Computer Science Journal of Moldova, vol.**26**, no.2(77), 2018

Prediction of the Survival of Kidney Transplantation with imbalanced Data Using Intelligent Algorithms

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Abstract

Kidney transplantation is one of the effective post-dialysis treatment methods for patients with chronic renal failure in the world. Most medical data are imbalanced and the output of algorithms is inefficient with imbalanced data. The aim of this study is to predict the two-year survival rate of kidney transplant patients and provide a more accurate model. We evaluate the data of renal transplant patients in Afzalipour Medical Education Center 2006-2010, Kerman, Iran. Survival prediction of kidney transplantation with MLP and RBF neural networks with two methods of sampling and investigating the factors affecting the survival of kidney transplant in renal transplant patients is considered by the binary particle optimization algorithm and nearest neighbor algorithm. Accuracy of the results can be increased by using the oversampling method in imbalanced medical data, and radial base network model is a suitable model for predicting the survival of kidney transplant patients.

Keywords: Neural network, imbalanced data, Binary particle optimization algorithm, nearest neighbor, Kidney transplantation.

1 Introduction

Kidney transplantation is an appropriate and effective strategy for patients with chronic renal failure. The end stage of the renal disease is associated with a significant reduction in the quality of life of patients and early death. Treatment for chronic renal failure includes two types of dialysis and kidney transplantation. The kidney transplant brings good and preferred treatment and a more favorable life and reduces the risk of death for patients in the final stage of kidney failure [1],[2], and [3].

The history of kidney transplantation dates back to 1954 in Germany that the transplant was given by the living relative. However, the first renal transplant in Iran was carried out in 1967 in Shiraz. Iran has the highest number of kidney transplants. It is in the first place in the Middle East, and it is the fourth in the world [3].

Providing an appropriate transplant is effective for every patient. Therefore, evaluation of renal graft survival after transplantation is very important and several studies have been carried out on graft survival. Researchers in the field of prediction of kidney transplantation survival include statistical studies and artificial intelligence. In 2012, in the United States, a model of body mass index, race, gender, and age were identified as the factors influencing the survival of kidney transplantation using the Bayesian method [5]. In 2012, the support vector machine was used to determine the effective variables of age and level of creatinine, gender, and recipient weight [6]. Nematollahi et al. studied 717 patients of Nemazee Hospital of Shiraz during 2008–2012, and they Predicted Survival of Kidney for 5 years by multilayer perceptron of artificial neural networks (MLP), logistic regression (LR), Support Vector Machine (SVM). Also they identified that SVM and MLP models could efficiently be used for determining survival prediction in kidney transplant recipients [2]. In [4], a model is proposed for Predicticting Graft Survival in Kidney Transplant by decision tree, and Cox regression and Ensemble learners. They revealed that early acute rejection in the first year is associated with a substantially increased risk of graft failure. Machine learning methods may provide versatile and feasible tools for forecasting graft survival.

This article examines the survival of kidney transplantation after two years using the neural network. The ratio of successful data to the total data is 0.09 percent and results in a convergence of data in a neural network class. Therefore, in the pre-processing of data, we prepare imbalanced data with the sampling method to provide balanced data for the input of the neural network. In the following, we obtain the effective factors in the survival of kidney transplant using binary particle optimization algorithm and the nearest neighbor algorithm.

2 Methods

In this section, technical aspects of machine learning and data mining Methods used for data analysis are described. The data of renal transplant patients were collected from the Afzalipour Educational Center in Kerman and were inconsistent. Therefore, the data are balanced by two sampling methods: under-sampling and oversampling, and then used in the neural network applying particle optimization algorithm and the nearest neighbor algorithm.

2.1 Dataset

The data of renal transplant patients of the Afzalipour Medical Center of Kerman city were collected during the years 2006–2010. Data were collected from 423 cases of kidney transplant patients of the Afzalipour Medical Center of Kerman city. 156 cases of kidney transplant patients with 14 attributes were selected after removing missing values or applying average method for missing values [7].

The dataset contains information on 156 renal transplantation patients with 14 features. Features include Recipients sex, Donors sex, Recipients age, Donors age, BMI, dialysis time before operation, blood group consistency, Recipient and donor of RH, Donors relationship, kidney transplantation history, diabetes of Recipient, donator type (Alive, corpse), Type of dialysis and result of the two-year graft survival. We consider weight and height with BMI. Table 1 shows the features of kidney transplant patients.

