

Comparative Analysis of Machine Learning Models for Credit Default Prediction Using Credit Score Dataset

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Abstract—Accurately predicting credit defaults is a key requirement for the proper financial risk management of a modern banking system. In this research, the approach suggested is calculating credit card default prediction through machine learning in the case of the dataset of 30,000 records with 25 features named Default of credit card clients. Exploratory data analysis was also done to know how variables relate to each other and what patterns exist that could be attributed to default behavior. Techniques of data preprocessing, such as treatment of missing values, irrelevant attributes, and outliers, were used to enhance data quality. Feature engineering was carried out to produce more attributes like average payment, average bill amount, and total repayment delay. In order to deal with the imbalance caused by classes, the Synthetic Minority Over-sampling Technique (SMOTE) was used. Some of the machine learning models were implemented and tested with accuracy, precision, recall, F1-score, and ROC-AUC values, such as Random Forest, CatBoost, XGBoost, and LightGBM. The LightGBM model presented results of the best performance of 86.59, 87.83, 84.95, 86.37, and 93.43, indicating its usefulness in credit default prediction.

Keywords—Credit default, Credit score, default prediction, Machine Learning, Financial Risk Management.

I. INTRODUCTION

In today's world, it has become irreversible to address sustainability in the financial industry [1]. The banking sector [2] is facing new challenges derived from increased competition and tightened regulations, forcing companies to project a solid image in terms of profitability and solvency, and to adapt their capabilities to new roles in the financial sector [3]. With the advent of the big data era, financial technology (FinTech) [4][5] has rapidly transformed the credit industry, accelerating the shift from traditional offline lending to online platforms and expanding access to diverse forms of consumer credit [6]. At the same time, the proliferation of digital credit reporting systems has significantly reduced the marginal cost of acquiring customer information, providing financial institutions [7] with unprecedented opportunities to evaluate borrower risk profiles. Thus, the need for accurate and reliable credit evaluation has turned into a pillar of

financial stability and a crucial factor in the efficient allocation of capital in the digital economy.

In the U.S. consumer credit grew USD 8.93 billion in June 2024, after a revised upward increase of USD 13.94 billion in the previous month and a dull print of a USD 10 billion increase, as compared to the market's projections. Predictive models for credit default can be very useful in credit risk management [8][9]. These models are mainly based on present technological approaches for the prediction of credit risk, and are constantly improved in operation. The research in academic literature on personal credit risk assessment [10] mainly deals with two issues: indicator selection and model building [11]. This manuscript focuses on the model construction part of personal credit risk assessment.

Consumer risk assessment has been based on traditional credit scoring models for decades [12][13]. One of the most widely used methods is logistic regression models that predict the likelihood of default based on structured data such as income, credit utilization [14], and past delinquencies [15]. They are popular because they are interpretable – financial institutions and regulators prefer to have models that offer clear and auditable decision rules [16]. One of the major issues that financial institutions are dealing with is risk management [17], particularly credit risk management.

In recent years, Artificial Intelligence (AI) [18] has had a profound impact on various industries, such as finance, healthcare, manufacturing, and agriculture [19]. Advanced artificial intelligence tools [20][21] have the attributes of handling non-linear relationships between data and can be best used in applications like risk assessment [22][23] and fraud detection [24] and financial forecasting [25][26]. With the help of technological developments, banks can process huge amounts of data on their clients, lowering the risk of making a loan [27]. This data is statistically and machine-learned (ML) processed into a single quality measure, called a credit score [28][29]. In the financial sector, predictive modeling is a crucial task, such as credit scoring and loan classification, which has been successfully addressed by ML techniques [30][31]. Compared with statistical models, machine learning

models can identify complex, non-linear relationships in the data, which can result in more accurate predictions [32]. Credit risk analysis is recently gaining a spotlight of interest for implementing deep learning (DL) [33] that is capable of learning hierarchical representation and modeling a highly complex nonlinear relationship [34]. While traditional DL models [35] can be adapted to handle structured tabular data, they are not specifically designed to process such data. Credit databases still primarily use tables as the data format. Proper credit default forecasting has been a significant dilemma for financial institutions because of the dynamism of financial behavior and the weaknesses associated with conventional credit rating systems. Failure to effectively perform risk assessment can result in losses of money as well as wrong lending [36]. The study aims to design a reliable predictive model that improves credit risk assessment and thus helps in efficient decision-making in the financial sector, because of the recent developments in ML and access to financial data. The key contributions are:

