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ORIGINAL PAPER

Comparing Three Data Mining Methods to Predict Kidney Transplant Survival

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ABSTRACT

Introduction: One of the most important complications of post-transplant is rejection. Analyzing survival is one of the areas of medical prognosis and data mining, as an effective approach, has the capacity of analyzing and estimating outcomes in advance through discovering appropriate models among data. The present study aims at comparing the effectiveness of C5.0 algorithms, neural network and C&RTree to predict kidney transplant survival before transplant. **Method:** To detect factors effective in predicting transplant survival, information needs analysis was performed via a researcher-made questionnaire. A checklist was prepared and data of 513 kidney disease patient files were extracted from Sina Urology Research Center. Following CRISP methodology for data mining, IBM SPSS Modeler 14.2, C5.0, C&RTree algorithms and neural network were used. **Results:** Body Mass Index (BMI), cause of renal dysfunction and duration of dialysis were evaluated in all three models as the most effective factors in transplant survival. C5.0 algorithm with the highest validity (96.77%) was the first in estimating kidney transplant survival in patients followed by C&RTree (83.7%) and neural network (79.5%) models. **Conclusion:** Among the three models, C5.0 algorithm was the top model with high validity that confirms its strength in predicting survival. The most effective kidney transplant survival factors were detected in this study; therefore, duration of transplant survival (year) can be determined considering the regulations set for a new sample with specific characteristics.

Key words: data mining; survival; kidney transplantation; C5.0 algorithm; C&RTree algorithm; neural network algorithm; CRISP methodology.

1. INTRODUCTION

Chronic kidney disease (CKD) refers to a stage in which performance of kidneys is less than 50% of their normal performance and when this reaches no more than 10%-15%, the patient is referred to as ESRD (End Stage Renal Disease). In the latter, kidney transplant or dialysis (hemodialysis or peritoneal dialysis) would be necessary (1). The prevalence of renal dysfunction in Iran is estimated at 360/1,000,000. The number of ESRD patients under treatment in Iran in 2009 was approximately 24,000; however, studies show that the number is growing (2, 3).

According to the data provided by Transplant & Special Diseases Management Center, the number of ESRD patients under alternative renal treatment in Iran in 2006 reached 25,000 (of the total 70m) and considering the annual 12% growth trend, it is expected to reach 40,000 in 2011. The annual ESRD prevalence and incidence were 357 and 57 cases per 1m, respectively (4). In early 2014, the number of advanced CKD patients under an alternative treatment in Iran reached 50,000 (5). Kidney Transplantation or Renal Transplantation refers to using the kidney of one person for another due to which the patient releases from dialysis restriction and reversible uremia manifestations. Based on the analysis on WHO data (2008) on 104 countries representing 90% of all transplantations across the world, about 100800 organ transplants are performed and there are 69,400 cases of renal transplantations (over 68% of all transplants in the world) (46% from live donors) (6). It can be said that renal transplantation is the treatment of choice for ESRD patients (7). Donors are selected based on success rate predictions of transplantation. However, despite all considerations, complications like rejection, acute tubular necrosis, surgical complications, infectious diseases and kidney drug poisoning threaten the chance of survival in transplantation (8).

One of the data categories desired by researchers is the duration of events like mortality; i.e. attending to a group of people in a manner that after some time, a specific point of time called "failure or accident" can be defined for every individual. Since this was previously used for mortality studies exclusively and was designed for this and it was called "survival time analysis" (9).

Considering the fast growth in size and number of databases, knowledge, regulation or high-level information discovery from database to maintain decision making and predict future behaviors seems necessary (10); so many organizations are practicing data mining (11). Data mining, automatic search for large data sources, is performed to find models and attachments which cannot be obtained through simple statistical analyses (12). The process tries to discover unknown relationships and appropriate models of data and is known as an effective method of discovering information from data (13). In fact, data mining is a specific step in Knowledge Discovery in Databases (KDD) including the application of particular algorithms for extracting models from data (26-30). Practically, the two major aims of data analyses are prediction and description (13). One of the areas requiring the application of this tool for analyzing extensive data and predictive modeling with new calculation methods is medicine. "Classification" is one of the predictive methods for estimating the rate of occurrence of an event. In computer-based clinical predictive systems, different approaches and algorithms including rule-based reasoning, case-based reasoning and machine learning can be used; machine learning algorithms have been used in many medical and medicine-related areas like Decision Tree, artificial neural network, Support Vector Machine and Bayesian Network. However, for more precise diagnosis and preventing diagnostic errors, artificial neural network and decision tree have been widely used due to their exclusive characteristics (19, 20).

