); maxQ4=max(Q4);
         Q4=-Q4+minQ4+maxQ4;
      end
       if num_Method==3    % ViKOR
         [Q1 R1]=sort(C1);
```

```
     minQ1=min(Q1);
     maxQ1=max(Q1);
     Q1=-Q1+minQ1+maxQ1;    % ReS inversion
   end
   C1x=Q1; C2x=Q2; C3x=Q3; C4x=Q4; C5x=Q5 ;

    if min(C1) <0    C1x=Q1+abs(min(C1));  end
    if min(C2) <0    C2x=Q2+abs(min(C2));  end
    if min(C3) <0    C3x=Q3+abs(min(C3));  end
    if min(C4) <0    C4x=Q4+abs(min(C4));  end
    if min(C5) <0    C5x=Q5+abs(min(C5));  end

   iQ1=C1x/sum(C1x)*100;
   iQ2=C2x/sum(C2x)*100;
   iQ3=C3x/sum(C3x)*100;
   iQ4=C4x/sum(C4x)*100;
   iQ5=C5x/sum(C5x)*100;

   if num_Method==1
     WQ=cat(2,Q1,Q2,Q3,Q4,Q5);
     WiQ=cat(2,iQ1,iQ2,iQ3,iQ4,iQ5);
     WR=cat(2,R1,R2,R3,R4,R5);
     WR1=R1; WR2=R2; WR3=R3; WR4=R4; WR5=R5;
   end

    if num_Method==2   % ORESTE
     WQ=cat(2,WQ,Q1,Q2,Q3,Q4);
     WiQ=cat(2,WiQ,iQ1,iQ2,iQ3,iQ4);
     WR=cat(2,WR,R1,R2,R3,R4);
    end

   if num_Method==3    % ViKOR
     WQ=cat(2,WQ,Q1,Q2,Q3,Q4);
     WiQ=cat(2,WiQ,iQ1,iQ2,iQ3,iQ4);
     WR=cat(2,WR,R1,R2,R3,R4);
   end



   if ( num_Method==1)
     fprintf('\n|rank --- Max -----|----- Sum ------|----- Vec ------|--- Max-Min ----|------ Dea -----|\n')
      fprintf('| #   Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai | Q     iQ   Ai |\n')
      fprintf('|------------------------------------------------------------------------------------|\n')

     for i=1:m

fprintf('%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d\n', ...
        i, Q1(i), iQ1(i), R1(i), Q2(i),iQ2(i), R2(i), Q3(i),iQ3(i), R3(i), Q4(i), iQ4(i), R4(i), Q5(i), iQ5(i), R5(i))
     end
   end
   if num_Method==3
     fprintf('\n|rank -- VIKOR ----|-- VIKOR(D,L1)-|-- VIKOR(D,L2)-|- VIKOR(D,Inf)-|\n')
      fprintf('| #   Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai |\n')
      fprintf('|------------------------------------------------------------------|\n')

     for i=1:m
        fprintf('%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d\n', ...
        i, Q1(i), iQ1(i), R1(i), Q2(i),iQ2(i), R2(i), Q3(i),iQ3(i), R3(i), Q4(i), iQ4(i), R4(i))
     end
```

```
        end
        if num_Method==2
          fprintf('\n|rank ---- Max ----|----- Sum ------|----- Vec ------|--- Max-Min ----|------ Dea -----|------  D  -----
|\n')
           fprintf('| #   Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai |  Q    iQ   Ai | Q    iQ   Ai |\n')
           fprintf('|-----------------------------------------------------------------------------------------------|\n')

          for i=1:m

fprintf('%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,%6.2f,%2d,%6.3f,
%6.2f,%2d\n', ...
              i, Q1(i), iQ1(i), R1(i), Q2(i),iQ2(i), R2(i), Q3(i),iQ3(i), R3(i), Q4(i), iQ4(i), R4(i), Q5(i), iQ5(i), R5(i))
          end
        end

end
[mx iM]=size(WR);  Wdisp=zeros(m,iM);
RngQ=max(WQ)-min(WQ);

for i=1:m-1
    for j=1:iM
     Wdisp(i+1,j)=(WQ(i,j) - WQ(i+1,j) )/ RngQ(j)  ;
    end
end