- Developed an ML-based framework for predicting credit card default using the Default of Credit Card Clients dataset.
- Performed massive data preprocessing, such as manipulation of missing values, elimination of irrelevant attributes, and dealing with outliers to enhance the quality of data.
- Built informative variables by applying feature engineering like average payment, average bill amount, and total repayment delay.
- Reduced the imbalance in the classes with the assistance of SMOTE, which allowed fairer learning and boosted the trustworthiness of the model.
- Tested several models such as Random Forest, CatBoost, XGBoost, and LightGBM on credit default prediction.
- Selected the best model that is LightGBM, which gave good predictive accuracy in determining the risk of default.
- Assessed the model performance using accuracy, precision, recall, F1-score, and ROC Analysis.

The novelty in the study is the development of a better ML framework to predict credit default using features by incorporating feature engineering and class imbalance management to improve the predictive power. Further behavioral attributes are created in order to represent customer financial trends, and SMOTE is used to equalize the data. Several ensemble models are considered, and LightGBM proves to be very effective in credit risk prediction. The justification behind conducting this study is that the growing demand of contemporary financial systems is to carry out the right credit risk assessment. As digital lending and big financial data expand, complex patterns are frequently lost with the use of traditional methods.

A. Structure of the Paper

The study is structured as follows: Section II presents relevant work on Credit Default Prediction; Section III details the procedures and materials used. Section IV presents the experimental findings of the proposed system. Section V concludes the investigation and provides an overview of its findings.

II. LITERATURE REVIEW

The section summarizes the latest research on the accuracy and complexity of traditional ML models for Credit default Prediction. Key findings and limitations, future work, highlighted in Table I, are as follows:

K. Wang (2026) conducted an interpretability analysis and evaluated the performance of various DL and ML models in predicting credit default. After resampling approaches were applied to the training data to address the class imbalance issue, five models—Logistic Regression, Random Forest, Gradient Boosting, Multilayer Perceptron (MLP), and Convolutional Neural Network (CNN)—were carefully analyzed. Five-fold cross-validation was used to further stabilize the experiment. The experimental results show that Logistic Regression outperformed other models, with an AUC of 0.7480 and an F1-score of 0.6676 [37].

S. Cahudhari et al. (2025) proposed an AI-driven credit scoring system that uses nontraditional data sources, including soil health, crop history, and weather patterns, to generate customized credit scores, enabling farmers to obtain loans even in the absence of formal credit histories. Two neural network models were created and evaluated for loan approval prediction: A Feedforward Neural Network (FNN) and a Deep Neural Network (DNN), using data on employment, credit history, and demographics. The DNN exhibited superior performance, achieving a test accuracy of 86.18% and a loss of 0.4610, an F1-score of 0.84, in contrast to the FNN, which recorded an accuracy of 83%, a loss of 0.4989, and an F1-score of 0.80 [38].

Sagar and H. Nagar et al. (2025) assessed various models starting with Logistic Regression through Decision Trees and then Random Forests, followed by Support Vector Machine (SVM) and finally Deep Neural Networks (DNN). A DNN generated superior predictive accuracy at 81.91% compared to alternative models included in this study. This study demonstrates that both feature scaling techniques along with hyperparameter adjustment led to enhanced DNN performance in predicting credit default behaviors [39].

P. K. Yemmanuru, J. Yeboah, and I. K. Nti et al. (2024) used a dataset from openml.org, and after data pre-processing, visualization, and exploratory data analysis, seven algorithms were applied. The models were evaluated using various performance metrics. Support Vector Machines (SVM) achieved the highest accuracy (80.67%) with a good Recall of 93.55%. Additionally, SVM showed the greatest accuracy (83.57%), F1 score of 84.70%, recall of 88.84%, and ROC AUC score of 83.44% when dimensions were decreased to 10 (from 20) using Principal Component Analysis [40].

