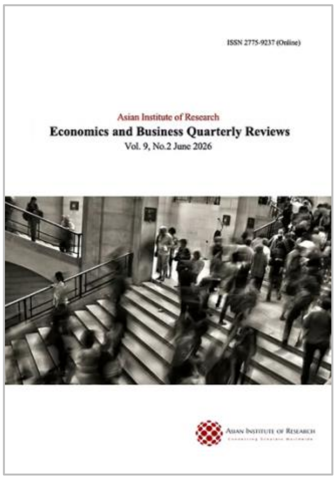


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# Predicted Repayment Behaviour of Borrowers in Urban Cooperative Banks in Assam: A Case Study of Nagarik Samabay Bank

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**Abstract**
The purpose of this study is to analyse the predicted repayment behavior of sample borrowers of Nagarik Samabay Bank, an Urban Cooperative Bank in Assam for the period 2023-24 by employing the Artificial Neural Network (ANN) model. The results indicate that eleven socio-economic factors were statistically significant in predicting the repayment behavior of sample borrowers, with the ANN model achieving a predicted default classification accuracy of 83.3%. However, in comparison, the logistic regression (LR) model demonstrated higher predictive performance, correctly classifying defaulters with an accuracy of 88.2%, thereby outperforming the ANN model. However, the ANN model predicted regular borrowers more accurately than logistic regression, achieving an accuracy of 98.9% compared to 97.6%. Based on these findings, it is suggested that financial institutions, particularly Urban Cooperative Banks, adopt robust risk assessment measures to strengthen their position in the banking sector.

**Keywords:** Repayment Behavior, Urban Cooperative Bank, Artificial Neural Network model (ANN), Logistic Regression (LR)

## 1. Introduction

For every productive activity, one of the important indicators of the economy is banking services and it is provided by the institutional and non-institutional sources of the economy. Cooperative banks are one of them which were established to cater to farmers, labourers, artisans, and small entrepreneurs of local communities. According to Master Direction on Priority Sector Lending, 2025 and Vision Document (2025–2030), the RBI emphasizes areas such as achieving a PSL target of 75%, at least 12% of credit to "weaker" sections, digitalization, recruitment of professional experts and DICGC insurance up to 5,00,000, etc., for more efficiency and productivity of UCBs. In this regard, repayment of loans plays an important role in assessing the efficiency and channelizing the deposits of financial institutions. In order to make rational decisions, borrowers ought to reduce the risk of default and ensure the benefits of banking services over the period of time. Under the latest RBI (UCBs Credit Risk Management Amendment Directions, 2025–26), credit scoring has become more structured and aligned with other financial institutions. There are different regulatory frameworks for unsecured loan ceilings, concentration risk, priority sector lending and risk-based premiums. Analyzing and predicting credit default is important in UCBs as it reflects future banking activities. The core concept of credit risk occurs when a borrower fails to meet their obligations in accordance with agreed terms. In the taxonomy of defaulters, RBI distinguishes different defaulters according to their intent and impact on banking activities. In this regard, overdue refers to payment not being made on the due date as fixed by the bank, and it becomes a non-performing asset (NPA) when it remains for 90 days. According to Master Direction on Wilful Defaulters, a borrower may have the capacity to honor obligations but chooses not to, and due to that there are some key reasons like siphoning of funds, diversion of funds, disposal of assets without the bank's consent, etc. To control credit risk, the Early Warning Signals (EWS) framework has been introduced to identify "stress" before it turns into a "defaulter" status.

Traditional approaches like financial ratios, Z-score analysis, and regression analysis have been used to analyze credit risk in financial institutions (Altman, 1968; Beaver, 1966; Sinkey, 1975). In recent times, Artificial Neural Network (ANN) models have been used for bankruptcy prediction to obtain more accurate results (Kaski et al., 2004; Kim & Kang, 2010; Pramodh & Ravi, 2007).
The primary objectives of the study are:
1. To predict the repayment status of sample borrowers using Artificial Neural Network (ANN) in the Nagarik Samabay Bank (UCBs) in Guwahati city.
2. To compare the predicted results of ANN with logistic regression of repayment status of sample borrowers in the Nagarik Samabay Bank.