Artificial neural network is one of the most important concepts of machine learning (21). In the last decade, application of artificial neural network techniques has been extensively accepted in medicine and relevant fields (22). Studies have shown that the application of such networks along with specialized clinical diagnosis can slightly reduce diagnostic errors. The neural network uses learning concept for problem solving and Gradient descent methods are widely used (23). Decision trees are used based on decision-making rules for prediction and classification and have several advantages. For example, following the completion of the tree, causes of deduction rules can be easily observed; i.e. decision trees unlike neural networks do not work like a black box and their logic is quite clear. Another advantage of decision trees is providing the possibility of learning more about significant fields. This can lead to creating an appropriate view toward the importance of variables before entering other data mining techniques like neural networks (24).

The present study aims at comparing the three predictive classification models of neural networks, C5.0 and C&R Tree in predicting kidney transplant survival before transplantation.

2. MATERIALS & METHODS

Participants

There were 7 urologists and nephrologists taking part in determining effective parameters in predicting renal transplantation survival for devising a questionnaire and checklist on necessary information of the patients.

Patient files of Sina Hospital Urology Research Center from September 2007 to September 2013 were studied. Incomplete files due to lack of recording full information were excluded in the primary phase of the study. Finally, 513 files of kidney recipients (and donors) were selected as the sample of the study.

Questionnaire

A researcher-made questionnaire was devised for information needs analysis distributed among urologists and nephrologists of Sina Hospital aiming at collecting required data items for predicting kidney transplantation survival.

The questionnaire consists of three sections (total 46 questions) including demographic information (7 questions) and data items required for predicting kidney transplantation survival (39 questions).

Content and face validity of the questionnaire was tested and the validity was confirmed by nephrologists and urologists participating in the study (7 faculties with minimum 3 years of experience). The result was a checklist used for extracting the data. Reliability was also tested using test-retest method; i.e. the questionnaire was re-filled by the subjects after some time and scores obtained from the two tests were examined and the resulting correlation coefficient was 92%. The checklist also had three sections including demographic information, kidney recipient/donor as input variables and kidney transplantation survival as output variables.

Data Gathering

The input factors were 11 classified in three sections. The first section was demographic information including age (years) and sex of donor/recipient; the second part was clinical information of the recipient including causes of ESRD (8 items), type of dialysis (hemodialysis, peritoneal and preemptive dialysis), duration of dialysis (month), panel test (in positive and negative states; negative=0, positive=100, percentage: 0-100); BMI (dividing weight in kilograms by height squared in meters); relationship between kidney donor and recipient (cadaver, related or unrelated).

The information on the third section comprising the model output was gathered through contacting patients asking them about the duration of transplanted kidney survival. After extracting the information from the said fields from all files, the data were entered into an Excel file from the checklist.

Data mining

The three predictive data mining models of neural network, C5.0 Decision Tree and C&RTree were modeled and analyzed using IBM SPSS Modeler 14.2. The data of the database were randomly divided into two parts: 70% (360) for training and 30% (153 cases) for testing.

In most cases, raw data are rarely proper for analysis; therefore, they are processed before final analysis using the relevant algorithms. Data preparation is one of the most important and usually most time-consuming phases of data mining projects. After determining the sources of data, the data should be selected, cleaned and put into the proper