T. Bhandari et al. (2024) provided a thorough analysis of credit risk identification using several ML algorithms to categorize clients into "good" and "bad" credit groups. This essay aids in recognizing these dangers so they may be avoided in advance. With an accuracy of 85.88%, the ANN model performs better than the others in terms of accuracy and ROC curve. The most balanced confusion matrix is produced by the Random Forest model, which is followed by the XGBoost confusion matrix [41].

H. Yash et al. (2023) suggested a method based on ML to forecast credit card default. The same has been done with a dataset of Taiwanese credit card customers. Predictive models have been created using a variety of ML techniques, such as

logistic regression, SVM, and ANN. The models are assessed using a variety of performance criteria, such as accuracy, F1 score, etc., and a set of feature scaling approaches that aid in producing accurate results. The SVC algorithm performs better than other algorithms with an accuracy of 82.03% [42].

M. Hans, E. Hikmawati, and K. Surendro et al. (2023) sought to create a predictive analytics model that used students' learning activities as a key component to forecast future trends in university carbon emissions. For students

majoring in computer science in particular, Institute Technology Bandung (ITB) was utilized as a case study. The SVR algorithm was used in the prediction modelling, which also made use of external information like weather, event-related data, and university data, as well as historical data like carbon emissions from the previous 30 days. Metrics were used to assess the model's performance; the results showed values of 129.41 for MAE, 158.03 for RMSE, 0.98 for R2, and 15.83 for MAPE [43].

TABLE I. SUMMARY OF EXISTING STUDIES ON CREDIT DEFAULT PREDICTION

Author	Methods	Dataset	Key Findings	Limitations & Future Work
K. Wang (2026)	Logistic Regression, Random Forest, Gradient Boosting, MLP, and CNN with resampling techniques and five-fold cross-validation.	Credit default dataset; exact dataset name not specified in the provided literature review.	Logistic Regression achieved the best performance, with an AUC of 0.7480 and an F1-score of 0.6676, outperforming the other evaluated models.	The study focuses on model performance and interpretability, while further investigation is needed into dataset-specific generalization, alternative feature selection techniques, and the robustness of models across different credit datasets.
Chaudhari et al., 2025	Feedforward Neural Network (FNN) + Deep Neural Network (DNN) with non-traditional data integration	Agricultural, demographic, employment, credit history, soil, crop, and weather data	DNN achieved 86.18% accuracy, loss 0.4610, F1-score 0.84; outperformed FNN (83% accuracy, F1 0.80)	Requires validation on larger and more diverse farming populations
Sagar & Nagar et al., 2025	Logistic Regression, Decision Tree, Random Forest, SVM, Deep Neural Network (DNN)	Credit default dataset	DNN achieved highest 81.91% accuracy; feature scaling and hyperparameter tuning improved performance	Limited performance improvement; needs larger datasets and real-world validation
Yemmanuru, Yeboah & Nti et al., 2024	SVM with PCA and multiple ML algorithms	OpenML credit dataset	SVM achieved 80.67% accuracy, Recall 93.55%; with PCA, 83.57% accuracy, F1 84.70%, ROC-AUC 83.44%	Performance dependent on dimensionality reduction technique
Bhandari et al., 2024	ANN, Random Forest, XGBoost	Customer credit dataset	ANN achieved the highest 85.88% accuracy and ROC; RF produced the most balanced confusion matrix	Limited generalization due to dataset dependency
Yash et al., 2023	Logistic Regression, SVM, ANN with feature scaling	Taiwan credit card client dataset	SVC achieved the highest 82.03% accuracy among all models	Requires advanced feature engineering and ensemble learning
Hans, Hikmawati & Surendro, 2023	Support Vector Regression (SVR)	ITB University carbon emission data with weather and event data	Achieved $R^2 = 0.98$, MAE = 129.41, RMSE = 158.03, MAPE = 15.83	Domain-specific model; not applicable to financial credit risk

