ORIGINAL ARTICLE

Identifying the Factors Affecting the Survival Rate of Kidney Transplant Patients in Isfahan Using Classification Techniques

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Abstract

Purpose: 10% of the world's population suffers from chronic kidney disease and millions of deaths occur annually due to lack of access to appropriate treatment in the world. Kidney transplantation is associated with several problems. These problems, including kidney rejection, the consequences of surgery, drug poisoning, and infectious diseases can reduce the chances of survival of these patients. The science of classification has been proposed in recent years to reduce medical errors due to inexperience, reduce the workload of physicians and provide a suitable model for making better decisions.

Materials and Methods: The data set includes information about patients for whom kidney transplantation was performed in Isfahan. The data set includes 2554 patients and 38 attributes. The techniques used in this study will include random forest, Principal Component Analysis (PCA), and Support Vector Machine (SVM).

Results: Among the studied techniques, PCA technique in three classes out of four classes had better performance than other techniques. The syndrome has the highest recurrence among traits. Five attributes include syndrome, blood type, dialysis time, weight, and age.

Conclusion: The results showed that the PCA method in the case of non-numerical data has a good performance in identifying attributes. Also, five attributes that affect the survival rate of kidney transplant patients were identified.

Keywords: Data Mining; Kidney Transplantation; Survival Rate; Random Forest; Principal Component Analysis; Support Vector Machine.

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1. Introduction

Ten percent of the world's population suffers from chronic kidney disease. Millions of deaths occur worldwide each year due to a lack of access to appropriate treatment. The kidneys play an essential role in blood purification and their function is vital for humans. When the efficiency of this part of the body falls below 50%, it indicates the occurrence of kidney disease [1]. When this efficiency reaches between 10 and 15%, the patient enters the so-called end stage renal disease [2]. There are two solutions to treat the disease in this case. The first condition is dialysis and the second condition is kidney transplantation [3,4]. If dialysis is not appropriate, the need for a kidney transplant is strongly recommended [5]. Kidney transplantation refers to the use of one person's kidney in another. Kidney transplantation is less expensive and longer lasting than dialysis [6]. Iran has the highest number of kidney transplants in the Middle East. By 2014, more than 32,000 kidney transplants have been performed in our country. About 2,500 to 2,700 kidney transplants are performed annually in Iran [5]. Kidney transplantation is associated with several problems. These problems include kidney rejection, surgical consequences, drug poisoning, and infectious diseases. These problems can reduce the chances of survival of these patients [7].

The science of classification has been proposed to reduce the workload of physicians. It provides a suitable model for making better decisions in recent years [8-10]. Involvement of classification in the analysis of the survival rate of kidney transplant patients can lead to appropriate decisions [11-14]. In [11], Shahmoradi examined 513 patients in the center of Sinai. The results showed better performance of the Decision tree (C5) than other methods. Nematolahi [12] examined 717 patients who referred to Shiraz Namazi Hospital for kidney transplantation between 2008 and 2012. The employed techniques are support vector machine (SVM), linear regression, and neural network. The results showed better performance of the SVM and neural network. Emami *et al.* [13] examined the data of kidney patients between 2001 and 2012 and pointed to the effect of unbalanced data on the improper performance of machine learning techniques. So, Emami *et al.* suggested using the pre-sampling method. The results showed better performance of the proposed method than other methods. Ashiku *et al.* used big data analysis in order to assign kidneys to the right candidates. Ahike *et al.* helped to identify waitlisted candidates to accept kidneys [14]. Tapak [15] used neural network and linear regression to predict graft failure. The results show that the neural network technique performs better than other techniques. Topuz [16] stated that predicting the graft survival for kidney transplantation is a high stake. The Bootstrap Forest (BF) has better performance than other techniques.