Table 1. Description of characteristics of kidney transplant patients

no	**Attributes**
1	Donor's age
2	Recipient's age
3	Donor's sex
4	Recipients sex
5	BMI
6	blood group consistency
7	Recipient and donor of RH
8	dialysis time before operation
9	Donor's relationship
10	kidney transplantation history
11	diabetes of Recipient
12	donator type (Alive, corpse)
13	Type of dialysis
14	result of the two-year graft survival

2.2 Neural network

An artificial neural network is a method of information processing that is inspired by neurological systems. An artificial neural network has the ability to model complex systems and relationships, and non-linear functions [8] and consists of a sum of neurons or the same processor elements. The relationship between the adjustable neurons depends on the conditions of the issue. The neurons of each layer are attached to subsequent layers with different weights.

Information is stored in the weights. The implementation of the neural network has three parts: sample provision, the training phase, and neural network testing. In this study, two types of the artificial neural network have been used: multi-layer perceptron network and radial base function network. We examine functioning of the neural network with input data after completing the training of the neural network and correcting its weight.

2.2.1 Multi-layer perceptron (MLP)

The most common neural network is reversible networks. Multi-layer perceptron network (MLP) is a model of reverse grids that maps the input data to the output data by adjusting the weight of the layers. MLP is a combination of at least three layers of neurons (input, intermediate, and output) that can contain one or more hidden layers [8],[9]. Neurons are arranged in several layers, so that each layer receives its inputs from the previous layer and sends its outputs to the next layer. The neural network is taught by the post-error algorithm [10].

The post-error algorithm is used to learn the weight of a multi-layer network. In this method, we try to minimize the square of the error between the network outputs and the target function using the descending gradient. The function of this method is greatly improved if the weights and the number of neurons are selected correctly and optimally. The goal of learning in learning algorithms is to minimize the output error of the network with the optimum output. Learning algorithms include two kinds: observer learning and uncontrollable learning [11].

2.2.2 Radial Basis Function (RBF)

Radial Basis Function is reversible Network with three inputs, hidden and output layers. In the hidden layer, the active function of the radial base function is used. The main advantage of the RBF network is to minimize input data errors. The RBF network approximates any function using symmetric and local radial functions [10]. The active function in the hidden layer is Gaussian function and in the output layer is generally a sigmoid or a linear function [12], [13].

2.3 Balanced data

In imbalanced data, the number of samples in a class is much higher than in the other classes. A class which has a greater number of data is called the class of majority, and the class with less data – a minority class. In the imbalanced data, the main challenge is to identify the correct lower sample class. Balanced data are used in classification algorithms. Therefore, the imbalanced data classification is not performed correctly, and categorization tends towards larger educational examples that increase the error in identifying a minority class. One of the methods for balancing the imbalanced data is the data level method. In this class of methods, the distribution of a imbalanced class is balanced by re-sampling in the data space [14].

Several approaches have been proposed for imbalanced data, such as sampling, data-level feature selection, and algorithm levels, such as cost-sensitive and single-class learning. Methods of pre-processing data are sampled by under-sampling and oversampling. In the under-sampling, the data are collected by deleting random samples of majority class, and in oversampling, it's collected by copying and adding random samples from the minority class. Oversampling is better than under-sampling [15].

2.4 Particles Swarm Optimization (PSO)

James Kennedy and Russell C. Eberhart are the main owners of the PSO idea [16]. Their first simulation was carried out in 1995. PSO is similar to evolutionary computation techniques like Genetic Algorithms, but does not incorporate any evolution operators[17]. In the PSO algorithm, there are a number of organisms that are referred to as particles and are spread in the space of the search function we intend to optimize. Each particle calculates the value of the objective function in the position of the space in which it is located. Then, using the current location information and the best location in the past, as well as the information of one or more best particles in the collection, it chooses a direction of movement. All particles are directed to move, and after completing the move, one step of the algorithm ends. These steps are repeated several times until the desired result is obtained. The PSO algorithm contains the following steps [18]:

1) Initialize a population of particles with random locations and velocities in dimension D in the search space

2) Calculate the merit function

3) Update the velocity of each particle and move to the next position based on the following relationships:

$$v_{id}(t+1) = w * v_{id}(t) + c_1 * r_1(x_i^{best} - x_{id}^t) + c_2 * r_2(x_g^{best} - x_{id}^t) \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{2}$$

$x_{id}(t)$ and $v_{id}(t)$ respectively indicate the position and velocity of the particle in the dimension D, x_i^{best} – the best position of the particle up to the moment t, x_g^{best} – the best global position, w – the coefficient of inertia, c_1 and c_2 – the learning coefficients, and r_1 and r_2 are two random numbers.

4) Stop the algorithm if it reaches a specified stopping point, otherwise go to step 2.

