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Credit Card Fraud Detection by Combining Neural Network and Grasshopper Optimization Algorithm

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Abstract

With the accelerated development of Internet finance, electronic funds transfer, and the rapid growth of credit card activity, credit cards play a very important role in every area of life today. There are some risks in this regard that are considered serious threats to both issuers and cardholders. The increasing number of fraudulent credit card transactions forged credit cards and fraudulent use of expired credit cards have led to increased losses. Therefore, finding fraud detection techniques accurately and quickly has become an important topic in current investigations. In this study, after normalizing and reducing the dimensionality of the data using the PCA algorithm, we used the modified perceptron neural network and the grasshopper algorithm to classify the data. In this study, we use the grasshopper algorithm to adjust the weights and biases of neural networks. In the end, we were able to achieve 99.20% accuracy.

Keywords*:* Fraud Detection, Grasshopper Optimization-Algorithm, Neural Network.

I. INTRODUCTION

In recent years, due to the rapid development of technologies such as the Internet, the processing of financial data has been combined with different information processing technologies such as machine learning, and many achievements have been achieved [1]. These models can improve performance and prediction accuracy [2-4].

With the accelerating improvement of the Internet economy, the rapid growth of electronic fund transfers, and credit card activities, credit cards play a very important role in all areas of life today. There are some risks in this regard that are considered to be a serious threat to issuers and cardholders [5-7]. The increasing number of fraudulent credit card transactions forged credit cards and fraudulent use of expired credit cards have led to increased losses. Therefore, finding an accurate and fast fraud detection method has become an important subject of current research [8-10].

Today, data mining algorithms based on Bayesian networks, neural networks, and decision tree algorithms are used to identify credit card fraud risks. However, these methods face problems in their practical application [11-14], which we describe in the next section:

1- There are several examples of credit card fraud. Occasionally, as irrelevant features, dominant features are over-tested and lead to the “curse of dimensionality” [15].

2- They are built entirely on large-scale sample recognition algorithms. Identification is only guaranteed when the sample size is large. However, the amount of calculation of a large number of samples increases accordingly, which requires a large amount of computer computing power and affects the actual time and efficiency of fraud.

3- Since the probability of credit card fraud transactions occurring is well below 1%, the credit card data model was collected. However, data mining algorithms directly use scattered data samples for modeling and cannot achieve the desired effect.

4- Most of these algorithms may suffer from problems such as over-learning and optimal local solutions. Therefore, there is a need for methods to improve detection speed and operational accuracy.

Ravisankar [16] uses neural networks for credit card fraud detection. This paper also introduces Bayesian Networks and Artificial Neural Networks to solve this problem. These patterns are too complex for fraud detection. They used neural networks to detect patterns of fraudulent transactions and effectively reduce feature redundancy. While Srivastava et al. [17] utilize Hidden Markov Models (HMMs) for credit card fraud detection. The results show

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that using HMM and learning cardholder specifications are very important in fraud detection. It is also evident that 80% of the results have good accuracy. Divia et al. [18] used Hidden Markov Models (HMM) for credit card fraud detection. The model is trained using the regular behavior of the cardholder. Therefore, if the trained HMM does not accept a transaction, the transaction is considered fraudulent. The authors also compare different methods with the proposed method to show that HMM has higher performance. Rama et al. [19] generate experimental data to detect fraudulent activity. The algorithm is known as an optimization method based on natural selection and genetic selection in complex problems. The authors recommend a method for credit card fraud detection and confirm the results using the value of the algorithm. Luo et al. [20] proposed an approach to fraud detection that involves monitoring collective activity to observe and predict bad behavior. Bad behavior includes intrusion, fraud, crime, etc. This article is about fake IDs and remote scams and different solutions that can help with related issues. Abhimanyu, et al. [**21**] evaluate a subset of deep learning topologies that can effectively detect fraud on a dataset of nearly 80,000,000 credit card transactions considered legitimate and fraudulent. The authors use a high-performance distributed cloud computing environment to analyze historical detection factors such as class scalability and imbalance. This study provides a complete controller for sensitivity studies of fraud detection factor modeling. It provides a framework for factor tuning of deep learning topologies for credit card fraud detection to reduce losses by preventing fraudulent activity. Analysis showed the presence of important time parameters. The LSTM and GRU models work significantly better than the preliminary ANN, suggesting that the transaction order of accounts contains useful information to distinguish between fraudulent and legitimate transactions. In the experiments, performance improves whenever the network size increases. Chunzhi, et al [**22**] proposes a credit card fraud detection technology based on a BP neural network optimized by a whale algorithm, aiming to solve the problem of slow convergence. In order to use this algorithm to optimize the BP network weight, first, use the WOA algorithm to obtain an optimal initial value, and then use the BP network algorithm to correct the error value to obtain the optimal value. The results of the Matlab model show that the WOA-BP algorithm proposed in this paper has high detection accuracy and fast convergence speed, which improves the accuracy of credit card fraud detection.