III. METHODOLOGY

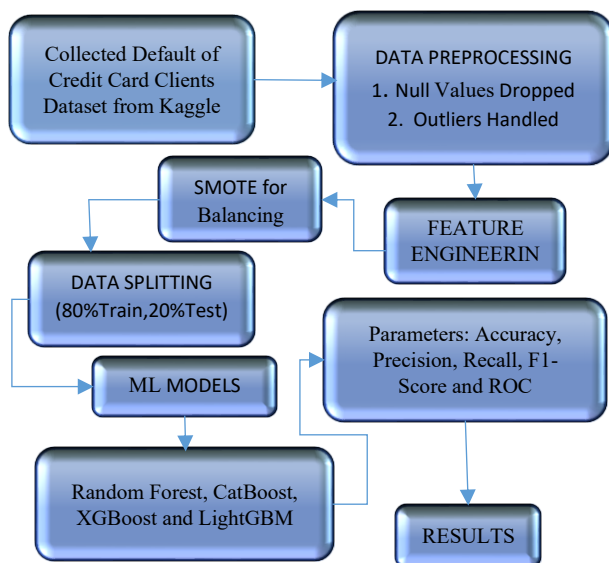


Fig. 1. Flowchart of Proposed Methodology for Credit Default Prediction

The suggested approach starts with an overview of the dataset of Default of Credit Card Clients, which is obtained on

Kaggle. Data is then taken through preprocessing, where null values are dropped, and outliers are taken care of to maintain the quality of data. Then feature engineering is carried out to generate other informative features, and balancing is done with SMOTE to address the issue of class imbalance in the data. The processed data is then split into training and testing sets (80% training and 20% testing). The machine learning models, such as Random Forest, CatBoost, XGBoost, and LightGBM, are trained and assessed. The performance measures applied to the models include accuracy, precision, recall, F1 Score, and ROC, and the end results are discussed to determine the efficiency of the proposed method to predict credit card defaults. The entire methodological framework is illustrated in Fig 1.

The suggested methodology's subsequent phases are briefly discussed below:

A. Data Collection

This study uses the Default of Credit Card Clients dataset, containing data on 30,000 credit card holders in Taiwan with 25 features. The variables include demographic information, credit limit, repayment history, bill amounts, and payment records. The target variable, default payment next month, shows if a client has a payment default for the following month (1 = default, 0 = no default). Exploratory Data Analysis

(EDA) serves as an important preliminary stage of the modeling pipeline as it gives a general idea about the data before feature engineering and model development. The EDA's utilized in this work are shown as follows:

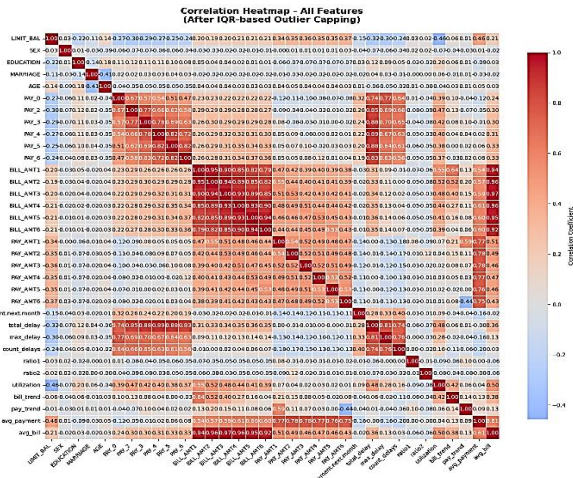


Fig. 2. Correlation Heatmap

Fig 2 illustrates the pairwise correlation coefficients among the considered variables. The color gradient reflects the magnitude and direction of correlation, with values ranging from -1 (strong negative correlation) to +1 (strong positive correlation). Diagonal elements exhibit a perfect correlation of 1.00, representing the self-correlation of variables.

