Research on Bank Credit Risk Assessment Based on BP Neural Network

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***Abstract*—Credit risk prediction is to forecast whether the borrower can fulfill the financial commitment in advance by taking the relevant information of the customer as the judgment basis. Banks still use traditional mathematical and statistical methods to forecast risks, which cannot meet the growing demand for credit risk forecast business, nor guarantee the quality of forecast. Therefore, this paper studies the application of deep neural network in bank credit risk. This paper presents a bank credit risk forecasting and management model based on multi-level deep neural network. By studying the relationship between each variable and the result of risk prediction, the model further summarizes some features with large impact factors by using the analytic hierarchy process (AHP), and inputs them into the deep neural network, so as to obtain the model's credit score for customers. The practical application of the system in a commercial bank shows that the system can further improve the accuracy of bank credit risk prediction, improve the management efficiency, reduce the cost of bank credit management, and enhance the competitiveness of the bank.**

Keywords—Deep Learning, BP Neural Network, Credit Risk, Model Construction

I. INTRODUCTION

With the development of economy and the change of economic model, the position of commercial banks in today's economic development is more and more important. In the course of operation, the main profitable business of commercial banks is credit business. While bringing in income, commercial banks must face the risks of credit business [1]. Therefore, the risk generated by the credit business has become the main risk that commercial banks must face. In the process of credit management, credit risk evaluation is the most basic and primary link. At present, although part of credit risk evaluation adopts the combination of quantitative and qualitative, most of it is still based on qualitative judgment. The method is too simple and cannot accurately identify risks [2]. Therefore, in the absence of an objective evaluation of credit risk, the possibility of loan deterioration will be greatly increased. The training process of artificial neural network has strong adaptability, fault tolerance and self-learning ability, and can deal with complex nonlinear classification and recognition problems well. The model building based on neural network is a non-statistical method. The classification problem based on non-statistical method does not require strict financial assumptions and a lot of analytical data [3]. Therefore, this paper builds a credit risk evaluation model based on three-layer BP neural networks, and applies the model to the credit risk evaluation of listed companies, and applies the Bayesian regularization and momentum gradient descent method to improve the accuracy.

II. STRUCTURE AND WORKING PRINCIPLE OF BP NEURAL NETWORK

A. BP Neural Network Structure

As shown in Fig. 1, BP neural network (BPNN) is composed of output layer, input layer and hidden layer. The input layer is in the leftmost part of the figure, and the model has 4 input variables. There are 5 hidden layer neurons in the middle [4]. The selection of the neurons number in this part determines the complexity of the model and the weight assigned by the excitation function. On the far right is an output layer, indicating that the model has one output variable [5]. The signal propagation process from left to right of the model is called "forward propagation", and the signal propagation process from right to left is called "error back propagation".

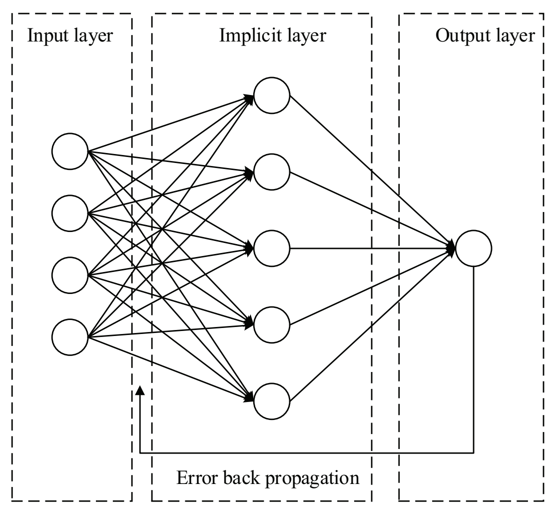


Fig.1. BP neural network structure

B. Working Principle of BPNN

Neural networks are a type of information processing system that mimics the structure and function of the human brain and is studied through physical and mathematical methods [6]. It is an information processing system. A neural network has many nodes called neurons, which are interconnected and connected by wires. Each node is connected to each other by wires. When data is fed into the neural network, it is propagated between the nodes, and each node then processes the data. In this case, the ANN nodes in the ANN will discover an optimal state, a process also known as training. From the basic mechanism of how it works it is clear that if suitable training data is found to train the neural network model, then it can easily deal with problems that are currently unsolvable [7]. Due to the specificity of the structure and processing of neural networks, they are used in image processing, robotics, data mining and many other areas, robotics, data mining and many other areas.

