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A MODEL FOR CREDIT RISK ANALYSIS USING ARTIFICIAL NEURAL NETWORK

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Abstract— Credit loans are like a lifeline that is vital to every financial institution. The process of estimating the probability that someone will pay back a loan is one of the most important mathematical problems of the modern world; as such, there's a need to analyse the credit risks they are exposed to, to profitably operate in the market. This study trained an intelligent model that analyses credit risk based on specific factors. The Back-Propagation Feed-Forward ANN (BP-FFANN) is trained by a technique called the Gradient Descent. The back Propagation neural network uses a supervised learning model and a back propagating network structure. The model was developed using Back-Propagation trained Feed-Forward Artificial Neural Network (BP-FFANN) basing on a Modified Hyperbolic Tangent Activation Function (MOD-HTAN). It is based on a modification to the Euler number, 'e'. The methodology we have adopted in this research work is an object-oriented model with recursive development (OOM/RD) and the research method used is the quantitative analysis method. Implementa-tion was carried out on MATLAB desktop simulation environment. The system has two major advantages over the existing system: it uses an improved activation function that does not restrict the magnitudes of the hidden activations - this is particularly very useful in situa-tions where the pattern can change over time such as in the case of the credit risk management problem. Secondly, since the system uses a sparse set of inputs during activation processing (squashing) it is therefore more efficient in terms of speed. The results of the credit risk model were found to be satisfactory based on an error response cose to zero. The predicted output accuracy was found to be highly dependent on the number of neurons in the hidden layer. It was found that this technique is advantageous to the existing system in terms of speed and control of explosive gradients. It was also observed that it is cheaper to construct and can be used without loss in precision. The ideas of the proposed neural activation function can be extended to other more biological plausible classification schemes. Thus, it is imperative that existing neural solutions employ more responsive neural activations with adaptive features. To improve accuracy, over fitting problem should be explored.

Index Terms— Activation Function, Artificial Neural Network, Back-propagation Feed-forward Network, Credit Risk, Error Response, Model, Modified Hyperbolic Tangent, Real Number Formula, Support Vector Machines, Vanishing Gradient.

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1. Introduction

Credit risk is economic loss that emanates from the failure of a counterpart to fulfill its contractual obligations or from the increased risk of default during the term of the transac-tion. Credit risk management has ranked very high on the corpo-rate agenda since the early 1990s, but the large losses expe-rienced in the last couple of years indicate that many firms are still a long way from managing their financial risks effectively. This occurs most often because traditional credit risk assessment methods are usually based on the experience and judgment of banking staff. With the rise of fin-tech over the years, new tech-nology has empowered businesses to better analyze data to as-sess the risk profile of various investment products and individu-al customers. But it is important to note that it is impossible for any lender to ever fully know whether a borrower will default on a loan or not. However, by applying relevant risk modelling in tandem with the latest credit risks measurement technology and Credit Risk Management techniques it is possible to keep default rates low and reduce the severity of losses. There is a need to invest in a good credit risk management system to maintain and manage acceptable levels of non-performing loans.

2. RELATED RESEARCH

The main risks that banks face are credit, market, and op-erational risks, with other types of risk including liquidity, busi-ness, and reputational risk. Banks are actively engaged in risk management to monitor, manage, and measure these risks Apostolik *et al*. [1]. Techniques such as Logistic regression and discriminant analysis are traditionally used in credit scor-ing to determine likelihood of default. Support Vector Machines (SVMs) are successful in classifying credit card for customers who default. They were also found to be competitive in discovering features that are most significant in determining risk of default when tested and compared against the traditional techniques. Belotti and Crooks [2]. Yeh and Lien [3] applied methods such as K-Nearest Neighbors (KNN), Logistic Regression, Discriminant Analysis, Naive Bayes, Artificial Neural Networks (ANN) and Classification Trees (CART) on a data set of customers' credit default in Taiwan.

In the last years, research has produced several studies about the application of artificial intelligence systems for the management and assessment of credit risks. Tam and Kiang [4] introduced a neural network approach to perform discriminant analysis in business research. Jiao *et al*, [5] explored the performance credit scoring by integrating back propagation networks with traditional discriminant approach. To demonstrate the inclusion of the credit scoring result from discriminant analysis would simplify the network structure and improve the credit scoring accuracy of the designed neural network model, credit scoring tasks are performed on one bank credit card data set. As the results reveal, the proposed hybrid approach converges much faster than the conventional neural networks model. Huang *et al.* [6] introduced a relatively new machine learning technique, support vector machines (SVM), in attempt to provide a model with better explanatory power. They use Back-Propagation Neural Network (BNN) as a benchmark and obtain prediction accuracy around 80% for both BNN and SVM methods for the United States and Taiwan markets.