According to studies, data mining methods have often been studied separately and fewer combinations have been studied with preprocessing methods. Also, the effect of the type of data sets and the degree of balance and imbalance of the data is less considered. This can be justified given the above because it cannot be said that one technique is suitable for all datasets. Considering that the kidney transplant patients in Isfahan have not been studied so far, the researchers intend to use three classification techniques, including random forest, SVM, and principle component analysis and SVM in order to identify the factors affecting the survival rate of the kidney transplant patients. These techniques are the most common classification techniques in predicting and identifying influencing factors in many diseases. Another reason for choosing these algorithms is their proper performance in previous research. Moreover, for extracting rules about survival rate of kidney transplantation, we used the random forest method.

2. Materials and Methods

The data set includes information about patients for whom kidney transplantation was performed in Isfahan. The data are related to patients who referred to Dr. Atapour's office for kidney transplantation. This collection is available electronically and has been collected from 1992 to 2020 by Dr. Atapour. The first step is checking the missing values. Of course, every data set may have missing values. The existence of these values can be due to various reasons. The first reason can be a user error in recording the data. The second reason is that sometimes some values are not specified by the doctor or the patient. The presence of these values will cause many problems in the accuracy of the method. Various approaches, such as the most probable values or the calculation of the mean value, can be used to determine the number of missing values. The second step is determining the target attribute. In this section, the target attribute is the survival rate for the disease for which the kidney transplant was performed. Survival rates can be one to two years, three to four years

and five to ten and more than 10 years. The data set includes 2554 patients and this set includes 38 attributes, including age, education, blood type, gender, platelet count, weight, ideal weight, syndrome, bacterial spontaneous peritonitis, white blood cell count, heart rate, glomerular filtration rate, blood sugar, 2-hour blood sugar, hematocrit, mean blood cell volume, blood urea nitrogen, blood creatinine, uric acid, blood triglyceride, high-density lipoprotein, low-density lipoprotein, calcium, phosphorus, sodium, aspartate, sodium Alanine aminotransferase, albumin, magnesium, iron, ferritin, parathyroid hormone, A1C blood hemoglobin, blood hemoglobin, vitamin D3, smoking, dialysis time, response time, and survival rate. The number of missing 2-hour blood sugar is about 2100, which is more than 80% of cases, so the attribute has been removed. Hematocrit, ferritin, A1C blood hemoglobin, parathyroid hormone, vitamin D3, magnesium, and iron are also removed because the missing value is more than 80%. And the number of attributes was reduced to 31. We want to determine the attributes that affect the survival of one to two years, three to four years and five to ten and more than 10 years. These 38 attributes are selected by receiving expert comments.

After collecting the required information, the data will be categorized using RapidMiner software version 7.1.

Before categorizing the data, the data set will be divided into two parts: train data set and test data set. Train data set is used to determine the survival rate of kidney transplantation based on the traits used. This template is then implemented on the test dataset. The way to divide a data set into two parts, i.e., training data set and test data set, is that 70% of the data set is used as training data set and 30% of it is used as test data set.

2.1. Techniques

This software uses various techniques to categorize information. The techniques include random forest, Principal Component Analysis (PCA), and SVM. Random Forest [17] operates randomly by creating several trees at random and making decisions based on them. In PCA, [18], it seeks to calculate the principal components. The SVM [19] is based on a linear relationship between independent variables and dependent variables. In fact, this method seeks a linear relationship with a high confidence margin between independent and dependent variables. The mentioned techniques are the most important and widely used data mining. Each of the techniques is implemented on train data set. Then, different survival rates, such as one to two years, three to four years and five to ten years, and more than 10 years are considered as a binary class. The techniques are then implemented separately on each data set.