2.4.1 Binary Particles Swarm Optimization (BPSO)

The binary particle optimization algorithm was proposed by James Kennedy and Russell Eberhart for solving binary problems [19]. In the binary version, the position of each particle in each dimension is limited to two values of zero and one. That is, every particle moves in a space that is limited to zero and one. The initial velocity of the particles is also in the interval [1 and 0]. The steps of the algorithm are as follows [20]:

1) Initialize a population of particles with random positions and velocities in dimension D in the search space

2) Calculate the merit function

3) Update the velocity of each particle based on the relationship 1. After calculating the velocity of each particle, it is necessary to check that the velocity of the particle is in the interval

$[v_{min}, v_{max}]$. If the particle velocity is extruded outside the range, we map the resulting velocity of the following interval using the following equation:

$$v_{id}(t+1) = max(min(v_{max}, v_{id}(t+1), v_{min}) \tag{3}$$

In order to update position of each particles, at first transform the velocity vector through as sigmoid limiting function:

$$S(v_{id}(t+1)) = 1/(1+e^{-v_{id}(t+1)}) \tag{4}$$

4) Update the position of each particle in accordance with equation 5.

$$x_{id}(t+1) = \begin{cases} 1 & rand < S(v_{id}(t+1)) \\ 0 & O.W \end{cases} \tag{5}$$

5) If the stop criterion is met, the algorithm stops; otherwise, it goes to step 2.

2.5 The nearest neighbor algorithm

In recognizing the pattern, the nearest neighbor algorithm is a method used for classification and regression. The input of the algorithm is the training samples, and the output is the class label. Examples of training are vectors in the D-dimensional space whose class labels are specified. To classify an unlabeled object, the distance to the tagged samples is calculated, and k of the nearest neighbor is identified and, based on the majority vote, the class label of the object is specified. The most common metric of distance or similarity is to calculate the distance between objects in Euclidean space [18], [21].

2.6 Model Evaluation Indicators

We need indicators that can be used to evaluate the function of models in comparison with the data set in order to evaluate the efficiency of neural network models. The best method for estimating the neural network is the mean squared error (MSE) and the root mean square error (RMSE) [22] and [23].

$$MSE == \frac{1}{N}\sum_{n=1}^{N}(\widehat{y_n} - y_n)^2 \tag{6}$$

$$RMSE = \sqrt[2]{MSE} \tag{7}$$

$\widehat{y_n}, y_n$ respectively indicate predictions and original data of N instances. In the following, two other important indicators, sensitivity and specificity, are considered for a better understanding of network performance. Thus, sensitivity is the ability to test for the proper diagnosis of people requiring kidney transplantation, and the specificity is the ability to test ability to diagnose people who do not need any transplant [24].

2.7 Proposed Algorithm

In this study, the prediction and identification of the effective features in the survival of the two-year kidney transplantation have been investigated in four stages. The first stage consists of data collection. At this stage, the information about renal transplant patients of the Afzalipour Medical Center of Kerman was collected with 14 characteristics during the years 2006–2011. The second stage is pre-processing the data. We first correct incomplete data with mode and average values. We used mode for discrete values and average for continues values, however, if a record contains more than two attributes with a missing value, it is deleted. Effective results depend on the appropriate data in the model and some values of data attributes are in a different range. Hence, a normalization formula is used to integrate data. Moreover, we normalize the data to improve the accuracy and effectiveness of the results. The normalization formula is as follows:

$$N_i = \frac{x_i - \mu}{\sigma} \tag{8}$$

x_i shows value of data i^{th} and μ, σ respectively indicate average and variance of data.

Due to the collected data are imbalanced, the unbalancing data lead to the convergence of the classification to the majority class, which reduces the efficiency of the classification. Therefore, in the third stage, sampling techniques have been used to balance the data which involves two methods of oversampling and under-sampling. Then in the fourth stage, which is modelled, two structures of the neural network, MLP and RBF, have been used to predict the two-year survival of kidney transplantation. 25% of sample data were considered for testing and 75% of sampling data – for network training. In the neural network MLP, we have perceptron with 13 inputs in the input layer and 6 neurons of the hidden layer and the output layer. In the following, a binary particle optimization algorithm has been used to identify the effective factors in the survival of the kidney transplant. The fitness function of the binary particle optimization algorithm is the nearest neighbor's algorithm accuracy. Initialization parameters involve determining the number of population, Inertia weight, learning factors, and number of iterations that are in this study, their values are 20, 0.48, 2, 200, respectively. At the end, confusion matrix, RMSE and MSE are used to determine the algorithm performance. Figure 1 shows the proposed algorithm.