The learning process of BPNN includes two parts: the forward propagation of signal and the back propagation of error [8]. Among them, the forward propagation process of the signal includes the input layer to the sample, the hidden layer to process the sample data, and finally output by the output layer [9]. The error signals obtained by the unit are taken as the basis when the weight correction is carried out for each unit.

The weight adjustment process is repeated in the signal forward propagation layer and the error back propagation layer. The learning and training process of neural network is the process of constantly adjusting the weight [10]. Through repeated execution of the above process, the output error of the network model will be continuously reduced. When the error is reduced to an acceptable level or reaches a predetermined number of learning times, the training results will be output.

The implementation process of BPNN is shown in Fig. 2.

Step1. Initialize the weight of the network and each connection, and set the maximum learning times, calculation accuracy and error function;

Step2. Enter training samples. Divide the training and test sets and input the training samples.

Step3. Positive information propagation. Calculate the training error of the output of the network model with respect to the training set.

Step4. The error is back-propagated. During this process, the weights and thresholds of the neurons at each level are continuously and dynamically adjusted until the model reaches a relatively stable state.

Step5. Determine if the model meets the requirements. If it does not meet the requirements, return to step 2 and start a new round of learning training; otherwise training stops.

Step6. Obtain the global error value through calculation.

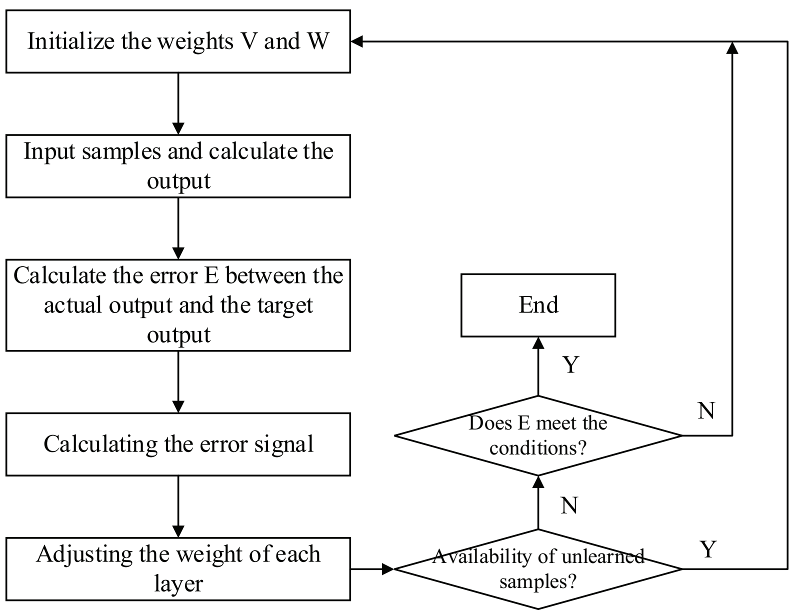


Fig.2. Flow chart of BP neural network algorithm

III. Construction of Credit Model Based on BPNN

A. Feature Normalization

Since different data have different units and value ranges, it is necessary to carry out normalization and other processing before sending the data into the deep neural network [11]. The original score of the system is in percentage system. In order to facilitate the DNN to process the data and accelerate the deep neural network operation speed, it need to preprocess the input data and map all the values to the interval of [0-1]. The normalization formula is shown in Formula (1). x represents the original value, x' represents the normalized value, x_{max} represents the maximum value of this type of data, x_{min} represents the minimum value of this type of data.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

B. Overall Network Structure

Since the training and prediction of the deep neural network is often time-consuming, in order to speed up the prediction speed of the deep neural network and quickly eliminate loan applicants with large credit risks, this paper designs and implements a multi-level deep neural network to forecast the credit risks of loan applicants at different levels [12].

The whole network is divided into two layers, namely H-Net and L-Net. H-Net input is the second-level characteristics of the loan applicant, L-Net input is the third-level characteristics of the loan applicant. The output of both networks is the credit risk score of the loan applicant [13]. Before making the prediction, the system first generates a score for each three-level feature for the loan applicant according to the three-level feature scoring table. Based on the weighted summation formula, each secondary feature score is generated for each loan applicant. Then, the system sends all the second-level characteristic scores generated by the loan applicant into H-Net, and H-Net calculates the credit risk score of the loan applicant. If the credit risk score of the loan applicant is lower than 60 points, the loan applicant will be judged as a high risk customer, the repayment ability of the applicant will be considered limited, and the credit will be refused. Conversely, if the applicant's credit risk score is higher than 60, the applicant will be judged as a low risk customer, and the applicant will be further scored. If the credit risk score of the applicant is lower than 60 points, the applicant will be judged as a high risk customer, the repayment ability of the applicant will be considered limited, and the credit will be refused [14]. On the contrary, if the credit risk score of the applicant is higher than 60 points, it will be judged as a low-risk customer, and the loan application of the applicant can be reviewed in the next step. As shown in Fig. 3, it is the entire network structure.

