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A Novel Method Based on Support Vector Machines to Classify Bank Transactions

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Abstract

Improvements in information technology have contributed to the development of the e-banking industry. Specifically, despite the reduction of bank charges, e-banking is one of the payment methods that, by employing it based on valid theory, can be successful in satisfying customers due to the easiness of access to financial transactions at any time and place with minimum required tools. A mobile device imposes an increasing amount of time, energy and expense in comparison with face-to-face visits. In spite of many benefits this channel has for customers, there are security concerns for service providers and users in the banking sector. Consequently, in this inquiry, the focus is on the role of the support vector machine neural network in the classification of Mellat mobile transactions. To implement the intended procedure, after compiling the information in the preprocessing stage and purification and normalization of data, feature selection is done with the main component analysis algorithm. Then, in post-processing stage, the Neural Network supports the Mobile Banking classification as a safe but fake system. In order to compare the suggested method, we use Bayon floors and multilayer perceptron. The outcomes demonstrate that the support vector machine neural network can fulfill the classification of user's mobile banking transaction with a mean square error of 0.216 and a precision of 94.6% of all data.

Keywords: Mobile banking transactions; Classification; Main component analysis algorithm; Support vector machine.

1. INTRODUCTION

The popularity of databanks increases every day concerning the increasing demand of the community to update data. This databank technology allows the employees to use mobile telephone sets to connect their

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organization's networks, store required data, work in network disconnection and reconnection status to synchronize with databank. Similar to many other novel technologies, such as Nanoelectronics and Nanorobotics, which have been considered by many researchers [1-8], the use of mobile databanks is increasing due to the rapid growth of hardware devices with higher memory capacity and stronger CPUs along with the rapid expansion of wireless technologies. Mobile devices are rarely used for databank-oriented applications such as entry of sale order, tracking of the inventory of products, managing of customer relation, connection to the network, storage of required data and working in offline and online status for synchronization with databanks [9]. Online business is a modern business method which performs sale and services using direct marketing methods. The development of the internet leads to the growth of e-trade [10].

Many researchers use data mining algorithms to detect fraud in transactions. Normally, there are more than one billion transactions in a day; thus, the optimum recognition process is time-consuming which is not usually done online. Group processing is frequently done in a period of time such as daily, weekly or monthly for the discovery of fake transaction. Machine learning focuses on fraud or defrauds detection in transactions with supervised algorithms such as classification. Thus, the system prevents fake transactions during performance using the predefined regulations and scenarios or static model [11]. The objective of this task is to use the neural network of support vector machine in the detection and discovery of crime in mobile banking transactions. The paper is organized as follows: In the second section, the algorithms of support vector machine and multilayer perceptron neural network will be explained. The procedures of research in the detection and discovery of crime in mobile banking transactions will be proposed in the third part. Finally, we conclude the paper with a brief description of the contribution.

2. A REVIEW OF ARTIFICIAL NEURAL NETWORKS

In this part, support vector machine and multilayer perceptron in neural networks will be explained.

2.1. Support Vector Machine (SVM)

SVM is a supervised learning method used for classification and regression. In this method, data which constitutes their class's boundaries are obtained using all borders and an optimization algorithm. This data is called support vectors. Some data with the least distance to classification boundary could be considered as a subset for defining the classification borders and as a support vector. Assume that X_i, i=1.l are training data of two classes with $y_i=+1$ and $y_i=-1$ labels. In this condition, the optimal margin method is used to calculate the classification border of two separated classes. The separating line of two classes is calculated as follows: first, all data in class with +1 label are placed in one side of the boundary and all data in class with -1 label are placed on the other side of the border. Second, the classification border is achieved when the shortest distance of training data of both classes is maximized and this vector is perpendicular to the classification border in the most possible extent. A linear separator can be shown as equation (1) [12].

$$w.x + b = 0 \tag{1}$$

where x is a point on classification border of n dimensions and w is a vector perpendicular to the separating line. By multiplying the sides of equation (1), the equality will still remain. In order to determine the values of b and w, we consider x_i as a support vector so that Y_i $(w.x_i+b) = 1$ will be established. In the case of $Y_i(w.x_i+b)>1$, x_i is not supported vector. The first step in the calculation of the optimal classification boundary is to find the training data with nearest distance of two classes. In the second step, the distance of those points in the perpendicular direction to the boundaries, that fully separate two classes, will be calculated. The optimal classification boundary is the one with the biggest confident margin. The optimal classification boundary will be calculated by solving the optimization problem (2) and performing a hierarchical and mathematical equation (2) in form of equation (3) [12].