3 Results

In this study, we predict the survival of renal transplant and identify the variables that affect the survival of kidney transplantation. Algorithms from MLP and RBF neural networks are used to predict the survival of kidney transplant, a binary particle optimization algorithm and the nearest neighbor algorithm are used to identify the variables that affect the survival of the kidney. The primary data for patients with renal transplantation are imbalanced. In order to increase the accuracy, the results of the data are balanced in two methods: oversampling and under-sampling. Balanced data were studied for modeling by intelligent systems. The data of kidney transplant patients in the MATLAB software are examined in two sampling methods in neural network models MLP and RBF.

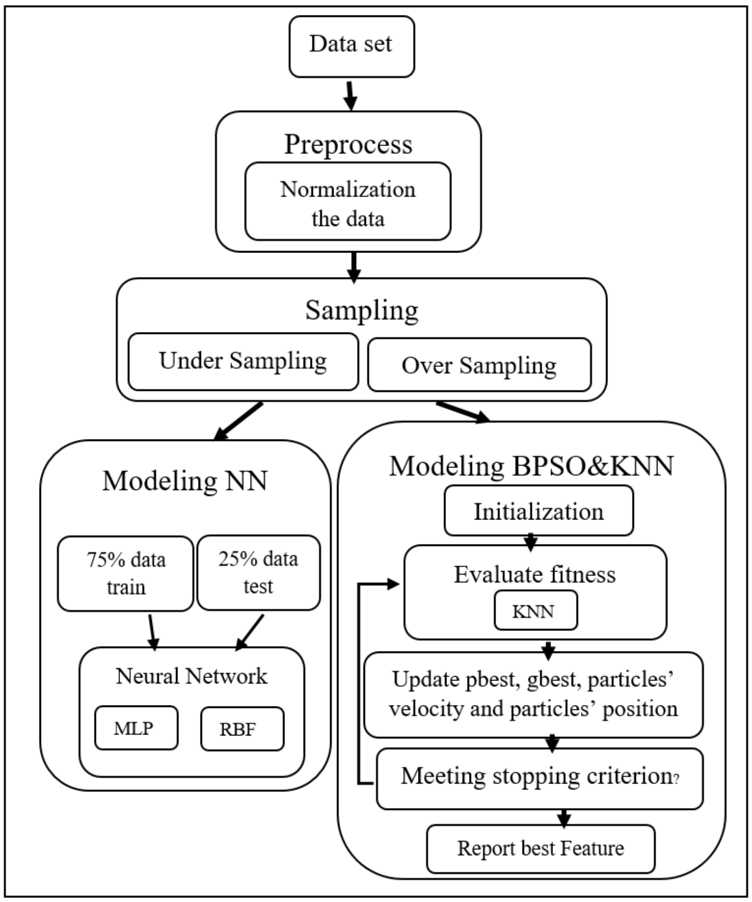

Figure 1. Proposed algorithm

In two sampling methods, we obtained the number of neurons and the appropriate neural network by trial and error method. 25% of sample data was considered for testing and 75% of sampling data for network training. In the neural network model, the laminated perceptron with 13 inputs in the input layer and 6 neurons of the hidden layer and the output layer were used to express the survival or lack of survival kidney transplantation. The results of the MLP and RBF neural networks using two sampling methods are shown in Tables 2 and 3.

In the MLP oversampling method we have accuracy with 93.57 percent, and in RBF – 98.16 percent, and in the MLP under-sampling method – with 81.48 percent and in RBF we have accuracy with 92 percent. The MLP and RBF neural networks oversampling methods were respectively 95.44% and 98.91%, and in the under-sampling MLP and RBF neural networks, the obtained precision was 83.47% and 92.85%, respectively.

In the oversampling, the sensitivity and specificity of the MLP network are respectively 93.6% and 91.4%, and for the RBF network they are respectively 98.2% and 97.4%. In the under-sampling method, the sensitivity and specificity of the MLP network are 88% and 62.5% respectively, and for the RBF network they are equal to 92% and 71.4% respectively. The oversampling method has the best output with precision, sensitivity, and specificity of the network, and RBF predicts the best performance compared to MLP.

In addition, the effective factors of kidney transplantation patients were identified using two algorithms: optimization of binary particles and nearest neighbor in two sampling methods. In the oversampling method, with factors such as *donator age, recipient age, gender, recipient mass index, consistency of the donator and recipient blood group, duration of preoperative dialysis, familial relative, history of kidney transplantation, presence of diabetes in the recipient*, the donator type was marked with 98.72% precision and 99.13% accuracy, and in the undersampling method, with factors such as *donator age, recipient age, recipient mass index, consistency of the donator and recipient blood group, duration of preoperative dialysis, history of kidney transplantation, presence of diabetes in the recipient*, the donator type was marked with 89.66% precision and 96.87% accuracy. Tables 2 and 3 show the results of the proposed model.