Angelinia *et al*. [7] describe the case of a successful application of neural networks to credit risk assessment. They develop two neural network systems, one with a standard Feed-Forward Network, while the other with a special purpose architecture. The application is tested on real-world data, related to Italian small businesses. They show that neural networks can be very successful in learning and estimating the in bonis/default tendency of a borrower, provided that careful data analysis, data pre-processing and training are performed.

In the study of Chauhan *et al*. [8], Differential Evolution algorithm (DE) is proposed to train a Wavelet Neural Network (WNN). The resulting network is named as Differential Evolution trained Wavelet Neural Network (DEWNN). The efficacy of DEWNN is tested on bankruptcy prediction datasets of US banks, Turkish banks, and Spanish banks. Moreover, Garson's algorithm for feature selection in multi-layer perceptron is adapted in the case of DEWNN.

More recently, Figini *et al*. [9] show that a multivariate outlier detection machine learning technique improves credit risk estimation for SME lending using data from UniCredit Bank. Neural networks have proven to be of significant value in the credit risk decision process, and their application in company distress predictions was reported to be beneficial in credit risk evaluation Wójcicka [10].

3. METHODOLOGY

A. Back-Propagation Feed-Forward Neural Network Approach

The Back-Propagation Feed-Forward ANN (BP-FFANN) is trained by a technique called the Gradient Descent. The back Propagation neural network uses a supervised learning model and a back propagating network structure. In this Neural Network, a set of first-order derivatives are calculated, and this is also systematically followed by network weight and bias update. A set of input values are fed to the ANN inputs which have weights connected or assigned to each of them. The inputs are multiplied by the connecting weights, added to a set of corresponding biases, and then summed up and fed to an ANN activation (Modified Hyperbolic Tangent) in a hidden layer. An output activation then processes the resulting activations obtained by the hidden layer in a manner similar to the aforementioned process to give an output prediction which is in turn compared to a target to generate a prediction error. This process is repeated in several iterations (also called training epochs) and at each iteration step, errors are checked against a set tolerance value. The training (or learning) process stops when several set iterations are reached or when a convergence (stopping criterion) is met. The overall methodology is represented in Figure 1.

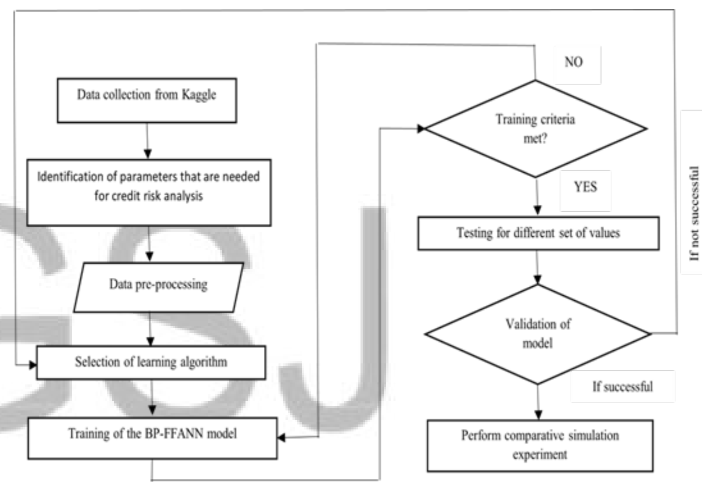

Figure 1: Process Workfow

The first step comprises of collecting credit loan dataset from Kaggle. Data preprocessing was performed on the dataset. Normalization on the training dataset was within the range of 0-1. Back-Propagation Feed-Forward Artificial Neural Network (BP-FFANN) technique was used for training a two-way iteration performance model; The first way is the forward propagation of input weights; the second iteration is the backward propagation for calculating errors and updating weights.

B. Data Source

Credit loan dataset consisting of over 111,000 records was collected from Kaggle. Eleven parameters that are based explicitly on high probability of loan default were identified. Data preprocessing was performed on the dataset. Normalization on the training dataset was within the range of 0-1, using equation 1.

$$\text{Xnew} = \frac{x - \text{xmin}}{\text{Xmax} - \text{xmin}} \qquad (1)$$

Where xnew is a new value, x is an original value, xmax is a maximum value, and xmin is a minimum value of a specific parameter.