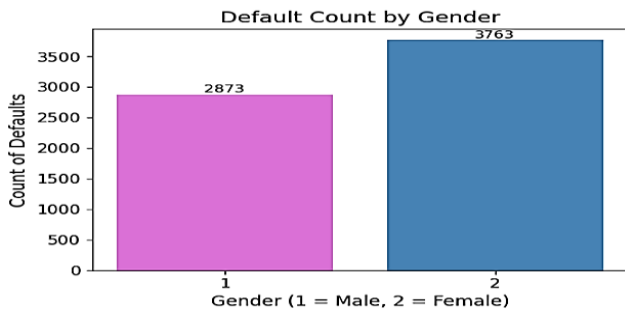


Fig. 3. Default Count by Gender

The number of defaults on the credit card by gender is shown in Fig 3; in the data set, the number of credit card defaults for females (3763) is greater than that of the male clients (2873).

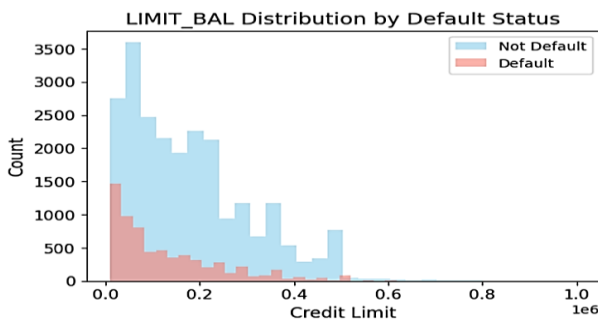


Fig. 4. Limit Balance Distribution

The plot in Fig 4 reveals that the majority of clients have lower credit limits, as well as there being more non-default cases than default cases within the range of credit limits.

B. Data Preprocessing

The pre-processing of the UCI Credit Dataset is emphasized due to inherent noise and inconsistencies. These involve dealing with missing values, dropping unnecessary columns, and outlier treatment (IQR method). These steps are similar to what is done in the literature to improve the performance and generalizability of the model:

- **Missing values:** The initial process of cleaning the data was to work on missing data. This was accomplished by examining if there were missing data in the information being looked at. Missing values were removed from records to ensure data quality and integrity for the study.
- **Column Removal:** The id column was found to have little effect on the classification objective and was dropped from the data set.
- **Outlier Handling using IQR Process:** The outliers for the days employed, the number of children, total income, and number of family members in the columns are identified with the box plot above and dealt with using the IQR method. An outlier is detected using the IQR method, which is the process of determining values outside of Q1 and Q3.

C. Feature Engineering

The model of feature engineering is the development of new variables using the current data to enhance the predictive accuracy of machine learning models. The following features were generated from the original dataset in this study: average payment, average bill amount, total repayment delay. These engineered features allow us to capture relevant financial client behavior. Any missing values created in the rolling computations were eliminated to have a clean and consistent dataset to yield a better feature set to train a model effectively.

D. Data Balancing Using Synthetic Minority Over-Sampling Technique (SMOTE)

The SMOTE is one of the data pre-processing techniques used to overcome the problem of class imbalance in classification problems. The risk classification dataset was used as a training dataset for SMOTE, which resulted in a balanced distribution between risk classes (0, 1, 2) with roughly equal numbers of samples in each class (as shown in Fig. 5). SMOTE creates instances of the minority classes through a synthetic process that builds on similarities between the features in the feature space, allowing the model to be trained on a more uniform distribution of classes. This method reduces bias in favor of the majority class, improving classifier performance.

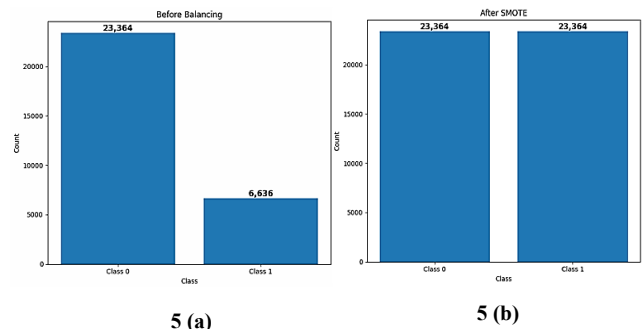


Fig. 5. Balancing With SMOTE

The class distribution was drawn in Fig 5 using the presence of SMOTE before and after SMOTE application. In Fig 5(a), the data is not balanced, as there were 23364 cases of non-default (Class 0) and 6636 cases of default (Class 1). With the use of SMOTE, Fig 5 (b) demonstrates a balanced distribution with 23,364 examples in both classes.