2.2. Evaluation Criteria

This study used test data sets to check methods. First, the complexity matrix is calculated, which includes various criteria such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The target group is a binary class of two values with sick and healthy values. The TP identifies the number of records that the group has correctly placed as sick. TN identifies records that have been correctly identified as healthy individuals. FN identifies records that have been incorrectly identified as healthy, and FP identifies the number of records that have been incorrectly identified as sick. Then, based on the matrix, the efficiency criteria of the classification methods are calculated. The criterion used is Accuracy [20], in a way that the closer the accuracy of this criterion, the better the result. This criterion is calculated based on the following formula (Equation 1):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2.3. Dataset

The research uses a dataset of people who have had a kidney transplant. The specifications of this data set, values, and the number of uses of these values are given in Table 1. The age of people is divided into five periods: 10 to 29, 30 to 49, 50 to 69, 70 to 89 and 90 to 100, with the highest number being related to people between 50 and 69 years old. Most people also have a high school or elementary school education. The number of men is more than women. Blood group O+ is higher than other groups. 1160 people weigh between 61 and 80 (Table 1).

Most people have moderate renal impairment. Only 122 people smoke. Dialysis time and the response of most people is short. In terms of blood sugar levels, 613 people have diabetes, which is about 25% of the population. In this data set, the target class includes four values with values of 1 to 2 years, 3 to 4 years, 5 to 10 years and more than 10 years. Each of the values of the target attribute is considered as a binary class (Table 1).

Table 1. Characteristics, values, and numbers related to the data set of kidney transplant patients

Count	Attribute	Count	Attribute
10-29 (102), 30-49 (578), 50-69 (1048), 70-89 (791), 90-100 (31)	Age	Normal (1984), abnormal (569)	platelet count
Illiterate (68), Primary (615), Middle (311), High School (665), University (456)	Education	Normal (1190), abnormal (1247)	blood urea nitrogen
Men (1482), Women (1072)	blood type	Normal (1096), abnormal (1371)	blood creatinine
(302)A+, (27)A-, (83)AB+, (5)AB-, (216)B+, (16)B-, (337)O+, (55)O-	Gender	Normal (551), abnormal (564)	uric acid
40-60 (540), 61-80 (1160), 81-99 (724), 100 or more (3)	Weight	Low-risk (349), Normal (1078), High-risk (45)	blood triglyceride
40-60 (982), 61-80 (1538)	ideal weight	Low-risk (977), Normal (130), High-risk (45)	high density lipoprotein
Azotemia (1525), Proteinuria < 1g (441), Anemia (3), nephrotic nephritic (6), Microalbuminuria (3), Asymptomatic (20), Edema (1), Hematuria (23), Hypetension (16), Nephrotic syndrome (42), Pain (37) , Proteinuria > 1g (6)	Syndrome	Low-risk (121), Normal (1158), High-risk (72)	low density lipoprotein
Normal (1775), abnormal (778)	white blood cell count	Normal (1498), abnormal (393)	Calcium
Normal (727), abnormal (1826)	bacterial spontaneous peritonitis	Normal (1332), abnormal (523)	Phosphorus
Normal (1726), abnormal (827)	blood hemoglobin	Normal (1759), abnormal (794)	Sodium
Low (31), Normal (2512), High (9)	heart rate	Normal (914), abnormal (1638)	Aspartate aminotransferase
Renal failure (275), Mild renal impairment (686), Moderate renal impairment (1042), Severe renal impairment (314), Normal renal function (235)	glomerular filtration rate	Normal (1040), abnormal (1512)	Alanine aminotransferase
Normal (1775), abnormal (778)	white blood cell count	Normal (1326), abnormal (179)	Albumin
Normal (727), abnormal (1826)	bacterial spontaneous peritonitis	Used (122), Non-used (2431)	Smoking
Normal (1726), abnormal (827)	blood hemoglobin	1-10 minutes (1849), 11-20 minutes (396), 21-30 minutes (207), 31-40 minutes (51)	dialysis time
Low (600), Normal (803), Pre-diabetes (536), diabetes (613)	blood sugar	1-10 minutes (2514), 11-20 minutes (32), 21-30 minutes (4), 31-40 minutes (2)	response time
Normal (1912), abnormal (641)	mean blood cell volume	One to Two year (39), Three to Four year (92), Five to Ten (2012), More than 10 years (379)	survival rate

3. Results

The accuracy of techniques in three-four-year survival is better than the other classes. PCA gets the best performance for three classes (one-two, five- ten, more than 10. (Random forest in just three –four class has better performance than other methods (Table 2).