**2. Review of literature**

Artificial Neural Networks (ANN) offer several advantages over conventional analytical methods. According to Shachmurove (2002), ANN models have the ability to analyze complex patterns with a high degree of accuracy. Unlike traditional statistical models, ANN does not require strict assumptions regarding data distribution. Since time-series data are dynamic in nature, non-linear tools are essential to identify underlying relationships, and ANN is particularly effective in capturing such non-linear patterns.

Hu and Su (2022) empirically assessed and compared two traditional credit risk prediction models—cluster analysis and factor analysis—with three commonly used ANN models. Their study evaluated the predictive performance of these models to identify the most suitable approach for credit risk assessment of corporate customers in commercial banks.

Similarly, Mohammadi and Zangeneh (2016) evaluated a Multilayer Perceptron Neural Network (MLPNN) for customer credit risk assessment. Their findings indicate that neural networks possess strong predictive power and are highly effective in estimating non-linear relationships. The results demonstrated that the proposed model achieved high classification accuracy and outperformed other models in predicting customer credit risk.

Zhu et al. (2016) examined credit risk prediction for small and medium-sized enterprises (SMEs) in China using logistic regression (LR) and ANN models. The empirical results revealed that the ANN model achieved higher accuracy in predicting "negative signals" compared to the LR model.

Altunöz (2024) compared LR and ANN models and provided significant insights into their respective strengths and limitations. The study emphasized the importance of advanced analytical techniques in enhancing the prediction of financial risks, thereby improving banking decision-making processes and promoting financial stability.

3. **Data and Methodology**

3.1 *Data source*

The study is conducted on Nagarik Samabay bank limited (NSB), consisting five branches in Guwahati city and also listed in the RBI website in the section of scheduled Urban Cooperative Banks in India. From the five branches of NSB, 330 Sample benefices are used the estimation and the study uses data for the year 2023-24.

*3.2 Sample frame*

To determine the adequacy of the selected sample, the Cochran's sample size formula for finite populations was applied:

$$N_0 = Z2 \cdot p \cdot q / e^2$$

Where:

- $N_0$ = required sample size
- Z= Z-value (e.g., 1.96 for 95% confidence level, 2.58 for 99% confidence)
- p = estimated proportion of the attribute present in the population (commonly 0.5 if unknown, as it gives maximum variability)
- $q = 1 - p$
- e= desired margin of error (e.g., 0.05 for ±5%

Thus, the statistically required sample size is approximately 309. The study has used 330 respondents, which is slightly higher than the minimum requirement, ensuring adequacy and reliability of results.

*3.3: Hypothesis of the study*

Null Hypothesis ($H_0$):
The ANN model has no significant ability to classify borrowers into "Regular" and "Defaulter" categories.
Alternative Hypothesis ($H_1$):
The ANN model has a significant ability to correctly classify borrowers into "Regular" and "Defaulter" categories.

*3.4 Variables and measurement:*

In this study, a binary dependent variable, default (Y), was used to predict the repayment status of borrowers, following the approach adopted by Agbemava et al. (2016). Table 3.1 presents the descriptive analysis of the variables included in the study:

$$Y = \begin{matrix} 1 = , if\ borrower\ is\ classified\ as\ defaulter. \\ 0 = , if\ borrower\ is\ classified\ as\ regular. \end{matrix}$$