E. Data Splitting

In the credit default prediction task, the data are split into two subsets: a training subset and a testing subset, with 80% for training and 20% for testing.

F. Model Classification: Light Gradient Boosting Machine Classifier (Lgbm)

This section discusses the best-performing model employed in Credit Default Prediction. The Light Gradient Boosting Machine Classifier was efficient in predicting the credit defaults and is discussed further below:

G. Lightgbm Classifier

The LightGBM for short, is an advanced, open-source machine learning framework that builds on GBDTs, markedly improving efficiency. GBDTs make forecasts by iteratively training decision trees on the data to correct errors from previous trees [44]. LightGBM is a fast gradient boosting framework using tree-based learners, optimized with histogram binning, GOSS, and feature bundling for efficiency, as shown in Equation (1):

$$\hat{y}(x) = \sum_{m=1}^M n f_m(x) \quad (1)$$

At first, the LightGBM (LGBM) model with default hyperparameters (random state = 42) was used to train a credit default prediction system to create a baseline. This baseline model was used as a reference for comparing the performance of later models.

The primary parameters, including the number of leaves, learning rate, number of estimators, maximum tree depth, subsample ratio, and column sampling rate, were then adjusted through hyperparameter optimization using Randomized Search CV. The parameter num_leaves was also tested with the values of 31, 40, 60, and 80, and the learning rate was also set at 0.005 to 0.1 to control the rate of learning in the model. The number of estimators varied between 300 and 900 to determine the optimal number of boosting iterations. Also, -1, 5, 8, and 12 values of max depth were experimented with to control the complexity of the trees. The subsample and colsample by tree parameter (0.7 to 1.0) were also set to regulate the percentage of data samples and features that were considered in the training process and helped to reduce the risk of overfitting and enhance the model's generalization.

H. Evaluation Metrics

A confusion matrix is used to record the results of projected vs actual classifications in order to assess how well the classification models used to the UCI Credit dataset performed. The matrix consists of four essential elements. The model's performance in terms of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) is summed up in the confusion matrix. This matrix is necessary to understand the errors a model makes, which is crucial for risk assessment.

1) Accuracy

The accuracy of the model is how well the model predicts or classifies instances. It calculates the ratio of correctly classified examples to the number of examples that are present in the training set (see Equation (2)). The overall correctness of the model can be evaluated by the accuracy of the model.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (2)$$

2) Precision

Precision, on the other hand, is a metric used to assess how accurate or dependable the model's predictions are. It computes the ratio of accurately predicted positive cases to the total number of instances anticipated as positive, concentrating on the instances that the model forecasted as positive (see to Equation (3)).

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

3) Recall

The ratio of true positive predictions to the total number of actual positive cases in the data is described as recall, also known as sensitivity or true positive rate. In other words, it measures the proportion of positive occurrences that the model correctly detects (see Equation (4)).

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

4) F1-Score

The F1-score is defined as the harmonic mean of precision and recall and is calculated using the following formula (Equation (5)).

$$F1 - Score = \frac{2(Precision * Recall)}{Precision + Recall} \quad (5)$$

5) ROC

One measure associated with the receiver operating characteristic (ROC) curve is the area under the ROC curve (AUC). The ROC curve is a useful tool for evaluating the trade-off between TPR and FPR for a threshold-based classifier. Different TPRs and FPRs result from different threshold levels. The area under the ROC curve, or AUC, may be calculated by plotting the ROC curve with the x-axis set to FPR and the y-axis to TPR.

IV. RESULT ANALYSIS AND DISCUSSION

The experiment results of ML models that are utilized for Credit Default Prediction Optimization in the Credit Source Dataset are provided in this section. Using a 3.3 GHz Intel dual-core i5 processor with 16 GB of RAM running the Windows 11 operating system. The criteria f1-score, recall, accuracy, and precision are used to evaluate the performance.

A. Results Demonstration

The performance appraisal of RF, CatBoost, XGBoost, and LightGBM models on credit default prediction is provided in Table II in terms of accuracy, recall, precision, F1-score, and ROC-AUC and demonstrates their reasonable performance in identifying cases of defaults and non-defaults.

