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.

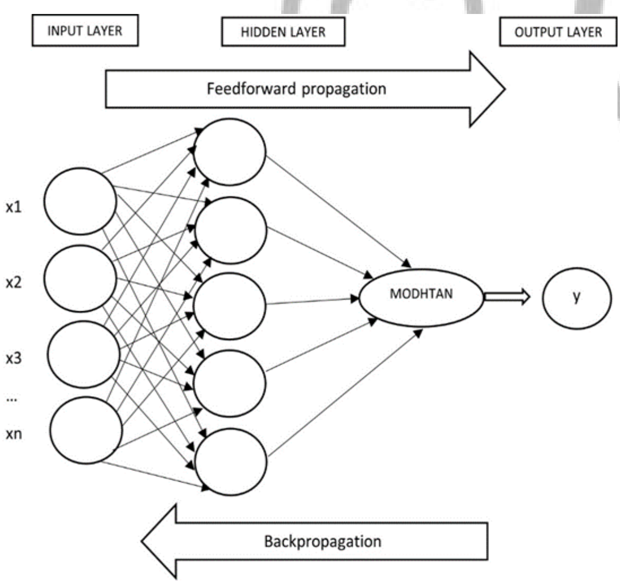

Figure 2: Proposed Neural Network Architecture

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).

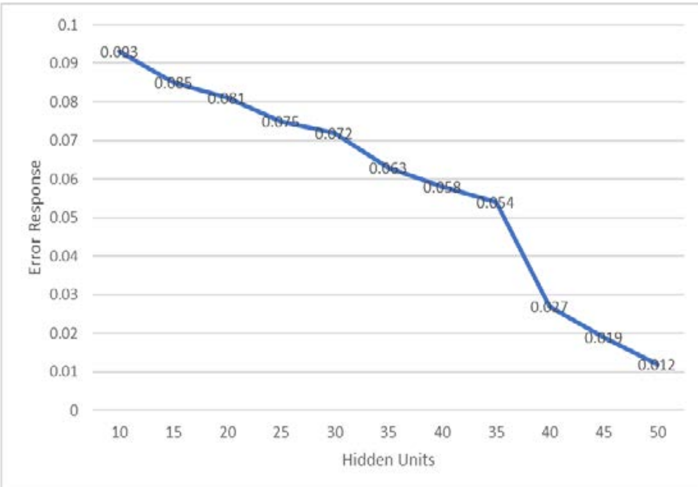

Figure 4: Error Response Graph

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.

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.

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

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.

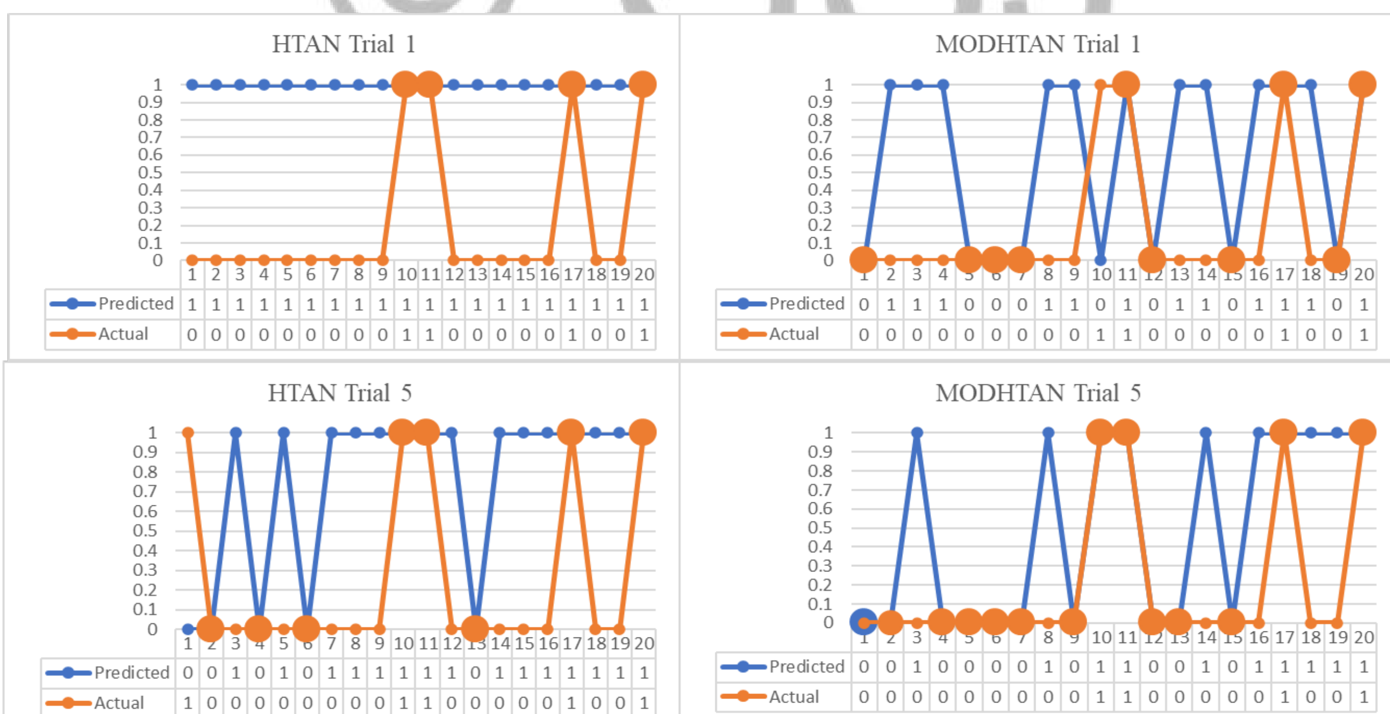

Figure 5: Graph Showing Predicted vs Actual Value

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