Table 3.1: Descriptive analysis:

| Variables | Type | Description |
|---|---|---|
| Age | Scale | Age of the borrower (years) |
| Gender | Scale | Gender of the borrower |
| Caste | Scale | Caste of the borrower |
| Education | Scale | Education status of the borrower |
| Occupation | Scale | Current employment status |
| Aggregate income | Scale | Total income of the borrower |
| Purpose of loan | Nominal | Use of loan applied: Priority sector=1, Non-Priority Sector =2 |
| Time to visit | Nominal | Loan disbursement duration |
| Sufficiency of loan amount | Binary | Did the borrower have prior credit sufficiently; yes=1, No=0 |
| Total loan repaid/ total loan outstanding Ratio | Nominal | Efficiency ratio = total loan amount repaid/ total amount of outstanding. |
| Fund Utilization | Scale | Utilization of loan amount. |
| Overdue | Binary | Overdue status of the borrower |

| | | |
|---|---|---|
| Repayment status ( Dependent Variable) | Binary | Credit status of a loan; Regular =0, Defaulter=1. |

*3.5 Empirical Models*

The study uses two models for predicting credit defaulters either they are defaulter or regular and then compared their performances of two models. Firstly, The ANN is the process where data are connected to a network by an associated value known as "weight" (Youn and Gu, 2010a). The common ANN model is the multilayer perceptron (MLP) network (Ciampi and Gordini, 2013a) that is made up of (1) an input layer, (2) an output layer, and (3) one or more hidden layers between the input and output layers. Referring to Zhang et al. (1999), this study developed a three-layer MLP network, as shown below (fig.3.1):

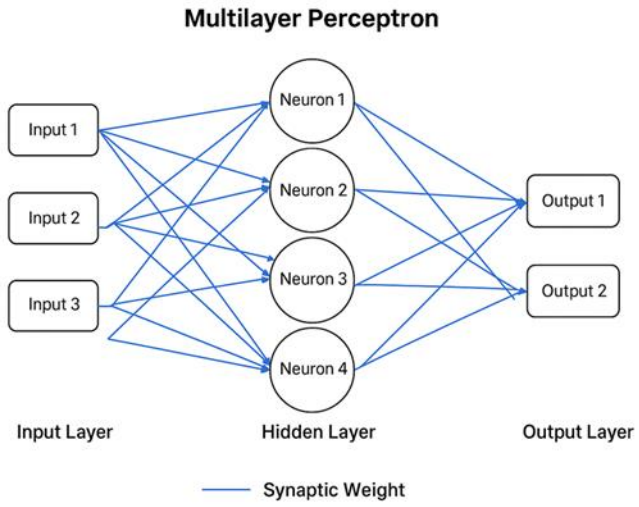


Figure 3.1: ANN model ( one hidden layer)

Artificial Neural Networks (ANNs) can be broadly defined as information processing systems that possess learning and generalization capabilities, enabling them to model complex patterns in data (Bahrammirzaee, 2010). According to Malhotra and Malhotra (2003), ANNs are non-linear models that utilize pattern recognition techniques for classification and prediction purposes. These models are particularly effective in capturing complex relationships between input and output variables, thereby facilitating pattern discovery and accurate forecasting. An ANN consists of a network of highly interconnected processing elements known as neurons or nodes (Malhotra & Malhotra, 2003; Lee & Chen, 2005). Typically, neural networks are structured into three main layers: an input layer, one or more hidden layers, and an output layer. This architecture is commonly referred to as a multilayer perceptron (MLP), which is widely applied in credit risk evaluation and classification problems (Tsai & Wu, 2008

Eftekhar (2005) has studied the performance of the ANN model and multivariate Logistic Regression (LR) model and found the accuracy of logistic model superior to ANN model. Len (2009), Ohlson (1980), Chen and Den (2009) and Geng et al., (2015) have used LR models for predicting financial difficulties in their studies. LR used in this study as :
**Repayment Status**:$\beta0+\beta_1 Age_{it}+\beta_2 Casteit+\beta_3 Genderit+\beta_4 Educationit+\beta_5 Occupation_{it}+\beta_6 AggregateIncome_{it}+\beta_7$ Timetovisit$_{it}$+ $\beta_8$ Sufficiency of loan$_{it}$ + $\beta_8$ Total loan repaid/total outstanding ratio$_{it}$ + $\beta_9$ Fundutilisation$_{it}$ + $\beta_{10}$ Purposeof Loan$_{it}$+ $\beta_{11}$ overdue$_{it}$.