Table 2. The accuracy of all three classification techniques

Accuracy	
81.24%	PCA
83.56%	SVM
77.87%	Random Forest
83.24%	PCA+ Bayesian Boosting
85.43%	SVM + Bayesian Boosting
80.02	Random Forest +Bayesian Boosting

Factors affecting the survival rate extracted by all three techniques are shown in Table 3. For each technique, five attributes affecting the survival rate are obtained. Based on the data in Table 4, the repetition rate of each attribute is shown in Table 3.

For each survival rate, we compute frequency in Table 5. According to Table 3, the syndrome has the most repetitions among the attribute. After syndrome, blood group, dialysis time and weight have the most repetitions with 6 repetitions. The next attribute is age, which has five repetitions. This recommended combination is: Syndrome, blood type, dialysis time, weight, and age.

4. Discussion

Iran has one of the most successful kidney transplantation programs in the world. In this study, we tried to investigate the factors affecting the survival rate of patients with kidney transplantation. Various techniques such as random forest, SVM, PCA, Random forest + Bayesian boosting, SVM + Bayesian boosting and PCA + Bayesian Bossting were used. The results suggested a combination of five attributes for predicting the survival of kidney patients. This combination includes syndrome, blood type, dialysis time, weight, and age. Scheffner stated that age, cardiovascular disease, type 2 diabetes, and graft function are important risk factors

Table 3. The factors affecting the survival rate of kidney transplant patients extracted by each classification technique

Survival Rate(year)	PCA	Support Vector Machine	Random Forest
One – Two	Phosphorus, Sodium, Albumin, white Blood cell count, Response Time	Syndrome, Education, Dialysis Time, Weight, Blood Type	Heart rate, blood urea nitrogen, Syndrome, Calcium, Age
Three – Four	Smoking, Gender, Weight, Ideal weight, Syndrome	Glomerular Filtration Rate, Response time, Dialysis Time, Weight, Syndrome	Blood Type, Dialysis Time, Uric acid, Blood Triglyceride, Blood sugar
Five – Ten	Smoking, Weight, Education, Blood sugar, Sodium	Blood Triglyceride, Dialysis Time, Age, Blood Type, Bacterial Spontaneous Peritonitis	Blood Type, Calcium, Age, Albumin, Dialysis Time
More than 10	Blood type, Dialysis time, Age, Syndrome, Weight	Education, Age, Syndrome, Blood Type, Opium	Heart Rate, Opium, Blood Sugar, Syndrome, Weight

Table 4. The sensitivity and specificity of all three classification techniques

Techniques Class	Result	Survival Rate(year)			
		One – Two year	Three – Four year	Five – Ten year	More than 10 years
PCA	Sensitivity	39.12%	50.33%	86.20%	48.34%
	Specificity	27.23%	24.56%	30.21%	13.33%
SVM	Sensitivity	25.48%	56.4%	89.18	45.12
	Specificity	19.12%	43.33%	33.33%	28.34%
Random Forest	Sensitivity	37.23%	54.56%	79.23%	43.33%
	Specificity	25.48%	26.4%	30.18%	25.12%
PCA+ Bayesian Boosting	Sensitivity	49.12%	63.33%	86.33%	58.34%
	Specificity	17.23%	44.56%	41.23%	33.33%
SVM + Bayesian Boosting	Sensitivity	55.48%	76.4%	90.18%	64.12%
	Specificity	29.12%	43.33%	37.33%	38.34%
Random Forest +Bayesian Boosting	Sensitivity	47.23%	54.56%	84.23%	53.33%
	Specificity	25.48%	36.4%	40.18%	25.12%

for survival after kidney transplantation [21]. Roshanaei represented that the important variables selected based on various criteria in RSF were age of transplant recipient, the patient's condition at discharge, hemoglobin of receptor, the last Creatinine and the use of immunosuppressive drugs [22].