4. Model Training

Input Unit

This provides the input data for ANN learning and prediction. This data is normalized to a suitable form prior to processing, by an equivalent input layer ANN. Ten parameters were considered as inputs. The input layer then multiplies these inputs with a fixed number of weights which is then added to a corresponding set of biases. The model was trained based on equation 2:

$$I_j = \sum_i w_{ij} O_i + \theta_j \tag{2}$$

Where, for a given set of inputs, Oi and a corresponding set of weight connections from input layer(s) i to hidden layer j, wij, and input biases, of unit θj, compute the net input of an ANN. Training of the ANN stops when the error is less than a stop value, the iterations process (epochs) is concluded or when the misclassification rate is less than a tolerable value.

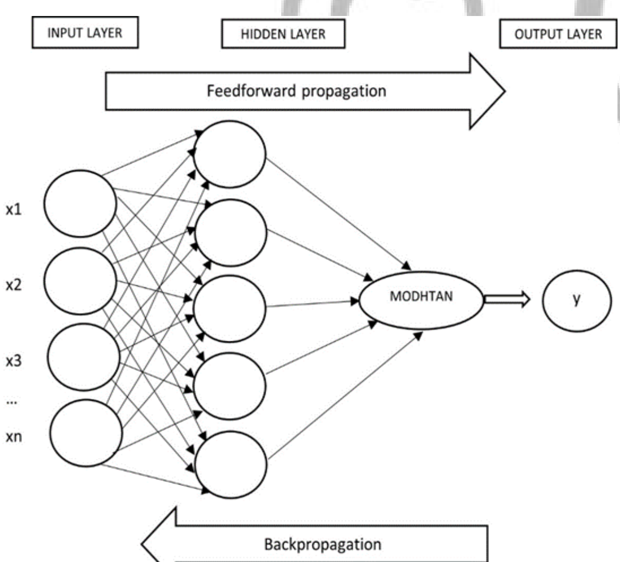

Figure 2: Proposed Neural Network Architecture

Input (x) parameters:
Revolving_Utilization_Of_Unsecured_Lines
Age
Number_Of_Time_30-59_Days_Past_Due_Not_Worse
Debt_Ratio
Monthly_Income
Number_Of_Open_Credit_Lines_And_Loans
Number_Of_Times_90_Days_Late
Number_Real_Estate_Loans_Or_Lines
Number_Of_Time_60-89_Days_Past_Due_Not_Worse
Number_Of_Dependents
Output (y) parameter:
Serious_Dlq_in_2yrs

Figure 3: Input and Output Variables

Processing (Hidden Layer) Unit

In this layer, the outputs from the input layer are passed through several hidden layer activations. The idea behind passing through more than one layered activation units is to generate a multilayer representation. This study uses a modified hyperbolic tangent activation (MODHTAN) that has been developed by Anireh and Osegi [11]. The activation function in equation 3 was used between the hidden and output layer

$$RNF_o = \left(\frac{a-n}{a-(m+x)}\right)^a \approx e^x \tag{3}$$

5. DISCUSSION AND CONCUSION

The accuracy of the developed model was found to be highly sensitive to the number of the hidden neurons. Due to over-fitting issue, the tuning factor in the MODHTAN can be adjusted as appropriate or fine-tuned automatically. The results presented in this research show clearly that it is still a challenge obtaining the classification efficiency very close to 100% performance on the credit risk problem set considered.

As seen in figure 4, Training the model using the back propagation feedforward ANN, with a Modified hyperbolic tangent as the activation function. Got an error response close to zero (0.012).

This result indeed shows that the proposed FF-ANN based credit-risk classification approach is robust to the explosive effects encountered by conventional neural solutions based on standard HTAN. Thus, the benefit of using an adaptive activation is thus validated in this research study.

It is still a challenge obtaining the classification efficiency very close to 100% performance on the credit risk problem set considered. The p-values showed that no significant difference exists in the simulated phenomena. See Tabe 1.

