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Credit Risk Modelling Using Deep Neural Network

Vaidehi Patil[1]; Shubham Bari[2]; Kairav Rajgariah[3]; Sumit Singh[4]

[1]AI&DS Thakur College of Engineering and Technology Mumbai, India
[2]AI&DS Thakur College of Engineering and Technology Mumbai, India
[3]AI&DS Thakur College of Engineering and Technology Mumbai, India
[4]AI&DS Thakur College of Engineering and Technology Mumbai, India

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Abstract: Credit risk modelling is essential for predicting a borrower's likelihood of default and ensuring financial stability. Traditional models like Logistic Regression often struggle with complex, non-linear financial data. This paper presents a Machine Learning–based approach using Deep Neural Networks (DNNs) to enhance prediction accuracy and adaptability. The proposed model is trained on publicly available credit datasets after preprocessing and feature engineering. Experimental results show an accuracy of ~85% and an AUC of ~90%, outperforming classical models by a significant margin. The study demonstrates that deep learning can effectively capture hidden patterns in borrower behaviour, offering a robust, scalable, and data-driven framework for modern credit risk assessment.

Keywords: *DNN (Deep Neural Networks), ROC AUC, Credit Default, Credit Risk.*

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I. INTRODUCTION

Credit risk represents the likelihood that a borrower will default on debt obligations, posing financial losses for institutions. Traditional models such as Logistic Regression and Decision Trees rely on linear assumptions and handcrafted features, which restrict their predictive capacity in high-dimensional datasets.

With the increasing volume of financial and behavioral data, Deep Learning provides a mechanism to automatically learn complex, non-linear patterns. Neural networks can process both structured data (income, credit score) and unstructured data (textual behavior), improving model generalization.

The objective of this work is to build a Deep Neural Network (DNN) capable of predicting default risk with higher accuracy and adaptability than classical models.

➢ *Problem Statement*

Existing credit scoring models used by banks and financial institutions are limited by their dependence on predefined statistical assumptions and handcrafted input variables. These models often fail to generalize when presented with new borrower profiles or dynamic economic conditions. Furthermore, issues such as class imbalance (fewer defaulters than non-defaulters), data noise, and lack of model interpretability further reduce their reliability.

II. METHODOLOGY

To The proposed framework for Credit Risk Modelling using Deep Learning follows a structured data science pipeline comprising data preprocessing, feature engineering, model architecture design, training, and evaluation.

➢ *Data Collection and Description*

The dataset was obtained from publicly available financial repositories such as Kaggle Credit Dataset and German Credit Data. Each record corresponds to a loan applicant with attributes including age (x_1), income (x_2), credit history (x_3), loan amount (x_4), and an output label $y \in \{0,1\}$, where $y = 1$denotes default.

$$D = \{(x_i, y_i) | x_i \in \mathbb{R}^n, y_i \in \{0,1\}, i = 1, \dots, N\} \quad (1)$$

Where $N$is the total number of samples and $n$is the number of input features.

➢ *Data Preprocessing*

Raw borrower data often contains missing, inconsistent, or heterogeneous entries.

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Preprocessing ensures data quality and consistency through the following steps:

- *Missing Value Imputation:*
  Numerical features were filled using mean imputation:

$$x_{ij}^* = \begin{cases} x_{ij}, & \text{if } x_{ij} \text{ exists} \\ \bar{x}_j, & \text{otherwise} \end{cases} \tag{2}$$

Where $\bar{x}_j$ is the column mean.

- *Categorical Encoding:*
  One-Hot Encoding converted categorical features into binary vectors.

- *Feature Normalization:*
  To ensure stable gradient descent, features were scaled to the range [0,1] using Min–Max scaling:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{3}$$

- *Dataset Split:*
  Data was divided into 80 % training and 20 % testing sets.

➢ *Feature Engineering*

Derived financial indicators enhance model discriminative power.

For each applicant:

- *Debt-to-Income Ratio (DTI):*

$$\text{DTI} = \frac{\text{Total Debt}}{\text{Annual Income}} \tag{4}$$

- *Credit Utilization Rate (CUR):*

$$\text{CUR} = \frac{\text{Credit Used}}{\text{Total Credit Limit}} \tag{5}$$

- *Payment-to-Income Ratio (PIR):*

$$\text{PIR} = \frac{\text{Monthly Installment}}{\text{Monthly Income}} \tag{6}$$

Highly correlated or redundant features ($|\rho_{ij}| > 0.9$) were removed using Pearson correlation analysis, ensuring dimensional stability.

➢ *Deep Neural Network Architecture*

A Feed-Forward Deep Neural Network (DNN) was constructed with three fully connected layers:

Table 1 Three layer Deep Neural Network

Layer	Neurons	Activation
Input	n	–
Hidden 1	64	ReLU
Hidden 2	32	ReLU
Output	1	Sigmoid

The ReLU activation function introduces non-linearity:

$$f(z) = \max(0, z) \tag{7}$$

And the sigmoid output yields the probability of default:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{8}$$

➢ *Model Training and Optimization*

Training minimizes the Binary Cross-Entropy Loss:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{9}$$

Parameter updates are performed using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{10}$$

Where $\hat{m}_t$ and $\hat{v}_t$ denote bias-corrected first and second moment estimates, respectively.

- *To Prevent Overfitting:*

✓ Dropout ($p = 0.3$) randomly deactivates neurons during training.

✓ Early stopping halts training when validation loss ceases to improve.

➢ *Model Evaluation*

The model's predictive ability was assessed using Accuracy, Precision, Recall, F1-Score, and AUC-ROC, defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN} \tag{12}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{13}$$

The ROC curve plots the True-Positive Rate (TPR) against the False-Positive Rate (FPR):

$$TPR = \frac{TP}{TP + FN}, FPR = \frac{FP}{FP + TN} \tag{14}$$

The Area Under the Curve (AUC) is computed as:

$$\text{AUC} = \int_0^1 TPR(FPR)\, d(FPR) \tag{15}$$

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The proposed DNN achieved an accuracy of 90.8 % and AUC = 0.924, outperforming Logistic Regression (80.2 %) and Random Forest (85.7 %), confirming superior discrimination between defaulting and non-defaulting borrowers.

III. LITERATURE SURVEY

Early credit risk models relied on statistical methods such as Logistic Regression and Linear Discriminant Analysis, which provided interpretable yet rigid frameworks. With the advent of machine learning, methods like Random Forests, Support Vector Machines (SVM), and Gradient Boosting improved prediction accuracy.

Recent studies have introduced Deep Learning for credit risk analysis. Lessmann et al. (2015) compared 41 classification algorithms for credit scoring and found that neural networks outperform logistic regression in most cases. Serrano-Cinca and Gutiérrez-Nieto (2016) used Self-Organizing Maps for peer-to-peer lending data and demonstrated the potential of unsupervised models. Zhang et al. (2021) applied Recurrent Neural Networks (RNNs) to temporal loan data, showing improved accuracy in default prediction.

However, challenges remain regarding explainability, data privacy, and regulatory compliance, motivating this study's focus on interpretable Deep Neural Network architectures for financial risk assessment.

IV. CONCLUSION

This study demonstrates that Deep Neural Networks can effectively improve credit risk prediction compared to traditional models. By leveraging feature engineering, optimized architecture, and regularization techniques, the proposed model achieved higher accuracy and better discrimination between defaulting and non-defaulting borrowers. The results highlight the suitability of deep learning as a scalable and data-driven approach for modern credit risk assessment. Future work may focus on improving model interpretability and incorporating temporal financial behaviour for further performance gains.

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