The first factor affecting the survival rate of kidney transplant patients is the syndrome. The syndrome has different values and each of these values corresponds to different conditions that lead to injury and cause problems in the kidney transplant patient. So, each of these factors can somehow affect the survival rate of kidney transplant patients. In a study of 357 patients, Hohag found that 58 percent of those with proteinuria syndrome survived for five years [23].

The second factor affecting the survival rate of kidney transplant patients is blood type. Grander addressed the problems of patients with blood group O kidney transplantation and the role of the blood group in kidney transplantation. The results showed that patients with blood group O increase the risk of death after kidney transplantation [24]. Blood types A and O are among the groups that affect kidney transplantation and can increase the risk of death [25].

The third factor is dialysis time. Resander *et al.* investigated the role of dialysis duration in kidney transplant quality and the patient survival rate. Resander *et al.* followed them up and the results showed that the longer the dialysis period, the lower the patient's chance of survival [26].

The fourth effective factor is the weight of kidney transplant patients. One of the complications that occurs after kidney transplantation is that the patients gain weight [27]. The average amount of overweight is about 4 kg. This overweight can cause many problems for the patient and can even lead to the death of patients [28]. The

Table 5. The frequency of each feature in factors affecting survival rate

Feature	Frequency in One-Two	Frequency in Three-Four	Frequency in Five-Ten	Frequency More than 10	Total Frequency
Syndrome	2	2	0	3	7
Blood Type	1	1	2	2	6
Dialysis Time	1	2	2	1	6
Weight	1	2	1	2	6
Age	1	0	2	2	5
Education	1	0	1	1	3
Blood Sugar	0	1	1	1	3
Albumin	1	0	1	0	2
Response Time	1	1	0	0	2
Heart Rate	1	0	0	1	2
Calcium	0	0	2	0	2
Opium	0	0	0	2	2
Blood Triglyceride	0	1	1	0	2
Smoking	0	1	1	0	2
Sodium	1	0	1	0	2
Uric acid	0	1	0	0	1
Blood Urea Nitrogen	1	0	0	0	1
Glomerular Filtration Rate	0	1	0	0	1
Bacterial Spontaneous Peritonitis	0	0	1	0	1
white Blood cell count	1	0	0	0	1
Gender	0	1	0	0	1
Ideal Weight	0	1	0	0	1
Phosphorus	1	0	0	0	1

fifth factor affecting the survival rate of kidney transplant patients is age. People who are young at the age of transplantation have a high risk of losing the transplant and even dying [29].

Another important factor is the right candidate for kidney transplantation. Ashile *et al*. consider big data analysis to detect the right patient in kidney waitlisted by 5 classification techniques. The Decision Tree and Random Forest had better performance than other techniques. It reached approximately 90 percent accuracy [14]. However, SVM + Bayesian boosting detects more accurately than other techniques and it reached approximately 84 percent accuracy. Many parameters can be effective on the performance of the classification methods such as the number of records, the type of attributes and method of handling missing values. The PCA method has the best performance among three of the four classes. This method, when data is non-numeric data, has a good performance.

5. Conclusion

This study identifies the five factors affecting the survival rate of kidney transplant patients in Isfahan using classification techniques. These factors include syndrome, blood type, dialysis time, weight, and age. Among the data techniques, SVM has better performance than other available techniques.

So, the factors, include syndrome, blood type, dialysis time, weight and age can input of SVM to predict survival rate.

In fact, the relationship between each of these influential factors and the survival rate can be expressed as a hypothesis. In other studies, the effects of each of these factors on the survival rate can be examined separately.

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