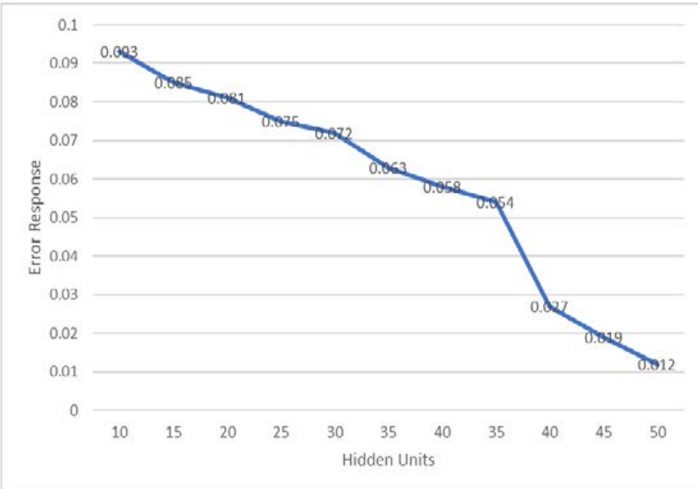

Figure 4: Error Response Graph

Table 1: T-test for Simulated Data

Parameter	p-value	Condition
$HTAN_{tca}$	0.0003881	Reject Null Hypothesis
$HTAN_{tp\text{-}tca}$	0.0000000	Reject Null Hypothesis
$MODHTAN_{tca}$	0.0010000	Reject Null Hypothesis
$MODHTAN_{tp\text{-}tca}$	0.0004459	Reject Null Hypothesis

During the first trial for the comparative experiment, the HTAN showed 30% predicted accuracy while the MODHTAN showed 50% predicted accuracy. Upon the fifth trial, HTAN showed 45% predicted accuracy and MODHTAN showed 70% predicted accuracy. See figure 5.

The proposed MODHTAN based ANN is promising as it can give reasonable accuracies and thus does not overfit. There is graded improvement in classification accuracy tp-rate as the size of hidden neurons is increased; however, the overall classification accuracy degrades.

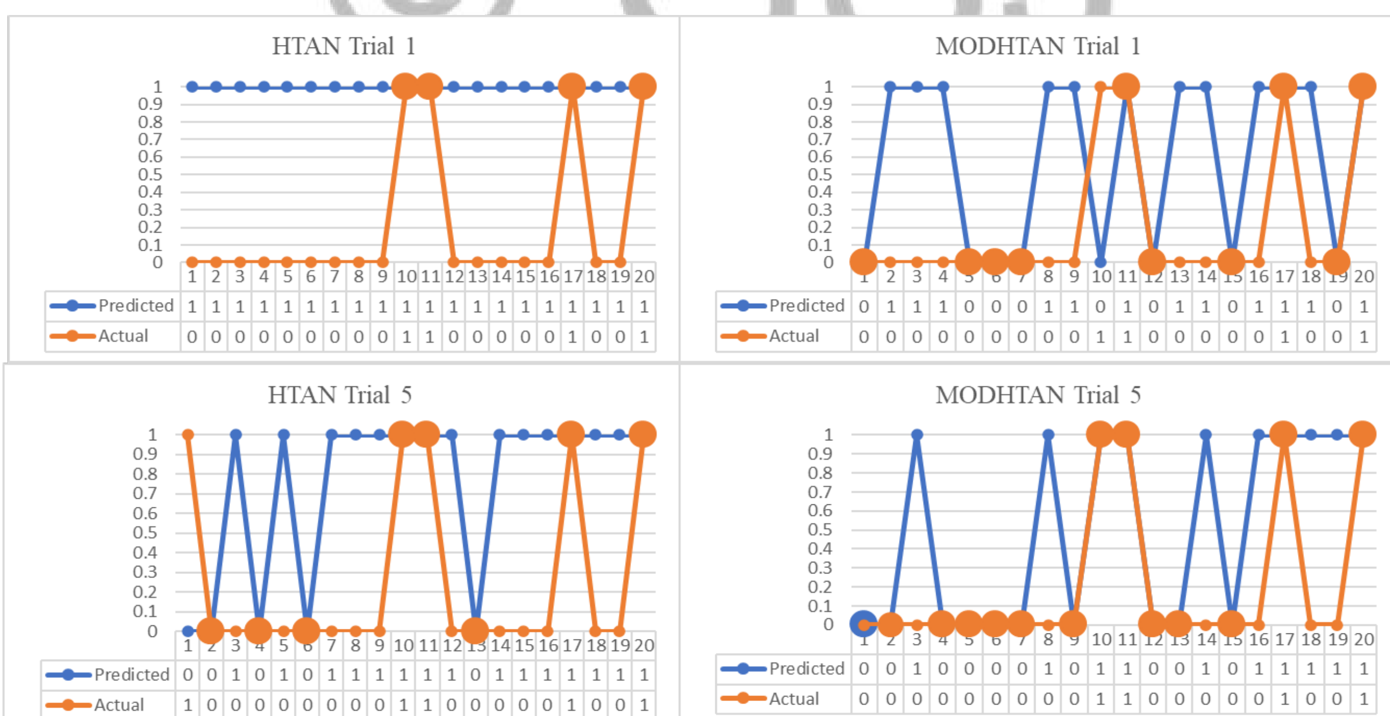

Figure 5: Graph Showing Predicted vs Actual Value

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