%--------------- Sum_Rank  for Max, Sum, Max-Min, Vector norm -------------
k_int=0;
Sum_Rank=zeros(m,m);  % rows(i)- Alternatives; Cols(j) Score Ranks (1...m)
Sum_Rank1=zeros(m,m);
SR1=zeros(m,m); SR2=zeros(m,m); SR3=zeros(m,m); SR4=zeros(m,m);SR5=zeros(m,m);

    for i=1:m      % 1 rows is 1 rank
        for j=1:iM
            is=round(WR(i,j));  % ò.ê tiedrank ìîæåò=1.5
            if floor(WR(i,j))~=ceil(WR(i,j))      % integer
               k_int=k_int+1;    % not integer   1.5
            end
            Sum_Rank(is,i)=Sum_Rank(is,i) + 1;
        end
    end

    %-- values of performance indicators of alternatives
    %-- are no differ at 5% level (dQ)
    dQ=0.05;
    for i=1:3      % 1 rows is 1 rank
        for j=1:iM
            is=round(WR(i,j));  % ò.ê tiedrank ìîæåò=1.5
            %if i==1
              if Wdisp(2,j) > dQ  & Wdisp(3,j) > dQ
                 Sum_Rank1(is,i)=Sum_Rank1(is,i) + 1;
              end
              if (i==1 | i==2) & Wdisp(2,j) < dQ  & Wdisp(3,j) > dQ
                Sum_Rank1(is,i)=Sum_Rank1(is,i) + 0.5;
              end
              if (i==2 | i==3) & Wdisp(2,j) > dQ  & Wdisp(3,j) < dQ
                Sum_Rank1(is,i)=Sum_Rank1(is,i) + 0.5;
              end
              if Wdisp(2,j) < dQ  & Wdisp(3,j) < dQ
                Sum_Rank1(is,i)=Sum_Rank1(is,i) + 0.33;
              end
```

```
        %end
      end
    end


[mx iM1]=size(WR1);
    for j=1:iM1
      for i=1:m
        is1=round(WR1(i,j)); is2=round(WR2(i,j));
        is3=round(WR3(i,j)); is4=round(WR4(i,j));  is5=round(WR5(i,j));
        SR1(i,is1)=SR1(i,is1) + 1;  SR2(i,is2)=SR2(i,is2) + 1;
        SR3(i,is3)=SR3(i,is3) + 1;  SR4(i,is4)=SR4(i,is4) + 1;
        SR5(i,is5)=SR5(i,is5) + 1;
      end
    end


LGND = cell(1,m);
for i=1:m
    H=[ num2str(i,'%d') ' rank' ];
    LGND(i)={H};
end

%--------------------- Bar diagramm for Sum_Ranks -------------------------
SP=Sum_Rank./iM.*100;
    SP12=zeros(m,1); SP123=zeros(m,1);
    for i=1:3      % 1 rows is 1 rank , 2 rows is 2 rank
      for j=1:iM
        is=round(WR(i,j));  % ò.ê tiedrank ìîæåò=1.5
        if floor(WR(i,j))~=ceil(WR(i,j))      % integer
          k_int=k_int+1;                  % not integer   1.5
        end
        if i<3
          SP12(is,1)=SP12(is,1) + 1;
        end
        SP123(is,1)=SP123(is,1) + 1;
      end
    end

SP12=SP12./(2*iM).*100; SP123=SP123./(3*iM).*100;
T1=char(T_Name);

SPx=cat(2,SP(:,1:3),SP12,SP123);


    figure('Name',T1,'NumberTitle','off');
    ylim([0 70])
    bar(1:m,SPx(:,1:3),'group')
T2=['Statistics Ranks of the Alternatives'];
T3=['in ', num2str(nM,'%d'),' MCDM rank methods  & 5 normalization methods '];
title({T2;T3},'FontSize',11);
ylabel('Rank score, %','FontSize',11)
xlabel('Alternatives','FontSize',11)
%legend(LGND')
legend({'I rank', 'II rank', 'III rank'})
set(gca,'XTickLabel',Alter,'FontSize',10)

    figure('Name',T1,'NumberTitle','off');
    ylim([0 70])
    bar(1:m,SPx(:,4:5),'group')
```