**4. Empirical Result and Interpretation:**

Before apply ANN model to analyse sample data, normality test of dependent variable (repayment Status) was conducted in the following table 4.1 (i)

*4.1. Tests of Normality for Repayment Status (Dependent Variable) of Borrowers*

Table 4.1: (i) Result of Normality Test :

**Tests of Normality**

| | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| Repayment status | .529 | 330 | **.000** | .348 | 330 | **.000** |

a. Lilliefors Significance Correction

Notes: Statistically significant values are in bold.

Table 4.1 (i) presents the results of the normality tests conducted on the variable Repayment Status using the Kolmogorov–Smirnov and Shapiro–Wilk tests. The Kolmogorov–Smirnov test result (Statistic = 0.529, $p < 0.001$) and the Shapiro–Wilk test result (Statistic = 0.348, $p < 0.001$) are both statistically significant. This indicates that the distribution of the repayment status variable significantly deviates from normality. Therefore, the data do not follow a normal distribution, and non-parametric statistical techniques are more appropriate for further analysis.

*4.2: Predicted Performance Analysis of sample borrowers using Artificial Neural Network Model (ANN)*

Table 4.2 (i) represents that out of 330 valid borrower records, 230 cases (69.7%) were used for training the Artificial Neural Network (ANN), while 100 cases (30.3%) were used for testing the model. From a probability theory perspective, the training set is used to estimate the conditional probability distribution $P(Y|X)$ , where Y is the repayment status and X represents borrower attributes such as income, age, education, and loan characteristics. The ANN learns these probabilities by adjusting its internal weights to minimize prediction error. The testing set acts as an independent random sample to evaluate how well the learned probability model generalizes to unseen data, ensuring that the model's predicted probabilities are reliable and not simply memorizing the training data.

Table 4.2: (i): Case Processing Summary for ANN Model (Training and Testing Samples)

**Case Processing Summary**

| | | N | Percent |
|---|---|---|---|
| Sample | Training | 230 | 69.7% |
| | Testing | 100 | 30.3% |
| Valid | | 330 | 100.0% |
| Excluded | | 0 | |
| Total | | 330 | |

The following structure enables the ANN to learn patterns in socio-economic and loan-related variables and accurately classify the likelihood of regular or defaulter loan repayment status.

Table 4.2: (ii): Network Architecture and Learning Structure of the Artificial Neural Network (ANN)

| | | | |
|---|---|---|---|
| Input Layer | Covariates | 1 | Age |
| | | 2 | Caste |
| | | 3 | Education |
| | | 4 | Occupation |
| | | 5 | Aggregate Income |
| | | 6 | Gender |
| | | 7 | Visit to bank |
| | | 8 | Fund Utilisation |
| | | 9 | Efficiency ratio |
| | | 10 | overdue |
| | | 11 | Purpose of loan |
| | Number of Units[a] | | 11 |
| | Rescaling Method for Covariates | | Standardized |
| Hidden Layer(s) | Number of Hidden Layers | | 1 |
| | Number of Units in Hidden Layer 1[a] | | 7 |
| | Activation Function | | Hyperbolic tangent |
| Output Layer | Dependent Variables | 1 | Repayment status (REPAYMNTSTSUS) |
| | Number of Units | | 2 |
| | Activation Function | | Softmax |
| | Error Function | | Cross-entropy |