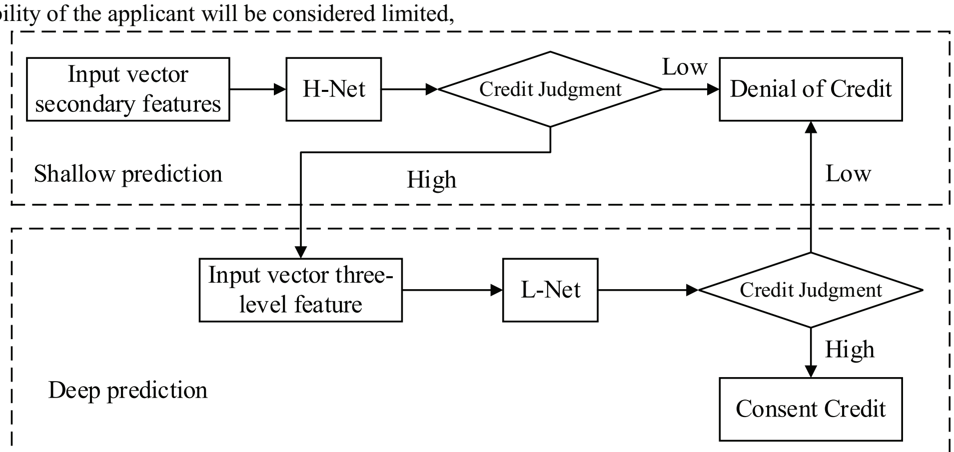


Fig.3. Overall structure of system network

C. Detailed Design and Network Parameters of DNN

DNN is a three-layer network structure. These three layers are the output layer, the hidden layer and the input layer [15]. In this paper, the input layer of the DNN uses the secondary and tertiary features of the loan applicant, so the number of neurons in the input layer of the L-Net layer sub-depth neural network is 20 and the number of neurons in the input layer of the H-Net layer sub-depth neural network is 6. In this paper, the credit risk of the loan applicant is predicted, so the number of neurons in the output layer of both the H-Net layer and the L-Net layer is 1.

The design of hidden layer is complicated. In practical application, the methods to determine the number of hidden layer neurons mainly include heuristic search method, formula method and experiment method [13]. If formula method is chosen, its calculation method is shown in Formula (2). In formula (2), the variable n represents the number of nodes in the input layer, the variable q represents the number of nodes in the output layer, and the variable a represents the regulation constant. The value range of a is [1-10], which represents the adjustment constant.

$$p = \sqrt{n+q} + a \qquad (2)$$

We used experimental methods to determine the value of each variable. In the processing principle, we follow the principle of increasing dimension first and decreasing dimension later. After repeated experiments, we finally determined that the number of hidden layers in H-Net layer network is 3. The number of neurons in each hidden layer is 32,32,16 respectively.

Using the same principle, the L-Net layer network has 6 hidden layers, each with 64, 48, 32, 32, 16, 8 neurons in turn..

IV. EXPERIMENTAL VERIFICATION

The experiment was run on a workstation with Intel Xeon E5-4603 CPU, NVidia GTX1080Ti commonly used in the field of deep learning GPU, 64G memory, and Windows 10 operating system. The Python version is 3.7.6 and the TensorFlow framework is 1.14.0.

The experimental data of this experiment comes from the real credit data of a commercial bank in the past five years. The entire data is partitioned, with 20% as the test set and 80% as the training set.

Before sending data into the deep neural network for network training, all input and output data need to be normalized first, and all data should be normalized to the interval range [0-1]. Second, build the entire network structure using the API provided by TensorFlow. Third, call the neural network parameter initialization function to initialize the neural network parameters. Fourthly, TF Record is constructed to input data into the neural network. Fifth, define parameters necessary for the network such as loss function, activation function, dropout and learning rate decay rate. The specific experimental process is shown in Fig. 4. In this paper, in order to verify the practicability of the model, we choose to use random forest algorithm and decision tree algorithm as comparative experimental methods.