Table 2. Results of suggested models for over sampling

	MSE	RMSE	Accuracy	Precision	Sensitivity	specificity
MLP	0.0456	0.214	93.57	95.44	93.6	91.4
RBF	0.0109	0.104	98.16	98.91	98.2	97.4
BPSO& KNN	0.0128	0.1132	99.13	98.72	100	96.68

Table 3. Results of suggested models for under sampling

	MSE	RMSE	Accuracy	Precision	Sensitivity	specificity
MLP	0.1653	0.406	81.48	83.47	88	62.5
RBF	0.0715	0.267	92	92.85	92	71.4
BPSO& KNN	0.1034	0.3215	96.87	89.66	100	89.63

4 Conclusion

Kidney transplantation is one of the most effective treatments for treating patients with advanced kidney disease. In this paper, we used two structures (multilayer perceptron neural network (MLP) and radial base networks (RBF)) in two methods (under-sampling and over-sampling) for unbalanced data. The sample size, the progress of medical treatment, the time and place studied are factors that influence the difference in the outcome. Several studies have been conducted to predict the survival of kidney transplantation in survival of 1, 3, 5 and 10 years. In the following, we compare the results of the proposed model with the best recent work to predict the survival of the kidney transplantation.

The best result of a 5-year survival prediction of a kidney transplant with a neural network structure was obtained in Egypt in 2008. It is also shown in this study that the neural network has the best result in regression. The accuracy and sensitivity of the neural network are respectively 88 and 88.43 percent [25].

In this study, 156 data from renal transplant patients performed a 2-year survival prediction of renal transplantation with a data balancing technique. In the MLP oversampling method we had the accuracy equal to 93.57%, in RBF – 98.16%, and in the MLP under-sampling method we had the accuracy equal to 81.48% and in RBF – 92%. In the oversampling, the sensitivity and specificity of the MLP network are respectively equal to 93.6 and 91.4 percent, and for the RBF network they are respectively 98.2 and 97.4 percent. In the under-sampling, the sensitivity and specificity of the MLP network are respectively 88 and 62.5 percent, and for the RBF network they are equal to 92 and 71.4 percent respectively

The oversampling method has a more predictable model with higher precision and sensitivity compared the previous work. Hence, the predicting model with imbalanced medical data can be implemented with greater reliability and precision by balancing the data. The oversampling method has a better performance than the under-sampling method and the RBF network performs better than multi-layered MLP perceptron network in two sampling methods.

In 2012, the Bayesian network method was used to model 5144 kidney transplants with 48 attributes. BMI, race, recipient gender, and donator age were identified as the effective factors in the survival of the transplant [5]. In 2012, the vector machine identified the following effective attributes: age, level of creatinine, gender, and recipient weight [6]. In [7] there were studied neural networks, decision tree, support vector machine, and information fusion. The accuracy of neural networks, decision tree, and support vector machine were 94%, 92%, and 92%, respectively, and the accuracy of information fusion was 95.74%. Now we are considering those data. We have used their dataset and have obtained high accuracy using the oversampling method. In 2017, Nematollahi et al have examined the prediction of renal transplantation for 5 years. The results of the SVM, MLP, and logistic regression model have been estimated as 90.4%, 85.9%, 84.7%. They showed that SVM and MLP models can efficiently be used to predict renal transplant recipient survival [2].

Identification of effective factors for transplantation in renal patients is very important, therefore, binary particles optimization algorithm and the nearest neighbor algorithm were used for obtaining effective factors in renal transplant patients in two sampling methods. In the oversampling method, precision equal to 98.72% and accuracy – to 99.13% were identified, and in the undersampling method the precision equal to 89.66% and accuracy – to 96.87% for the selected effective factors were identified. In general, donator age, recipient age, recipient mass index, blood group consistency, dialysis time before operation, kidney transplantation history and donator type were chosen as the most important factors. Table 4 shows the comparison between the best results of previous studies and the proposed method. According to the previous work, the proposed method has a better performance.

Table 4. Comparison of the proposed method with other existing studies

	Method	Best accuracy
2008 [25]	neural network, regression	88
2017 [2]	SVM, MLP-ANN, and logistic regression	90.04
Proposed Algorithm	MLP	93.57
	RBF	98.16
	BPSO&KNN	99.13

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