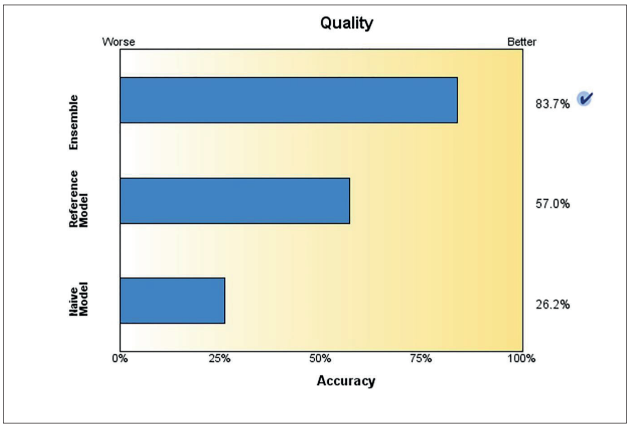

Figure 1. Validity of reference model

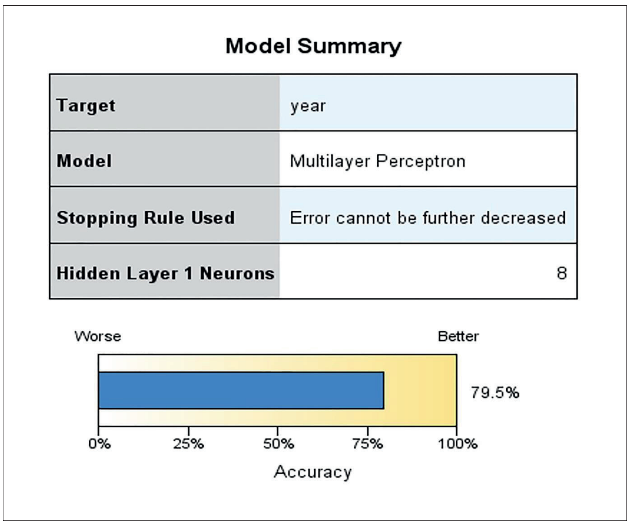

Figure 2. Accuracy of Optimum C&RTree

format (12). After several analyses, a series of the recorded data were omitted due to being incomplete or incorrect. The outlier data were also specified to minimize errors in final results. Also, in some records in which age of the donor was not specified, mean was calculated. Height and weight fields were combined using BMI= Weight(kg)/(Height(m))^2 formula and BMI was determined for every recipient to be used in modeling. The Table 1 was obtained after refining the data (the 11 independent variables (input) are demonstrated in Table 1). Also, the independent variable (output variable) has six different outputs including less than 1, 2, 3, 4, 5, 6 year(s) and more than 6 years' survival (Table 2).

By modeling human brain, artificial neural networks can discover the hidden relationship among data, even when non-linear data have many deficiencies or are incomplete (21). There are several algorithms for learning neural networks and multilayer perceptron models are the most popular ones (8, 25-27). In this study, the number of required layers in the network was selected through testing, repeating and comparing the results; the obtained results indicate more precision of the system using double layer networks. The first layer, also called "hidden layer" has some neurons or neural units because in previous studies, the number of hidden layer neurons was very effective in increasing network function (26, 28-35). In the present study, hidden layer neurons of neural network were considered at 1-50 in order to increase the performance of the survival prediction model; network performance with the current topology was calculated with a different number of neurons in the hidden layer and the structure with an 8-neuron topology in one hidden layer was selected. The validity of the reference model was estimated at 79.5% (Figure 1).

Classification and Regression Tree (C&RTree) node is a method of classification and prediction based on the tree. Like C5.0, this method divides educational records into sections with equal output fields. First, the C&RTree node tests input fields for the best result to minimize the gross indicator obtained from analysis. In order to reach the highest accuracy, the model resulting from the decision tree and regression or C&RTree produces 20 C&RTree and combines their relationships to provide the possibility of creating and generating an optimum model via boosting. The accuracy of the boosting and reference models was estimated at 83.7% and 57%, respectively (Figure 2).

The C5.0 algorithm was used for making the decision tree or series of rules that it is the modified version of C4.5 and ID3 algorithms acting as a powerful approach for increasing classification precision. This algorithm has a specific method for improving the rate of prediction precision, called "Boosting". In this study, the survival rate of each case was estimated at 96.77%. This model functions consecutively by making multi-purpose models. The first model is made conventionally. Then, the second model is constructed by focusing on records that are not classified by the first model. The third model is based on the errors of the second on and this goes on. In the end, records are classified based on the series of models and are combined into a single prediction model by valuing the votes (24). A portion of decision making levels of C5.0 is demonstrated in Figure 3. Using this tree, the survival rate of every new transplantation case is estimated at 96.77%.

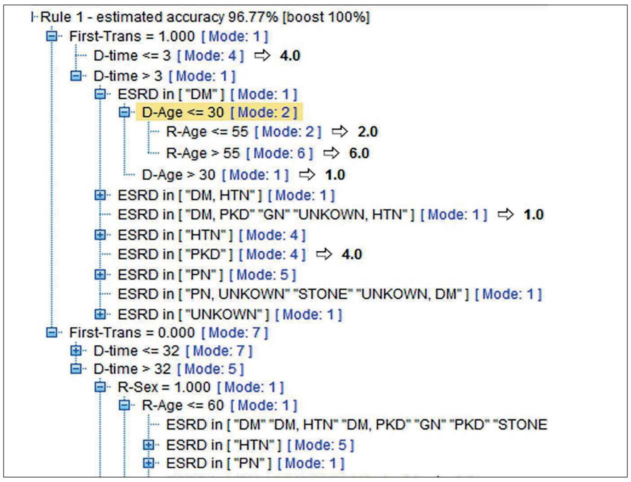

Figure 3. Portion of decision making levels of C5.0 Tree with 96.77% accuracy

Evaluation

Evaluation results improve the model and make it practical. Gains figure is used for evaluating classification models; i.e. a table is designed based in real responses and model predictions and a figure with vertical (real response) and horizontal (model prediction) axis is drawn accordingly. Evaluation results as well as training and testing data are visually displayed.