The structure of this paper is as follows: In the second part, we will define the perceptron neural network and the Grasshopper algorithm. The third section introduces the simulation steps, and the fourth and fifth sections state the results and conclusions, respectively.

II. Materials and Methods

- Neural networks(NN) These networks are called a set of interconnected nodes, and they are modeled to declare the functioning of the human brain. Each node has a weighted connection to another node in the next layer. A single node takes input from the node and uses the weights of the connected nodes to evaluate the output value. These networks are created for supervised and unsupervised learning.

The user determines the number of hidden layers and the number of nodes in a particular hidden layer. The output layer of a neural network can include one or more nodes. Recently, the authors have developed several methods related to numerical and statistical investigations. The nonlinear mapping relationship from the input space to the output space is in the given case [23].

TABLE 1. Comparison of different techniques in fraud detection

disadvantages	advantages	Fraud detection methods
Cannot be used on nonlinear data. At the time of the transaction is not useful for credit card fraud detection	This method produces a simple probability formula for classification. Works well with linear data to detect credit card fraud.	logistic regression
It involves a complex algorithm, and even a minor variation of data has the ability to distort the structure of the tree. It does not have the ability to detect fraud at transaction time.	This method has the ability to manage nonlinear data.	decision tree
The value of the components is adjusted before the training. There are no rules for adjusting components. The network deals with the connection between neurons. To date, there is no method to control the optimal topology for a particular case.	This method can detect fraudulent activity at transaction time.	Artificial Neural Networks
HMM-based patterns predict False Positive (FP)	This method can detect fraudulent activity at the transaction time	Hidden Markov model
It fails to detect fraud cases	This method can detect fraudulent activity at the transaction time	Support vector machine
Correctness of the technique depends on the distance measurement Fraud could not be detected at the time of the transaction.	There is no need for a prediction pattern before classification.	K nearest neighbor

- Multilayer perceptron neural network

Multilayer perceptrons are the most well-known type of neural network. A perceptron neural network would be classified as a feedforward neural network. There are two types of single-layer network and multi-layer network. Single-layer perceptrons can only classify linear problems. A multilayer feedforward network consists of one or more hidden layers. In a feedforward neural network, nodes are in successive layers, their connections are unidirectional, and when an input pattern enters the network, the first layer evaluates its output value and provides it to the next layer. The next layer takes this value as input and passes its output value to the next layer. Each node transmits the signal to the nodes in the next layer. The MLP network is trained using the backpropagation method [23]. The first path is the forward path, where the input vector of the multi-layer perceptron network is applied, the effect of which is propagated through the intermediate layers to the output layer. The output vectors in the output layer form the actual answer of the multilayer perceptron. In this way, network components are considered immutable. The second path is called the backward path. In this path, the components of the perceptron network are multi-layered. The error value is the difference between the expected answer and the actual network answer. The evaluated error values are distributed throughout the various layers of the network. This distribution is the opposite of synaptic weighted connections. So the term backpropagation is called correcting network behavior [24].

- Grasshopper optimization algorithm

One of the newest optimization algorithms introduced in 2017 is the Grasshopper Optimization Algorithm (GOA). The Grasshopper Optimization Algorithm (GOA) is inspired by the swarming behavior of grasshoppers in nature. The GOA algorithm is designed to solve complex optimization problems in multiple domains.

Simulation results show that the GOA algorithm can provide better results than the recently known algorithms. The simulation results also prove that the GOA algorithm can solve practical problems. The fitness function is used to evaluate the fitness of each grasshopper. The state of all grasshoppers is considered to be the location that defines the new location of the grasshopper. There are differences between GOA and PSO algorithms. In PSO, there are two vectors for each particle: a position vector and a velocity vector. However, in each grasshopper's GOA, there is only one position vector [25].

III. ARTICLE PREPARATION METHOD

A. Database

This study uses the Kaggle database for credit card fraud detection. We considered 2500 pieces of data from this database, of which 483 belonged to the fraudulent category and 2027 belonged to the legitimate category.