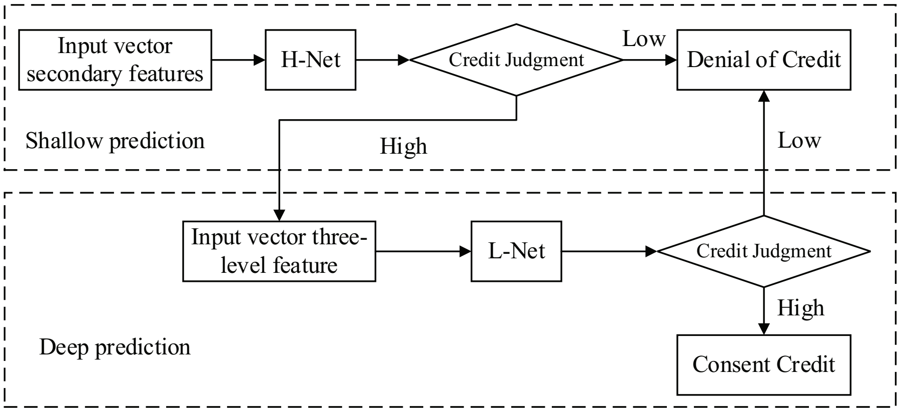
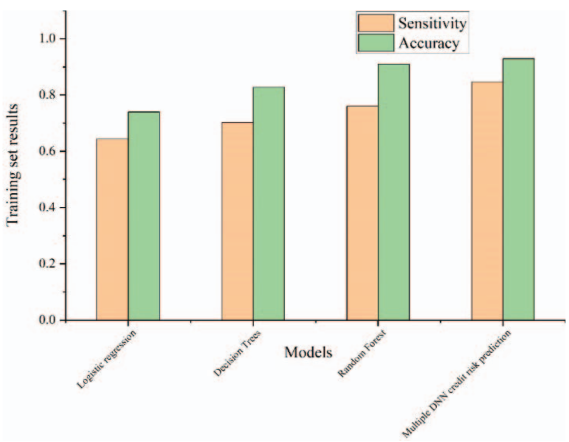
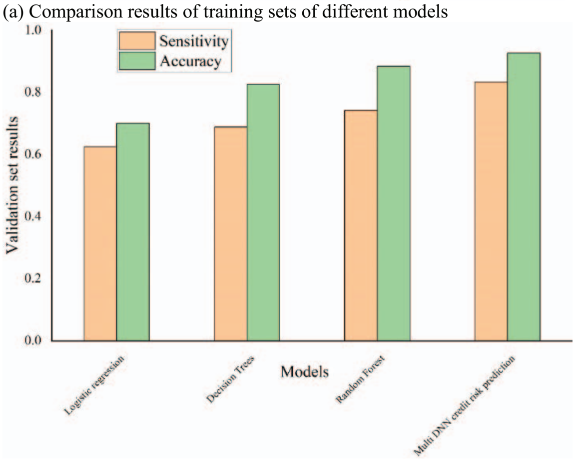


Fig.4. Schematic diagram of experimental flow

It can be seen from the data in Figure 5 that the results obtained by the four methods on the training set are slightly higher than those on the prediction set, which indicates that we are correct in the division of the data set. The multi-level DNN credit risk prediction model proposed in this paper has the highest accuracy and sensitivity scores compared with the other three models, which can reach 83.26% and 92.58% respectively, which further verifies the practicability and accuracy of the method designed by us. Therefore, the model proposed in this paper can be well deployed in the credit risk assessment system.



(a) Comparison results of training sets of different models



(b) Comparison results of validation sets of different models

Fig.5. Model comparison results

V. Conclusion

At present, the proportion of credit business in the overall income of banks is gradually increasing, which reflects that the proportion of credit business volume is also gradually increasing, along with the increase of credit risk. How to effectively identify and control credit risk has become the core issue of today's credit business for banks. Based on BP neural network technology, this paper proposes a bank credit risk forecasting and management model based on multi-level deep neural network. The accuracy of BP neural network model reached 92.58% in the assessment of risk grade. I hope to have a greater breakthrough in my future study and work, and apply the results of this study to my work correctly, so as to improve work efficiency and control credit risks.

The bank credit risk assessment system implemented in this thesis has also achieved more desirable practical results in the actual application environment, effectively speeding up the efficiency of bank credit risk forecasting operations and improving the management level of bank credit work. However, there are still some shortcomings. In terms of the performance of the system, it is necessary to further strengthen the security of the data and improve the performance of the deep neural network, and these are the directions that need to be worked on in the process of future system construction hopefully.

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