$$\max_{w,b} \min_{i=1,\ldots,l} (y_i \frac{w.x_i + b}{|w|}) \quad (2)$$

$$\min_{w,b} \frac{1}{2}|w|^2 \;\; s.t. \;\; y_i(w.x_i + b) - 1 \geq 0 \quad (3)$$

Solving the optimization problem (3), for which Lagrange coefficient method is used, is a difficult task and the equation will turn to equation (4) where α_is are Lagrange coefficients.

$$\max(-\frac{1}{2}\sum_i \sum_j \alpha_i y_i x_i x_j \alpha_j y_j + \sum_i \alpha_i) \quad (4)$$

After solving equation (4) using quadratic programming method and finding Lagrange coefficients, w can be calculated using this equation $w = \sum_i \alpha_i y_i x_i$. α_i , values for non-support vectors, are zero and the vectors are bigger than zero for support. Therefore, concerning equation $w = \sum_i \alpha_i y_i x_i$ and zero value of α_i, which is related to data and is not support vector, a few numbers of training data are used to obtain classification border. The mentioned few numbers are support vectors and there is no need to employ all data. Therefore, the classification of data using support vector machine will require a limited number of training data. After calculation of w, parameter b will be calculated in respect of various support vectors and final b will be calculated by averaging [12].

$$b = \frac{1}{|s|}\sum_{i \in S}(w_{Yi} - w.x_i) \quad (5)$$

where s is the set of support vectors and the final classifier will be obtained from equation (6).

$$y = sgn(w.x + b) \quad (6)$$

Sgn is the sign of function, w is the normal vector, b is interception, x is input vector and y is output.

In 1992, Bernard Bowser, Isabelle Guyon, and Vapnik proposed a method for nonlinear classification using nuclei to find hyperplane with maximum margin. Our algorithm is apparently similar to their proposed method except that all doc products are replaced by a nonlinear nuclei function and make the algorithm to be appropriate for hyperplane with maximum margin in a deformed feature space. The deformation might cause nonlinearity and the deformed space has higher dimensions. To sum up, a classifier is a hyper place in a feature space of high dimensions that might be nonlinear in input space [13].

Types of nuclei functions for nonlinear support vector machine are [13]:

1. polynomial function

$$\mathrm{kernel}(\mathrm{x_i}, \mathrm{x_j}) = (\mathrm{x_i}.\mathrm{x_j})^{\mathrm{d}} \quad (7)$$

2. Gaussian function

$$\mathrm{kernel}(\mathrm{x_i}, \mathrm{x_j}) = e^{\frac{-1}{2\sigma^2}(\|\mathrm{x_i}-\mathrm{x_j}\|)^2} \quad (8)$$

3. Hyperbolic tangent function (MLP)

$$\mathrm{kernel}(\mathrm{x_i}, \mathrm{x_j}) = \tanh(p_1 \mathrm{x_i}\mathrm{x_j} + p_2) \quad (9)$$

2.2. Multilayer Perceptron Neural Network

Neural networks have appeared as a practical technology successfully used in different areas. The main advantage of the neural network is self-adaptive, self-organizing and real-time operation and etc. The structure of this network includes an input layer, one mid layer, and an output layer. In each layer, there are one or several processor components (neuron) that are related to each other with all neurons of next layers accompanied by weighted connections. The number of neurons in each input and output layers depends on the number of input and output variables of the model; however, the selection of the number of neurons of mid layer is determined by error and trial which is achieved by 10 neurons in hidden layer in our case [14].

In neural networks, the neurons of each layer are associated with all neurons of the previous layer through a directed connection. Each of these connections is given a weight whose value determines the effect of each neuron on the neuron of the output layer.

Weighted sum of input values to each neuron is calculated and put into a mathematical function and the neuron output is calculated through this function. This mathematical function is a so-called activation function. Sigmoid and linear functions are the most common functions used for progressive multilayer networks.

In this study, hyperbolic tangent function in neurons of the hidden layer and neurons of the output layer is used. The weights of network neuron's connectors are determined by training. The intelligent optimization algorithms are one of the powerful optimization techniques that could facilitate the achievement of optimized weights in the neural network [14].