B. Simulation Steps

1) Data Preprocessing

In this step, data related to financial transactions is first read from the database. Then in the next step, the data is normalized. Data normalization is considered as one of the important preprocessing steps in data mining. Let the interval associated with the number of two features vary widely from each other, for example, suppose the interval associated with a feature is the interval [0, 1], which is associated with another feature of the dataset [1, 500], in this case, it is clear that features with smaller intervals actually have no noticeable effect on the evaluation. In this regard, in order to obtain good results, it is important that the intervals associated with the different factors are similar or closely related to each other.

Different standardization methods are used in articles and studies. In this work, we will use the min/max normalization method. This study determined that datasets were delineated to arbitrary intervals. Suppose the attribute A maps from min-A to max-A to the arrays New-Min to New-Max. In this regard, each initial value of V in the initial interval is converted to a new value according to the following equation:

$$v' = (v - min_A)\frac{newMax - newMin}{maxA - minA} + (newMin) \qquad (1)$$

- Dimension reduction

In this step, the dimension of the feature space is reduced by the PCA algorithm. The lower dimensional space reduces the redundancy of input features. As a result, the training performance of the neural network will improve and the final accuracy will increase. Principal component analysis (PCA) methods using mathematical relationships can transform multiple dependent variables into lower-valued independent variables. The new variable or feature is the principal component. The method aims to find a hyperplane that preserves the maximum variance of the data. Analysis is a transformation in vector space that creates the greatest dimensionality reduction in the dataset used. The algorithm first normalizes the data and then computes orthogonal vectors, called principal components, in the next step. The input matrix is a linear combination of principal components. After that, the principal component dimensions are sorted in descending order of importance. In this section, the term importance refers to the variance of the dataset. In the last step, less important parameters are removed. The steps of the algorithm are as follows.

- Step 1: Data normalization.
- Step 2: Evaluate Orthogonal Vectors. These vectors are identified as principal components. The input matrix is a linear combination of principal components.
- Step 3: Principal components are sorted in descending order of importance. The word "importance" here refers to the variance of the dataset.

- Step 4: Less important parameters (less variance) are removed

- Data segmentation

A neural network takes input data and divides it into two parts. These parts include the following:

a) Training data: This data is used to train neurons. In fact, in this part of the data, the input and output are determined. Using this data, neurons can adjust components such as weights and biases. In this work, 70% of the data is considered training data.

b) Test data: After the training process, this data is available to the neurons. Use this data to determine the prediction error of the neural network. In this work, 30% of the data is considered as test data.

2) Classification Using Perceptron Improved with The Grasshopper Optimization Algorithm

In neural network algorithms, the choice of initial weights affects network training. Since this is not an easy job, it has to be optimized. Optimizing algorithms has always been challenging, especially in different fields such as data mining, computational intelligence, and machine learning. Bionic algorithms efficiently optimize data. So far, many metaheuristics have been mentioned, including the grasshopper optimization algorithm. The grasshopper algorithm, based on grasshopper swarms flying towards food sources, has been shown to have fewer optimization problems than proposed algorithms such as particle swarm, bat, and firefly algorithms. Therefore, in order to optimize the selection of the weights and biases of the neural network and reduce the detection error, the grasshopper optimization algorithm will be used. Feedforward neural networks are the simplest type of ANN, and the associations between nodes do not generate loops. In this network, there are no loops or loops in the network, data is transmitted forward from input nodes, through hidden nodes to output nodes.

3) Coefficient Adjustment Process

The figure below presents the structure of a neural network.

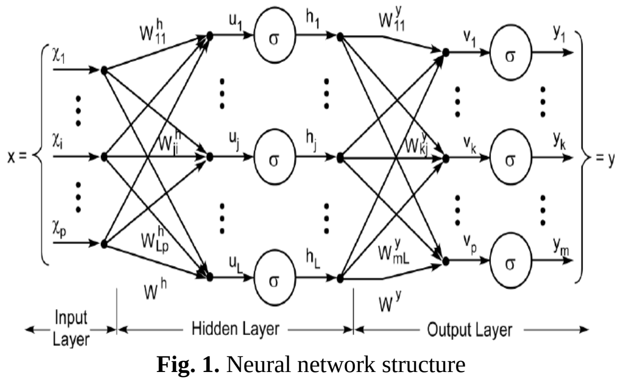

Fig. 1. Neural network structure

In perceptron neural networks, weights are updated in the following equation:

$$w_i(new) = w_i(old) + x_i y. \quad (2)$$

In this equation, xi refers to the desired property and y also refers to the actual output. In a neural network, x represents the input. Our goal is to predict the output, y = output. In this case, y is the target that must be predicted, indicating whether the credit card is fraudulent.