```
T2=['Statistics of Ranks of the Alternatives'];
T3=['in ', num2str(nM,'%d'),' MCDM rank methods & 5 normalization methods '];
title({T2;T3},'FontSize',11);
ylabel('Rank score, %','FontSize',11)
xlabel('Alternatives','FontSize',11)
%set(axes_handle,'YGrid','on')
LGND1(1)={'I+II rank'};
LGND1(2)={'I+II+III rank'};
legend({'I+II rank', 'I+II+III rank'})
set(gca,'XTickLabel',Alter,'FontSize',10)

  SP=Sum_Rank1./iM.*100;
  figure('Name',T1,'NumberTitle','off');
  ylim([0 70])
  bar(1:m,SP(:,1:3),'group')
T2=['Statistics Ranks of the Alternatives'];
T3=['in ', num2str(nM,'%d'),' MCDM rank methods  & 5 normalization methods '];
T4=['(values of performance indicators of alternatives'];
T5=['are no differ at 5% level)'];
title({T2;T3;T4;T5},'FontSize',10);
ylabel('Rank score, %','FontSize',11)
xlabel('Alternatives','FontSize',11)
%legend(LGND')
legend({'I rank', 'II rank', 'III rank'})
set(gca,'XTickLabel',Alter,'FontSize',10)
'-- Rank Alternatives (A1, A2,..., Am) for all Methods/Modifications --'

fprintf('\n        Total:   \n')
fprintf('method  number of alternatives for j-th rank\n')
fprintf(' #    I  II III  IV   V ...rank  \n')
fprintf('-----------------------------------')
for i=1:iM
  fprintf('\n%2d   ',i)
  for j=1:m
    fprintf('%2d  ',WR(j,i)')
  end
end
fprintf('\n-----------------------------------\n')

fprintf('\n   number of variants of rank    \n')
fprintf('      I  II III  IV   V ...  \n')
fprintf('-----------------------------------\n')
for i=1:m
  fprintf('\nA%2d   ',i)
  for j=1:m
    fprintf('%2d  ',Sum_Rank(i,j))
  end
end
fprintf('\n\n------- The best alternatives --------')
[s3,ix]=max(Sum_Rank); %-- find Max  & index Alternatives , for all Score
fprintf('\nA%d   ',ix)

cMethod0=['--- rank: ';'  SAW:    '; '  AHP:    ';' VIKOR:  ' ];
cMethod={'SAW', 'AHP', 'VIKOR'};
LGND0 = cell(1,m);
for i=1:m
  H=[ 'r' num2str(i,'%d') ];
  LGND0(i)={H};
end
fprintf('\nFor aggregation methods:')
```

```
fprintf('\nSAW, AHP, VIKOR\n')
fprintf('       number of alternatives for j-th rank\n')
fprintf('    I    II    III   \n')
fprintf('----------------------------------------')

cat(2,cMethod0(2,:), num2str(cat(2,WR1)'))

%cMethod0={' SAW ', 'CODAS ', 'MABAC ', 'COPRAS ', 'TOP,L1 ', 'TOP,L2 ', 'TOP,Inf ', 'DIdeal ', 'GRA ' ];
% Introduced in R2013b
% array2table(WR1','RowNames',cMethod0,'VariableNames',LGND0)

fprintf('\n\n------- SAW method --------\n')
%WR2
cat(2,cMethod0(3,:), num2str(cat(2,WR2)'))

fprintf('\n\n------- AHP method --------\n')
%WR3
cat(2,cMethod0(4,:), num2str(cat(2,WR3)'))

iPlot=1;
  if iPlot==1
%===========================================================================
   figure('Name',T1,'NumberTitle','on','Position',[100 100 675 400]);
[nx my]=size(WR);
for i=1:4
   for j=1:5
      X(5*(i-1)+j)=6*(i-1)+j;
   end
end
   for j=1:4
      X(20+j)=24+j;
   end
for i=6:9
   for j=1:5
      X(5*(i-1)+j-1)=6*(i-1)+j-1;
   end
end
   for j=1:6
      X(44+j)=53+j;
   end
for i=11:12
   for j=1:4
      X(10+4*(i-1)+j)=10+5*(i-1)+j;
   end
end
Xz=[6 12 18 24 29 35 41 47 53 60 65];
y1=min(min(WiQ(1:3,:)));
y2=max(max(WiQ(1:3,:)));
ylim([y1 y2])
xlim([0 70])