3. Proposed Method

In this part, the research procedures are expressed. The recognition of mobile transactions consists of five general stages: 1. data collection from Hamrahe Avval databank, 2. data normalization, 3. feature selection, 4. recognition of successful and unsuccessful transactions using support vector machine neural network, 5. A comparison between results of the proposed model with multilayer perceptron network is done in final section.

3.1. Data Collection

Databank of mobile transactions of Refah Bank is the classification of mobile transactions including 100 samples with 17 features, 80% of data are used in training and 20% in testing.

3.2. Data Normalization

Concerning the different range of changes in features and different units of variables, the bigger values have a higher effect on the current functions that do not necessarily have important role in the system. Data normalization is done to remove this problem. In this study, data are normalized to [-1, 1] interval through linear normalization function

$$X = 2 \times \frac{x - \min(x)}{\max(x) - \min(x)} - 1 \qquad (10)$$

where min (x) is minimum x input vector and max(x) is maximum x vector and X is its normalized vector[15].

3.3. The Selection of Feature

Analysis algorithm of main components is one of the multivariable data analysis methods whose main aim is to minimize the dimension of our studied problem. One of the main applications of analysis of main components is in classification. The analysis algorithm of main components maps the

Table 1. ***The results of using the neural network of support vector machine in the mobile transaction classification.***

Data	MSE	RMSE	MAE	SSE	Kernel Function
Train Data	0.24	0.489	0.12	192	**Gaussian**
Test Data	0.22	0.469	0.11	44	**Gaussian**
All Data	0.236	0.486	0.118	236	**Gaussian**

Table 2. ***Standard performance measurement for neural networking in the mobile transaction classification.***

Data	Sn	Sp	PPV	NPV	Precision	Kernel Function
Train Data	89.5	100	100	87.7	94	**Gaussian**
Test Data	89	100	100	90.1	94.5	**Gaussian**
All Data	89.4	100	100	88.2	94.1	**Gaussian**

data from input space to new space so that the specifications are sorted based on variance and there is no affiliation between the features in new space. In this study, using the analysis algorithm of main components, from 17 existing features in the databank, 7 features have been selected for more precise classification.

3.4. The Results of the Neural Network of The Support Vector Machine

In this part, the results of classification of mobile transactions by a neural network of support vector in respect of test and training and total data are presented. Table 1 shows the results of using the neural network of support vector machine in the classification of mobile transactions in terms of the type of error and Gaussian nuclei function in terms of training, test and total data.

Table 2 presents the standard efficiency criteria in the classification of mobile transactions by a neural network of support vector machine with Gaussian nuclei function in terms of test, training and total data.

Figure 1 shows the error graph in terms of training, test and total data in the neural network of support vector machine when the neural network of the Gaussian nuclei function of dispersion parameter equal to 0.8.

Figure 2 represents the regression graph in terms of training, test and total data in the neural network of support vector machine when the neural network of Gaussian nuclei function and dispersion parameter equal to 0.8.

Fig. 2. Regression diagram for data types in the neural network of a support vector machine in the classification of mobile transactions.

3.5. Use of Multilayer Perceptron Neural Network

In the classification of mobile transactions with multilayer perceptron neural network, 7 inputs in the input layer, 8 neurons in hidden layer and one neuron in the output layer are used; in addition, the activation function of neurons in the hidden layer is hyperbolic

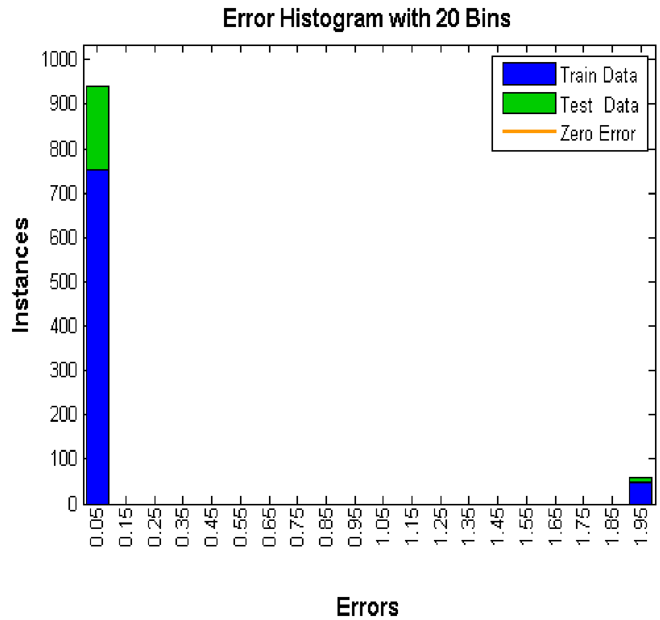

Fig. 1. Error types in the neural network of a support vector machine in the classification of mobile transactions.