a. Excluding the bias unit

The following figure 4.1 shows the internal parameters (weights and biases) of a neural network model designed to predict repayment status. In this network, each input variable—such as age, caste, education and others—is connected to six neurons in a hidden layer. Each entry in the table under "Hidden Layer 1" represents the weight that links a specific input to a specific hidden neuron, indicating how much influence that input has on that neuron's activation. The bias values in this layer adjust the activation thresholds for each neuron. After processing through the hidden layer, each of the six neuron outputs is then passed to the final output layer, which has two output neurons representing repayment statuses (0.00 and 1.00). The weights connecting hidden neurons to output neurons, as well as the output biases, determine the final prediction probabilities. In summary, the table quantitatively describes how each input feature and each hidden neuron contributes to the prediction of whether an individual will be categorized as having a repayment status of 0.00 or 1.00. Figure 4.1. Multilayer Perceptron (MLP) Neural Network Showing Input, Hidden, and Output Layers for the Prediction of Loan Repayment Status using socio-economic and loan related indicators:

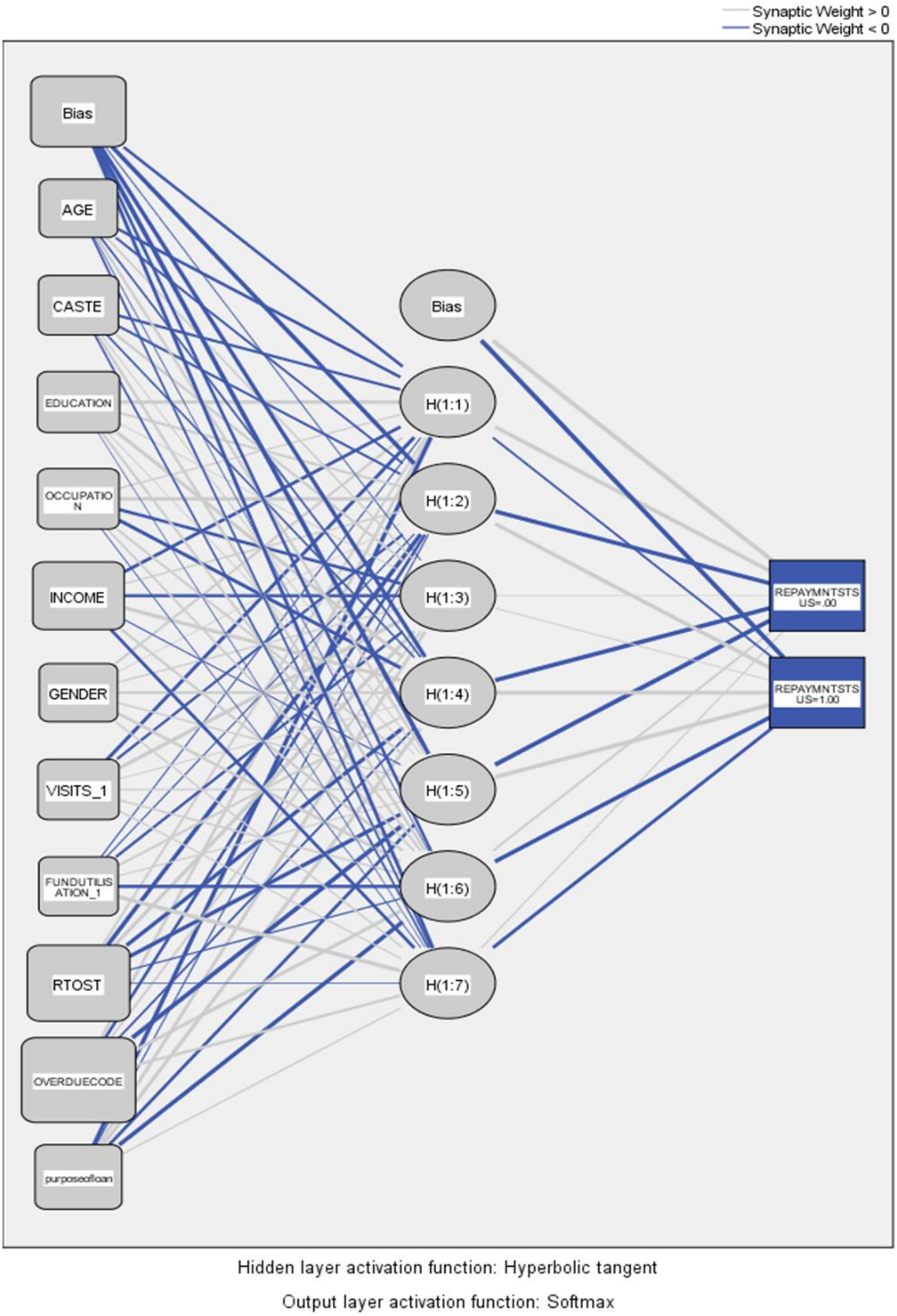


Figure 4.1: Neural network predicated repayment status model

Notes: RTOST= Total loan repaid/ total loan outstanding Ratio (Efficiency Ratio), OVERDUECODE= overdue amount.

The Artificial Neural Network (ANN) model was constructed using a multilayer perceptron architecture to classify the Repayment Status of borrowers. The model summary (Table 4.2 (iii)) indicates strong performance in both training and testing stages. During the training phase, the ANN achieved a Cross-Entropy Error of 11.281 with only 1.7% misclassification, demonstrating a high level of learning accuracy. The training process automatically halted after one consecutive step without a decrease in error, following the built-in early-stopping criteria designed to prevent over fitting (Haykin, 2009). The total training time recorded was 0.35 seconds, highlighting the computational efficiency of the model. When evaluated on the testing dataset, the ANN produced a Cross-Entropy Error of 13.283 and a misclassification rate of 3.0%, confirming its strong generalization capability to unseen data. Consistent with previous empirical studies that use ANN models for credit risk and repayment prediction (Zhang et al., 2019; West, 2000), the results reinforce the suitability of neural networks for classifying borrower Repayment Status.