In order to examine the accuracy of the modes, the data were divided into education (70%) and testing (30%). Models were prepared using the education section's data; the data of the testing section and a few other records check the models. There are various factors for evaluating the validity of classification methods. Therefore, sensitivity, specificity and accuracy are applied (16, 36, 37).

In the above formula, positive label refers to one of the labels of less than 1, 2, 3, 4, 5, 6 or more than 6 year (s) and negative label includes all series of data, except the positive group label.

3. RESULTS

In the present study, data of 513 kidney recipients (and the same number of donors) were modelled using the three data mining algorithms of neural networks, C5.0 and C&RTree and after entering the data in Table 1, the survival rate of the recipient was predicted in one of the seven output groups (Table 2).

The significance of effective factors in predicting transplantation survival in the three models can be seen in Table 3.

The three predictive models were evaluated according to accuracy, sensitivity and specificity. Confusion matrix was used for calculating the indices. The said matrix is a useful tool for analysing the performance of classification method in determining data or observations of various classifications. If the data is in M category, the table classification method with the minimum size is M*M. It is ideal to have most data associated with observations on the main diameter of matrix and the rest are zero or close to 0 (16, 36, 37). Considering the confusion matrix of the models, sensitivity, specificity and accuracy of each is demonstrated in Table 4.

No.	Feature	Note	Nominal variable	Range
1	ESRD	Cause of renal dysfunction	Diabetes, Glomerulonephritis, Hypertension, Polycystic kidney, Kidney stone, Unknown	
2	R-AGE	Recipient's age		[9-68]
3	BMI	Recipient's BMI		[16-38]
4	D-Time	Duration of dialysis (month)		[0-98]
5	R-SEX	Recipient's sex	Male Female	
6	TYPE-DIALYSIS	Type of dialysis	No dialysis Hemodialysis Peritoneal dialysis	
7	PANEL-TEST	Panel test		[0-100]
8	FIRST-TRANS	History of transplantation	Yes No	
9	RELATIONSHIP	Relationship	Non-relative Relative Cadaver	
10	D-AGE	Donor's age (yrs.)		[17-58]
11	D-SEX	Donor's sex	Male Female	

Table 1. Input data and their type after cleaning

>1 year	Transplanted kidney survival: 0-12 month(s)
>2 years	Transplanted kidney survival: 12-24 month(s)
>3 years	Transplanted kidney survival: 24-26 month(s)
>4 years	Transplanted kidney survival: 36-48 month(s)
>5 years	Transplanted kidney survival: 48-60 month(s)
>6 years	Transplanted kidney survival: 60-72 month(s)
<6 years	Transplanted kidney survival: <72 month(s)

Table 2. Model's output group label

No.	Neural network	C&RTree	C5.0
1	BMI	ESRD	ESRD
2	ESRD	BMI	D-Time
3	D-Time	D-Time	BMI
4	First-Transplant	First-Transplant	Relation
5	R-Sex	R-Sex	R-Sex
6	R-Age	R-Age	Type
7	D-Age	D-Age	R-Age
8	D-Sex	D-Sex	Panel-Test
9	Panel-Test	Type	First-Transplant
10	Relation	Relation	D-Age
11	Type	Panel-Test	D-Sex

Table 3. Priority of effective, predictive kidney transplant factors in three models

	C&RTree Model			Neural Network Model			C5.0 Model		
	Sensitivity(%)	Specificity (%)	Accuracy(%)	Sensitivity(%)	Specificity (%)	Accuracy(%)	Sensitivity(%)	Specificity (%)	Accuracy(%)
<1 year	95	61	89	91	66	87	96	50	91.5
<2 years	100	100	100	100	100	100	100	100	100
<3 years	86	46	81	84	100	86	92	33	87
<4 years	76	50	73	82	60	79	76	50	73
<5 years	73	42	76	84	41	77	84	33	79
<6 years	89	55	79	76	61	74	91	50	87
>6 years	88	61	85	93	27	83	97	50	93
Total	86.85	57.28	83.28	87.14	65	83.71	90.85	52	87.21

Table 4. Calculating sensitivity, specificity and accuracy of model's testing data

Training data were calculated for each model separately using IBM SPSS Modeler 14.2, taking into account the three factors of sensitivity, specificity and accuracy. The accuracy of C&R Tree and neural network model was estimated at 83.7% and 79.5%, respectively; also, the accuracy of survival rate of each new case was estimated at 96.77% in the C5.0 model.