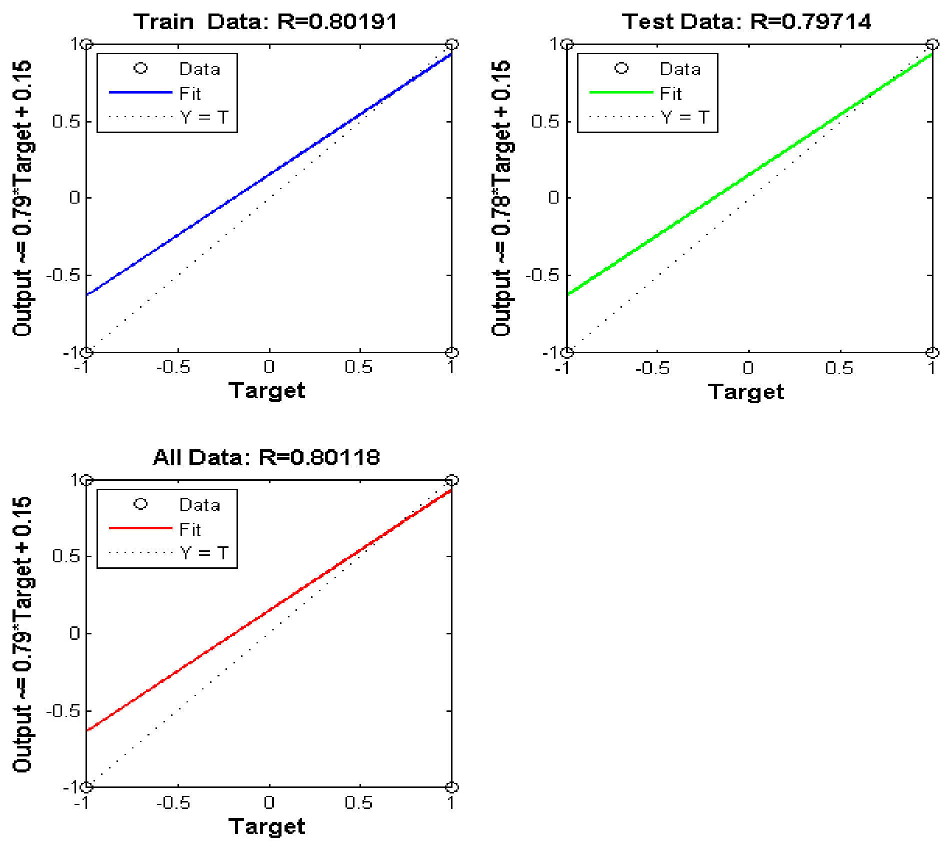

Fig. 2. Regression diagram for data types in multilayer perceptron neural network in mobile transaction classification.

Table 3. ***Results of multilayer perceptron neural network in the classification of mobile transactions.***

Data	MSE	RMSE	MAE	SSE
Train Data	0.24	0.489	0.12	**192**
Test Data	0.32	0.566	0.16	**64**
All Data	0.256	0.506	0.128	**26**

Table 4. ***Results of multilayer perceptron neural network in the classification of mobile transactions.***

Data	Sn	Sp	PPV	NPV	Precision
Train Data	89.3	100	100	88	**94**
Test Data	86.3	100	100	83.8	**92**
All Data	88.7	100	100	87.2	**93.6**

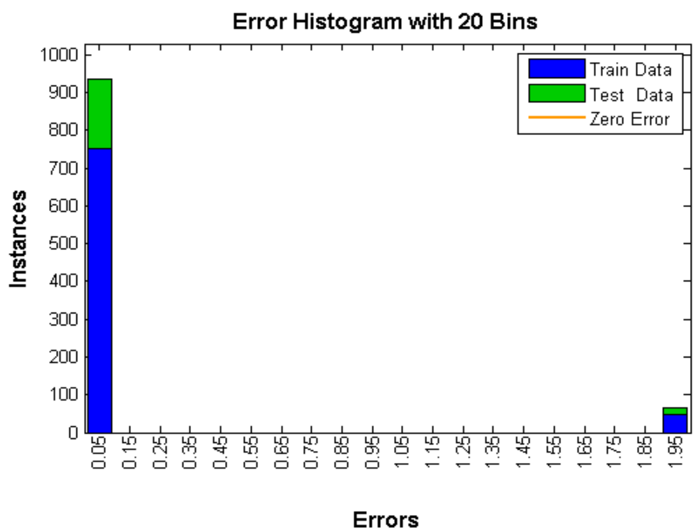

Fig. 3. Error types for data types by multilayer perceptron neural network in mobile transaction classification.

tangent. In the output, the layer is signed. Table 3 shows types of error in terms of test, training and total data by multilayer perceptron neural network in the classification of mobile transactions.