TABLE II. PERFORMANCE OF MACHINE LEARNING MODELS IN PREDICTING CREDIT DEFAULTS

Metrics	RF	Cat Boost	XGBoost	LGBM
Accuracy	86.27	86.45	85.95	86.59
Recall	84.33	84.67	83.97	84.95
Precision	87.73	87.79	87.43	87.83
F1- Score	86.01	86.2	85.66	86.37
ROC-AUC	93.28	93.54	93.27	93.43

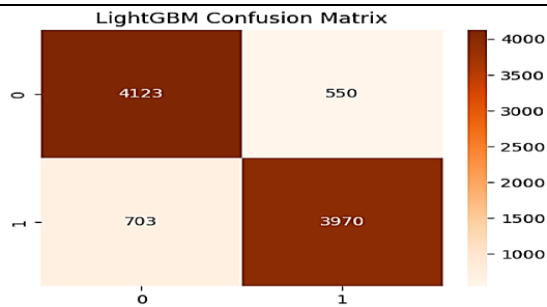


Fig. 6. Confusion Matrix of the LGBM Model

Fig 6 shows confusion matrix of the LightGBM model for credit default prediction. The matrix indicates the count of the correctly and incorrectly identified cases, with the vast number of both default and non-default cases being accurately identified, showing that model has a high classification effectiveness.

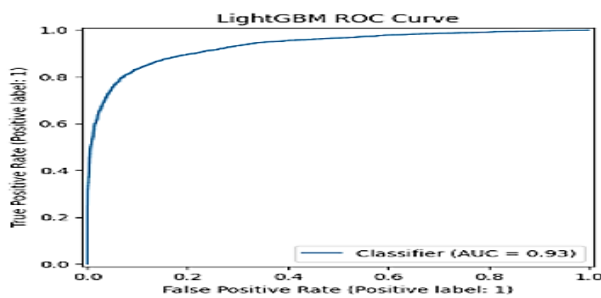


Fig. 7. ROC Curve of Lightgbm Model

Fig 7 presents the ROC curve of the LightGBM model for credit default prediction. It is shown that curve can discern well cases of default and non-default cases, which is reflected in the high area under the curve (AUC), showing good performance in classification and strong predictive abilities.

B. Comparative Analysis and Discussion

Table III presents the comparison of different models used for credit default prediction, including LightGBM (LGBM), Deep Neural Network (DNN), K-Nearest Neighbors (KNN), and Gradient Boosting Classifier (GBC). The table displays the predictive capabilities of these methods in terms of accuracy that shows effectiveness of ML models in predicting credit default trends.

TABLE III. COMPARISON ON CREDIT DEFAULT PREDICTION OPTIMIZATION

Models	Accuracy
LGBM	86.59
DNN [8]	81.80
KNN [45]	80.60
GBC [46]	82.45

The findings indicate that machine learning models are capable of forecasting credit card default behavior. Ensemble-based methods are highlighted as potential methods to detect patterns in financial and behavioral attributes. The confusion matrix also verifies the fact that the identified model can successfully classify defaulted and non-default cases with relatively less inaccuracy. Moreover, the ROC curve demonstrates that the model has a high discriminatory ability between the two classes, which suggests good prediction results. The comparative study of the approaches already reported shows that the model under offer can compete in terms of credit default prediction, and the advanced machine

learning methodology can be efficiently applied in financial risk evaluation.

V. CONCLUSION AND FUTURE WORK

Credit risk assessment is an essential part of financial institutions' risk management strategies, as it assesses the probability of borrower default and helps to mitigate potential losses for financial institutions. This research shows that ML techniques can be applied with financial and behavioral data to accurately predict the risk of credit card default. From the experimental results, we can see that ensemble models can detect complex patterns of customer repayment behavior and financial features. The LightGBM classifier model was found to have the best accuracy of 86.59%, separating default clients from non-default clients. The results underscore the effectiveness of gradient boosting techniques in dealing with structured financial data and enhancing the reliability of the classification results. The results also highlight the significance of balanced data and informative features on model performance. Predicting credit defaults accurately can assist financial institutions in determining customers who are at high risk and enhance credit assessment and risk management techniques. Overall, the findings indicate that the machine learning model proposed in this study has the potential to be a valuable tool for credit risk monitoring, and it could be improved by incorporating other financial indicators and real-world data.