In a neural network, the input (x) is multiplied by a coefficient (w) to get y. The goal is to have the lowest error in y or the predicted value. To do this, ws must be specified. In order to determine ws and bias, the network must be trained. ws changes at each stage to minimize prediction error. The grasshopper algorithm changes w each time and calculates the error. This is repeated until the best ws is found and the error is reduced and the prediction is more accurate [26].

4) Evaluation Criteria

The evaluation criteria are responsible for determining the best way to perform the test. In this work, accuracy, precision, recall, and F1 criteria are used for this purpose; the equations are as follows.

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Negative}{TP+TN+FP+FN} \quad (3)$$

Accuracy criteria, as mentioned above, indicated the percentage of information that is correctly classified.

$$Precision = \frac{\sum TP}{\sum Test\ Outcome\ Positive} \quad (4)$$

As mentioned above, the Precision criterion expresses the ratio of correctly detected fraudulent messages to all correct detections. The main focus of this standard is the correctness of the algorithm for the recognition of "yes".

$$Recall = \frac{\sum True\ Positive}{\sum Realy\ Positive} \quad (5)$$

As the name suggests, recall criteria are designed to evaluate all data. It can be seen that the focus of the recall criterion is the opposite of the accuracy criterion to the already "yes" data, and the recall criterion is also called the sensitivity criterion.

$$F1_{measure} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

The F1 criterion is actually a balanced combination of accuracy and precision criteria that can be used when there is a difference between false negative and false positive values. If the false negative and false positive values are equal, the accuracy criterion can be used. Also, if the data is not evenly distributed among the classes, it is better to use the criteria of precision, recall or F1.

IV. Results

A confusion matrix is used to present the results. A confusion matrix is a technique for summarizing the performance of a classification algorithm. In this matrix, labels one and two represent fraud and legal activity, respectively. The rows in this matrix represent the predicted classes, and the columns represent the actual classes. Diagonal rows are associated with correctly classified observations, and values outside the slash are associated with misclassified observations. The number of observations and their total percentage are shown in each cell. The target variable has two values: positive or negative. A true positive (TP) means that the predicted value is equal to the actual value. True Negative (TN) means that the predicted value is equal to the actual value. A false positive (FP) means that the expected value is wrong. False Negative (FN) means that the predicted value is mispredicted, the true value is positive but the model predicts a negative value.

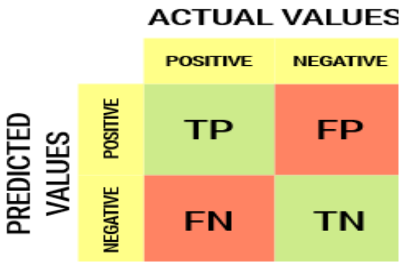

Fig. 1. Confusion matrix

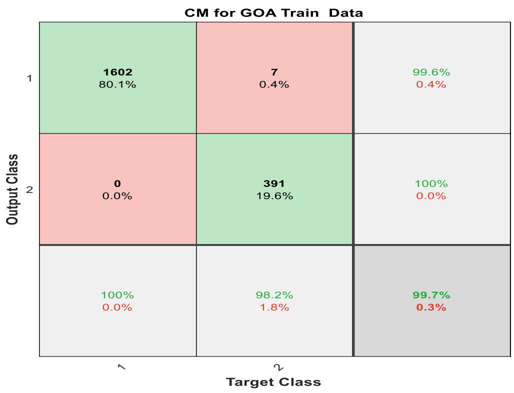

Fig. 3. Confusion matrix for training data

Observe that 80.1% of the data are correct in the first category and 19.6% in the second category. In the end, the accuracy on the training data reached 99.7%. This indicates that the neural network has been trained correctly.

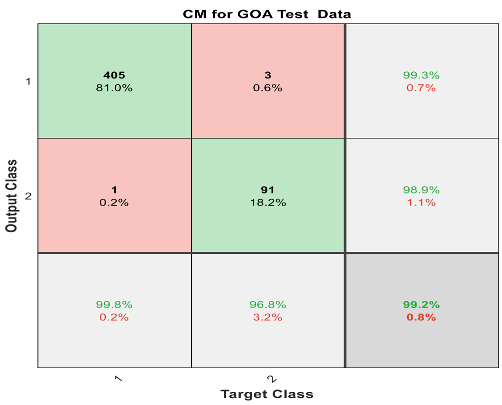

Fig. 4. Confusion matrix for test data

It is presented that the achieved accuracy for test data is 99.2% and only 0.8% of the data were incorrectly detected.