Table 4 shows the standard efficiency criteria by multilayer perceptron neural network in the classification of mobile transactions in respect of training, test and total data.

Figure 3 shows the error graph in respect of test and training data by multilayer perceptron neural network in the classification of mobile transactions.

Figure 4 shows the regression graph in respect of training, test and total data by multilayer perceptron neural network in the classification of mobile transactions.

4. CONCLUSION

In this research, we first gathered Mobile Banking data from the Refah Bank and after linear normalization of the data with the algorithm analysis of the main components

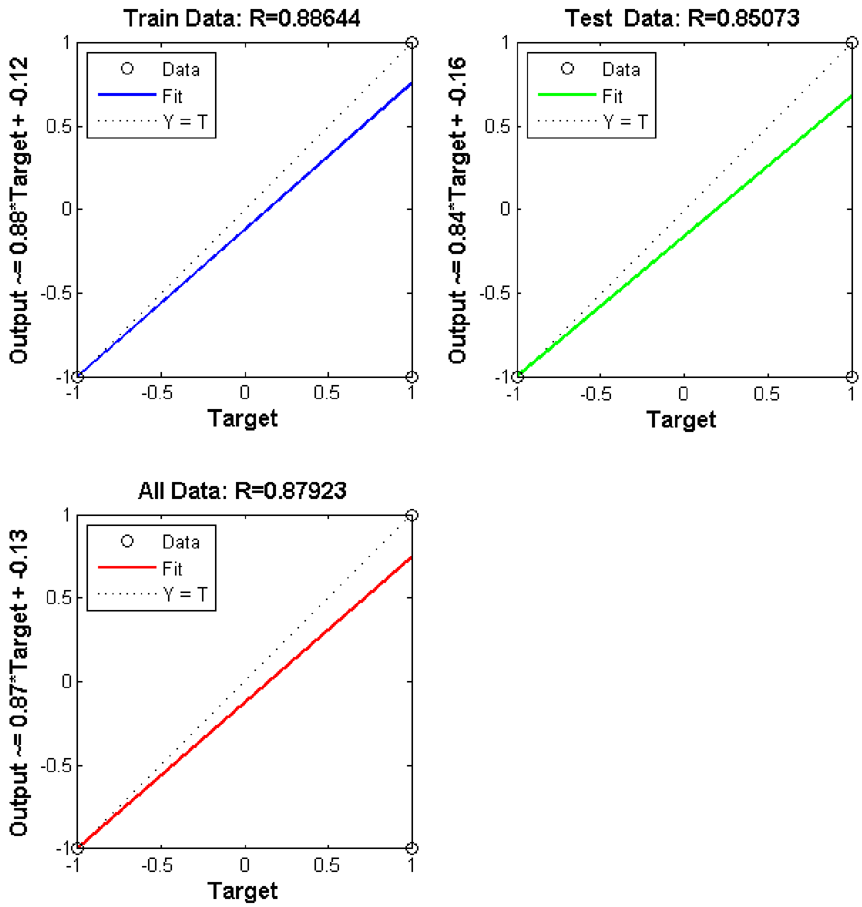

Fig. 4. Regression diagram for data types in multilayer perceptron neural network in mobile transaction classification.

of the feature selection, 7 characteristics out of 17 characteristics were selected. Then, Neural network support vector machine and multi-layer perceptron mobile transaction classification are employed on the system. According to Tables (1) to (4), the support vector machine neural network has a better performance in terms of some types of errors and standard performance measurement than the multi-layered perceptron neural network, in terms of training, experimental data and total data. According to Tables (1) to (4), it can be concluded that the support vector machine neural network with a mean square error of 0.236 and a precision of 94.1% for the total data has better performance than the multi-layer perceptron neural network with a mean square error of 0.256 and accuracy 93.6%.

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