Table 4.2: (iii).: Summary of the Artificial Neural Network for Predicting Borrowers' Repayment Status

**Model Summary**

| | | |
|---|---|---|
| Training | Cross Entropy Error | 11.281 |
| | Percent Incorrect Predictions | 1.7% |
| | Stopping Rule Used | 1 consecutive step(s) with no decrease in error[a] |
| | Training Time | 0:00:00.35 |
| Testing | Cross Entropy Error | 13.283 |
| | Percent Incorrect Predictions | 3.0% |
| Dependent Variable: Repayment Status | | |

a. Error computations are based on the testing sample.

*Source: The Authors.*

From table 4.2 (iv), the classification results demonstrate that the model performs well in predicting repayment status. In the training sample, the model correctly identified 98.6% of regular borrowers and 95.5% of defaulters, achieving an overall accuracy of 98.3%.While validation using the testing sample confirmed the robustness of the model, with 98.9% correct classification for regular borrowers and 83.3% for defaulters, and an overall accuracy of 97.0%.

Table 4.2: (iv) Classification results:

**Classification**

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | Regular | Defaulter | Percent Correct |
| Training | Regular | 205 | 3 | 98.6% |
| | Defaulter | 1 | 21 | 95.5% |
| | Overall Percent | 89.6% | 10.4% | 98.3% |
| Testing | Regular | 87 | 1 | 98.9% |
| | Defaulter | 2 | 10 | 83.3% |

| | | | |
|---|---|---|---|
| Overall Percent | 89.0% | 11.0% | 97.0% |
| Dependent Variable: Repayment Status | | | |

*Source: The Authors.*

Figure 4.2 shows a diagram of the model's sensitivity and specificity (answers "Yes" and "No"), constructed based on training and testing of the network model. The 45-degree line from the upper right corner of the graph to the lower left represents a random guess of the answer. The more the curve deviates from the 45-degree reference line, the more accurate the classification. The measured area under the curve and the best score of 0.981 indicate that the MLP model has a very good ability to classify users depending on their answers ("Yes" and "No").