A. Results of the classification by the ROC curve

The ROC curve consists of 3 parts, as described below:

• Above the bisector

There are several points in this section that are more sensitive to false positive rates. This means that in that part, the true positive rate is higher than the value of the false positive rate. Points in this area are considered desirable [27].

• on the bisector

In this section, the true positive rate and the false positive rate are numerically equal. In other words, for every 100 samples, the experiment correctly detected a diagnosis in 50 instances and misdiagnosed in the other 50 samples. These points are not considered desirable [27].

• Below the bisector

In this section, the true positive rate value is less than the false positive rate. The placement of points in this section is simply not desirable.

Figure 5 shows that the curve lies above the bisector of the classifier used in this work, which is desirable and indicates that the true positive detection rate is higher than the false positive detection rate [27].

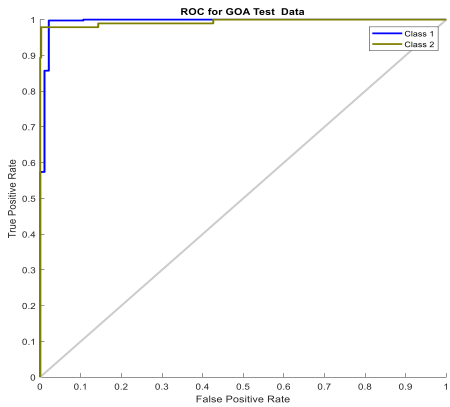

Fig. 2. 1. ROC curve for test data

The following figure shows the results of the classifier for the criteria of accuracy, precision, recall, and the F score for one-time implementation of the algorithm.

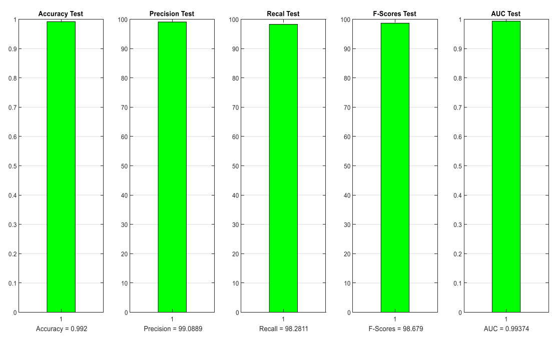

Fig. 3. Results of the classifier

TABLE 1. results for test data

Accuracy	99.2%
Precision	99%
Recall	98.28%
F	98.67%
AUC	99.37%

B. Comparing results

The table below compares the proposed method results with other methods (including the reference article method) on training and test data. The result obtained is an average of 10 times the algorithm execution.

TABLE 2. Comparing results of training data

F-Score	Recall	Precision	Accuracy	Method
95.44%	97.81%	93.18%	92.75%	**WOA-BP**
95.35%	97.23%	93.54%	92.65%	**GA-BP**
94.42%	97.16%	91.83%	91.10%	**PSO-BP**
95.01%	96.45%	93.61%	92.15%	**COMMON-BP**
99.44%	**99.12%**	**99.78%**	**99.65%**	**Proposed**

TABLE 3. comparing results of test data

F-Score	Recall	Precision	Accuracy	Method
98.4%	97.83%	98.25%	96.40%	**WOA-BP**
97.93%	97.61%	98.25%	96.20%	**GA-BP**
97.83%	97.83%	97.83%	96.00%	**PSO-BP**
96.67%	94.78%	98.64%	94.00%	**COMMON-BP**
98.67%	**98.28%**	**99.08%**	**99.20%**	**Proposed**

The results show that the proposed method for training data outperforms other methods by 8%, 6%, 2%, and 4% in the evaluation criteria accuracy, precision, recall, and F-score, respectively, while for test data, the numbers will be 5%, 1%, 5% and 2%.

V. CONCLUSIONS

In this paper, the perceptual neural network method is used to improve the accuracy of credit card fraud classification and detection. In order to double the classification ability, the weights and biases of the network are obtained through the grasshopper algorithm, and the weights and biases of the network are regarded as grasshoppers, and the obtained values are evaluated by the objective function of classification accuracy. In the end, we were able to achieve 99.2% accuracy.

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