According to Table 4, the data following testing C&RTree model indicate 86.85% sensitivity, 57.28% specificity and 83.28% accuracy. Moreover, sensitivity, specificity and accuracy of the neural network model are estimated at 87.14%, 65% and 83.71%, respectively. The highest rate of accuracy belonged to the C5.0 model (87.21%) as well as sensitivity and specificity at 90.85% and 52%.

4. DISCUSSION AND CONCLUSION

As kidney transplantation is increasing every day in the world and fear of transplantation rejection, high costs and growing number of ESRD patients on the other hand, designing a model for predicting transplantation survival would be a great help leading to increasing survival rates and consequently, decreasing transplantation waiting times and costs.

In the present study, factors affecting kidney transplantation survival are determined through information needs analysis conducted on nephrologists/urologists and a researcher-made questionnaire. After screening the data and omitting incomplete records, modelling was performed using neural network and the two decision making trees of C5.0 and C&RTree and their accuracy, specificity and sensitivity were evaluated and compared.

In the study of Ashrafi et al conducted on 316 kidney transplant patients, demographic information of recipients and donors, type and location of transplant, recipient's BMI and diabetic status were extracted from patient files and death or transferring patients to dialysis were considered as the end point (38). In order to analyse 10-year survival of transplanted kidney and determining the effective factors, Hassanzadeh et al added cold ischemic time, relation to recipient (relative, non-relative), side of donated kidney, predialysis duration, creatinine level at discharge and duration of hospitalization to the said factors (7). The retrospective study of Hashiani examined the survival rate of kidney transplantation by studying variables like age and sex of donors and recipients (39). The strong point of the present study compared to the previous ones is the method of determining data effective in predicting survival which was conducted scientifically and through questionnaires distributed among nephrologists and urologists. Evaluating a series of factors affecting kidney dysfunction was a determining factor in predicting survival which were not, except one (diabetic status of recipient) taken into account in the study of Ashrafi et al.

In another study conducted by Saleh Nasab et al (39), a checklist was prepared (like the present study), information was extracted from files of kidney patients and modelling was performed based on the information. Although, the said study also aimed at extracting effective models in predicting survival using data mining, some factors like immunosuppressive regimen, cold ischemic time, creatinine level at discharge and duration of hospitalization were ignored due to the difference in the study's perspective because the aim of the present study is predicting transplantation survival prior to surgery; however, factors similar to this study in the previous ones were post-transplant variables that cannot be considered in this present study.

In the study of Ashrafi, statistical methods of Kaplan–Meier, Cox regression and goodness of fit were compared in the artificial neural network and the neural network model was introduced as the highest one among others with 72% precision (38).

In a study titled "predicting chronic allograft kidney disease using decision making tree" by Lou Faro et al, C4.8 algorithm and laboratory factors if transplant patients were used; the validity of the model was <83% (40). In the same year, Greco et al predicted transplantation survival or rejection using a binary tree at 4 levels' sensitivity and specificity of the tree were estimated at 88.2% and 73.8%, respectively. In the present study, C5.0 algorithm, the optimized version of C4.8 algorithm was used and the validity of the survival rate of the model in each transplantation case was estimated at 96.7%. On the other hand, the target field, in this study, should be classified; the difference between the recent study and that of Lou Faro and Greco is in the output of the tree. The output in the latter studies was merely failure or success of transplantation but the output of our study was not binary and could express duration of transplantation survival in 6 different conditions (41).

In this study, the three data mining algorithms were compared to estimate transplantation survival in kidney patients; the highest accuracy belonged to C5.0 model (96.77%) followed by C&RTree (83.7%) and neural network model (79.5%).

Evaluating the significance of transplantation survival predicting factors in the present study, cause of kidney dysfunction, BMI and pre-transplant dialysis were determined as the most effective factors that are compatible with the findings of previous studies. By comparing preceding researches in the area of data mining and kidney transplantation survival, it is clear that the C5.0 model offered in our study has the highest accuracy; moreover, another strong point of the study is implementing all phases of knowledge discovery according to CRISP standard that was not mentioned in other studies. On the other hand, in order to facilitate the application of the model, the researchers designed and run a mobile application under android and iOS platforms. Using the said apps, the user can see the predicted survival rate of transplanted kidney in one of the rows of Table 2 after filling out input fields according to Table 1.

Since the findings of our study are obtained from the data of one single hospital, it is suggested that data of different research centres are used and compared for further evaluation of the subject.

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