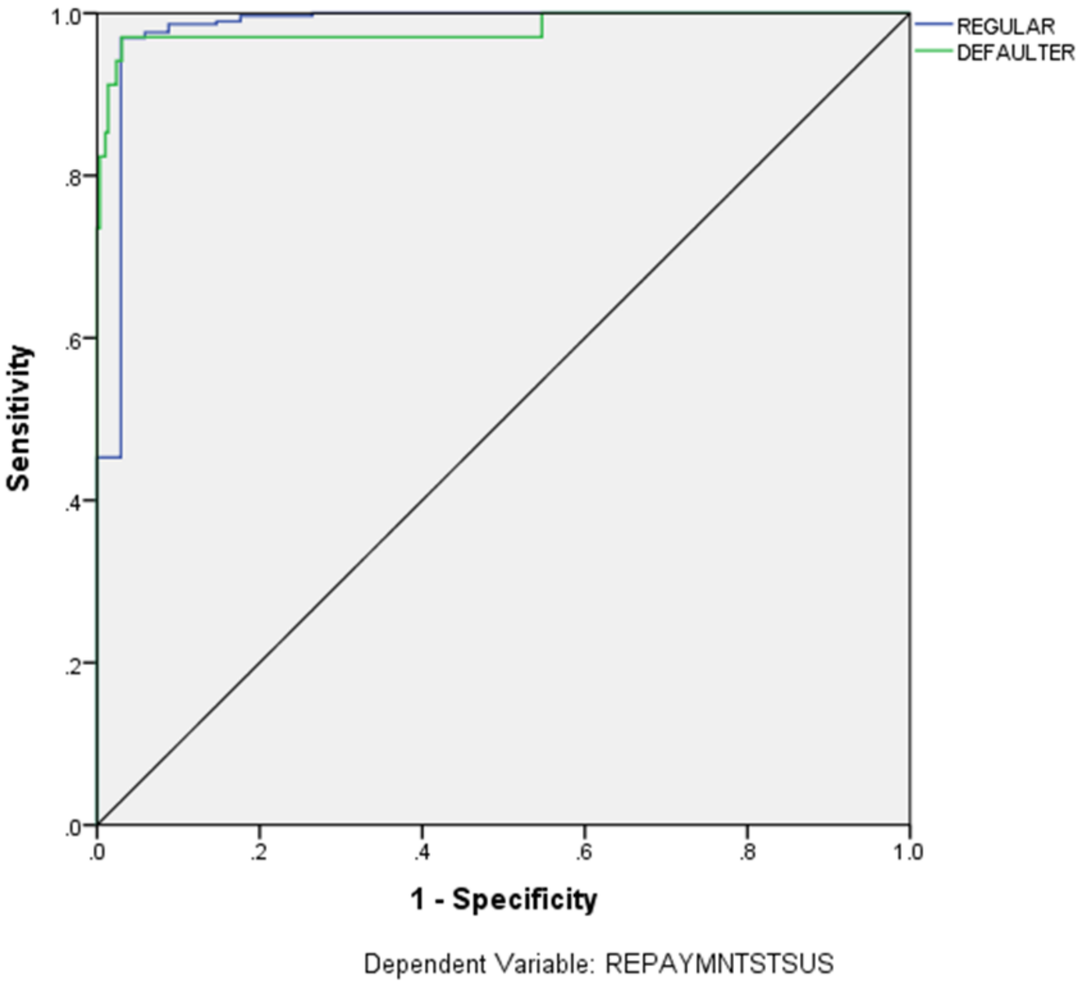


Figure 4.2: Area Under the Curve (AUC) for both *Regular* and *Defaulter* repayment status classifications: (0.981)

Note: REPAYMNTSTSUS= Repayment status of borrowers.