% xTi=[3 9 15 21 26 31 37 43 49 56 62 68];
% set(gca,'XTick',xTi)
% set(gca,'XTickLabel',cMethod,'FontSize',7)
%
% xlabel({'Agg. methods'},'FontSize',11)
% ylabel({'iQ,%'},'FontSize',11)
% title({'Intensivity of Performance indicator  (iQ)';'for normalization methods: MAX,SUM,VEC,M-
M,DEA'},'FontSize',11)
% text(X(2),y2-(y2-y1)*0.1,'Points are no fill with color :','Color',[0.1 0.1 0.1],'FontSize',9)
```

```
% text(X(2),y2-(y2-y1)*0.15,'values of performance indicators of alternatives','Color',[0.1 0.1 0.1],'FontSize',9)
% text(X(2),y2-(y2-y1)*0.2, 'are no differ at 5% level','Color',[0.1 0.1 0.1],'FontSize',9)
% hold on
% p1=plot(X, WiQ(1,:),'or','MarkerEdgeColor','r','MarkerFaceColor','r','MarkerSize',5 );
% p2=plot(X, WiQ(2,:),'sg','MarkerEdgeColor','g','MarkerFaceColor','g','MarkerSize',5 );
% p3=plot(X, WiQ(3,:),'vb','MarkerEdgeColor','b','MarkerFaceColor','b','MarkerSize',5 );
%
% hold on

[k1 k2]=size(Xz);
for i2=1:k2
    line([Xz(i2) Xz(i2)],[y1  y2],'LineStyle','-','LineWidth',0.25,'Color',[0 1 0])
end
for i2=1:iM
    line([X(i2) X(i2)],[WiQ(1,i2)  WiQ(3,i2)],'LineStyle','-','LineWidth',0.01,'Color',[0.1 0.1 0.1])
end

dQ=0.05;
hj1=0; hj2=0; hj3=0;
for i2=1:iM
   if Wdisp(2,i2) < dQ
      line([X(i2) X(i2)],[WiQ(1,i2)  WiQ(2,i2)],'LineStyle','-','LineWidth',0.1,'Color','r')
      plot(X(i2), WiQ(1,i2),'or','MarkerEdgeColor','r','MarkerFaceColor','w','MarkerSize',5 )
      plot(X(i2), WiQ(2,i2),'sr','MarkerEdgeColor','r','MarkerFaceColor','w','MarkerSize',5 )
      hj1=hj1+1;
   end
   if Wdisp(3,i2) < dQ
      line([X(i2) X(i2)],[WiQ(2,i2)  WiQ(3,i2)],'LineStyle','-','LineWidth',0.1,'Color','m')
      plot(X(i2), WiQ(3,i2),'vb','MarkerEdgeColor','b','MarkerFaceColor','w','MarkerSize',5 )
      plot(X(i2), WiQ(2,i2),'sb','MarkerEdgeColor','b','MarkerFaceColor','w','MarkerSize',5 )
      hj2=hj2+1;
   end
   if Wdisp(2,i2)+Wdisp(3,i2) < dQ
      line([X(i2) X(i2)],[WiQ(2,i2)  WiQ(3,i2)],'LineStyle','-','LineWidth',0.1,'Color','m')
      plot(X(i2), WiQ(2,i2),'sm','MarkerEdgeColor','m','MarkerFaceColor','w','MarkerSize',5 )
      plot(X(i2), WiQ(3,i2),'vm','MarkerEdgeColor','m','MarkerFaceColor','w','MarkerSize',5 )
      plot(X(i2), WiQ(1,i2),'om','MarkerEdgeColor','m','MarkerFaceColor','w','MarkerSize',5 )
      hj3=hj3+1;
   end
end


% legend([p1 p2 p3] ,{'I rank','II rank','III rank'},'FontSize',9)

  end   % plot


%- Total Time (s)
total_Time=etime(clock,tm);
fprintf('\nTotal Time=%5.0f sec.\n', total_Time)
figure
histogram(s3)
      title('VIKOR Ranking')
      xlabel('Patients')
      ylabel('Rank')
      %%
     disp(['Paitients with priority 1 are: ', num2str(length(find(s3==1)))])
     disp(['Paitients with priority 2 are: ', num2str(length(find(s3==2)))])
     disp(['Paitients with priority 3 are: ', num2str(length(find(s3==3)))])
     disp(['Paitients with priority 4 are: ', num2str(length(find(s3==4)))])
```

```
%%
s3=s3';
for i=1:length(s3)
   if s3(i,1)==1
      TAR(i,1)=1;
   elseif s3(i,1)==2
      TAR(i,2)=1;
   elseif s3(i,1)==3
      TAR(i,3)=1;
   elseif s3(i,1)==4
      TAR(i,4)=1;
   end
end

%%

x = data';
t = TAR';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Scaled conjugate gradient backpropagation.

% Create a Pattern Recognition Network
hiddenLayerSize = 15;
net = patternnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'crossentropy';  % Cross-Entropy

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
   'plotconfusion', 'plotroc'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
tind = vec2ind(t);
```

```
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
figure, plotperform(tr);title('Best performance for "trainlm" function')
figure, plottrainstate(tr);title('Train state for "trainlm" function')
figure, ploterrhist(e);title('Error histogram for "trainlm" function')
figure, plotconfusion(t,y);title('Confiusion matrix for "trainlm" function')
figure, plotroc(t,y);title('ROC for "trainlm" function')

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
  % Generate MATLAB function for neural network for application
  % deployment in MATLAB scripts or with MATLAB Compiler and Builder
  % tools, or simply to examine the calculations your trained neural
  % network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
```

Appendix C (Numerical example)

Expert opinion as random for each criteria:

w=[.109 .105 .101 .097 .094 .094 .094 .093 .088 .071 .078 0.83];

Process for first instance:

Table2. Normalization methods

Max normalization	0.789473684210526	0	0.0740363821396769	0	0.25000000000000000	1	0.311764705882353	0.202127659574468	0.878378378378378	1	0	0.0140350877192982
Sum normalization	0.00412329555331713	0	0.00334540438006553	0	0.00175638886449460	0.00952380952380953	0.00336533360267855	0.00455886940038870	0.00318229663900517	0.00515463917525773	0	0.000102701037280477
Vec normalization	0.0699776993161650	0	0.0297863955797805	0	0.0290069306925016	0.0975900072948533	0.0545627431690976	0.0633386082515269	0.0549984734474334	0.0717958158617738	0	0.00152625715257185
Max-Min normalization	0.636363636363636	0	0.0713192140852258	0	0.0909090909090909	1	0.290823130076373	0.157303370786517	0.485714285714286	1	0	0
Dea normalization	0.998042222602031	0.994117647058824	0.996655592154081	0.994252873563218	0.995212638634006	1	0.996664879369820	0.996866945438899	0.994707438988533	1	0.995073891625616	0.993926556725096

Table3. Weighting based on SAW for different normalization methods

Max normalization	0.926041984912125
Sum normalization	0.0111651060016734
Vec normalization	0.136856315347281
Max-Min normalization	0.858709704754372
Dea normalization	1.37529753903807

Table4. Weighting based on AHP for different normalization methods

Max normalization	81.1854567848315
Sum normalization	0.116049442973142
Vec normalization	2.70990324003860
Max-Min normalization	79.9678809873079
Dea normalization	0.0967794513687373

Table5. Ranking based on VIKOR for different normalization methods

	Weight	Rank
Max normalization	149.724298526829	296
Sum normalization	0.211171623924737	73
Vec normalization	8.04446266550373	174
Max-Min normalization	150.172399189676	296
Dea normalization	0.198326811666083	17

Table6. Ranking based on VIKOR and expert opinion for different normalization methods

Max normalization	8
Sum normalization	79
Vec normalization	8
Max-Min normalization	8
Dea normalization	8

Table7. Last labeling based on VIKOR and ranking

Rank	8
Label	4

Table8. Target for neural network

Instance 1	0	0	0	1

Table8. Output of neural network

Instance 1	0.500000000000073	0.500000000000000	0.500000000000585	0. 999999999999343

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