*Source : The Authors.*

Figure 4.2 reflects the sensitivity analysis of the observed predictors. Each of the input variables is ranked based on their degree of importance in predicting the output variable. An input variable was inferred to be a significant predictor if the variable's importance value was greater than 0.10 (Youn and Gu, 2010b).

*4.3. Comparison of Predicated results: Logistic Regression and ANN model*

The data used to build the neural network model for predicting repayment status of borrowers was used for building a logistic regression model in order to verify the effectiveness of neural networks. Logistic regression has traditionally been one of the most widely used statistical models in banking and credit-risk analysis because of its interpretability, ability to handle categorical dependent variables, and robustness under minimal distributional assumptions (Menard, 2005; Flury, 1997). In recent years, however, machine-learning techniques—particularly the Multilayer Perceptron (MLP) form of Artificial Neural Networks (ANN)—have gained importance due to their capacity to learn complex, nonlinear relationships between borrower characteristics and loan-repayment outcomes. Unlike logistic regression, which assumes a linear association between predictors and the log-odds of default, MLP-ANN models use interconnected hidden layers to automatically capture nonlinearities and interaction effects without requiring prior specification (Haykin, 1999). Numerous studies have shown that ANN models often outperform traditional statistical methods in predicting credit default, classification accuracy, and risk segmentation because of their superior generalization and pattern-recognition ability (West, 2000; Kumar & Ravi, 2007). In the context of banking, combining logistic regression with MLP-ANN provides a complementary analytical framework: logistic regression offers interpretability and hypothesis testing of determinants of loan outcomes, while the ANN model enhances predictive performance, especially for complex borrower behaviour. Hence, using both approaches improves model reliability and strengthens decision-making in credit appraisal, loan-utilisation assessment, and repayment prediction. The predicted result of logistic regression is shown in Table 4.3 (i)

Table 4.3: (i) : Predicted Results of Logistic Regression :

**Classification Table[a]**

| Observed | | | Predicted | | |
|---|---|---|---|---|---|
| | | | Repayment status | | Percentage Correct |
| | | | Regular | Defaulter | |
| Step 1 | Repayment Status | Regular | 289 | 7 | 97.6 |
| | | Defaulter | 4 | 30 | 88.2 |
| | Overall Percentage | | | | 96.7 |

a. The cut value is .500

*Source: The Authors.*

From Table 4.3 (i) and table 4.2 (iv), it is evident that logistic regression is more accurate in predicting default loans than neural network model (88.2% vs. 83.3%). However, neural network performed better than logistic regression in classifying non default loans (98.9% vs. 97.6%).The results indicate that neural network is more powerful and accurate than logistic regression in screening non default loans.

## 5. Conclusion

In this paper it statistically proved that though the ANN model has predicated results of repayment status on the socio-economic indicators for sample Urban Cooperative Bank in Assam. It should be noted that in the training sample, the model correctly identified 98.6% of regular borrowers and 95.5% of defaulters, achieving an overall accuracy of 98.3%.While validation using the testing sample confirmed the robustness of the model, with 98.9% correct classification for regular borrowers and 83.3% for defaulters, and an overall accuracy of 97.0%.

Again it is proved from the logistic regression, it is more accurate in predicting non default loans than neural network (88.2% vs. 83.3%) and neural network model performed better than logistic regression in classifying default loans (98.9% vs. 97.6%). The empirical findings support the alternative hypothesis ($H_1$) and reject the null hypothesis ($H_0$), indicating that the ANN model demonstrates a statistically significant and robust predictive capability in accurately classifying both regular and defaulter borrowers of Nagarik Samabay Bank.

In the context of limited number of Urban Cooperative Banks (UCBs) in Assam, it is important to analyze the predicted credit risk associated with borrowers' repayment behavior to ensure bank solvency and operational efficiency. In addition, advanced models such as Artificial Neural Networks (ANN) enhance the accuracy of prediction by effectively incorporating socio-economic indicators.

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