Future investigations can concentrate on the development of deep learning with hybrid ensemble models to further enhance credit default prediction performance. Further financial, behavioral, and real-time transactional data can be included to increase the accuracy of prediction. Additionally, it is possible to consider explainable AI methods to enhance the model interpretability and facilitate transparent decision-making in financial risk management.

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REFERENCES

- [1] S. Kakkar, "Explainable AI Models for Credit Risk Scoring in Banking: Balancing Accuracy and Regulatory Transparency," *SSRN Electron. J.*, vol. 3, no. 2, pp. 1–6, 2025, doi: 10.2139/ssrn.5471407.
- [2] H. Kapadia and K. C. Chittoor, "Quantum Computing Threats to Web Encryption in Banking," *Int. J. Nov. Trends Innov.*, vol. 2, no. 12, pp. a197–a204, 2024.
- [3] C. Gutiérrez-López and J. Abad-González, "Sustainability in the Banking Sector: A Predictive Model for the European Banking Union in the Aftermath of the Financial Crisis," *Sustainability*, vol. 12, no. 6, p. 2566, Mar. 2020, doi: 10.3390/su12062566.
- [4] A. Nerella, P. Badri, K. Sundravadevelu, and R. Murugesan, "Navigating Regulatory Hurdles in AI-Driven Credit Card Approvals: Balancing Innovation and Compliance," *J. Inf. Syst. Eng. Manag.*, vol. 8, no. 4, pp. 1–9, 2023.

- [5] A. R. Bilipelli, "Forecasting the Evolution of Cyber Attacks in FinTech Using Transformer-Based Time Series Models," *Int. J. Res. Anal. Rev.*, vol. 10, no. 3, pp. 383–389, 2023, [Online]. Available: <https://www.ijrar.org/papers/IJRAR23C3692.pdf>
- [6] M.-L. Ding, Y.-L. Ma, and F.-Q. You, "Domain-Constrained Stacking Framework for Credit Default Prediction," *Mathematics*, vol. 13, no. 21, p. 3451, Oct. 2025, doi: 10.3390/math13213451.
- [7] A. Parupalli, "The Evolution of Financial Decision Support Systems: From BI Dashboards to Predictive Analytics," 2023. [Online]. Available: <https://kelvinpublishers.com/>
- [8] R. Bhandary and B. K. Ghosh, "Credit Card Default Prediction: An Empirical Analysis on Predictive Performance Using Statistical and Machine Learning Methods," *J. Risk Financ. Manag.*, vol. 18, no. 1, p. 23, Jan. 2025, doi: 10.3390/jrfm18010023.
- [9] S. Kakkar, "Advancing Credit Risk Modeling Through Generative Artificial Intelligence: Methods, Applications, And Challenges," *Int. J. Financ. DATA Sci.*, vol. 3, no. 2, pp. 30–48, Sep. 2025, doi: 10.34218/IJFDS_03_02_003.
- [10] H. Prakash and C. Kapadia, "Reducing Cognitive Load In Online Financial Transactions," *IJCS PUB*, vol. 12, no. 2, pp. 792–797, May, 2022, doi: 10.3390/e26100861.
- [11] S. Wang and X. Zhang, "Research on Credit Default Prediction Model Based on TabNet-Stacking," *Entropy*, vol. 26, no. 10, p. 861, Oct. 2024, doi: 10.3390/e26100861.
- [12] S. Garg, "AI, Blockchain and Financial Services: Unlocking New Possibilities," *IJIRCT*, vol. 8, no. 1, pp. 1–4, 2022, doi: 10.5281/zenodo.15537568.
- [13] I. Mapfumo and T. Shongwe, "Performance Evaluation of Machine Learning and Deep Learning Models for Credit Risk Prediction," *J. Risk Financ. Manag.*, vol. 19, no. 3, p. 210, Mar. 2026, doi: 10.3390/jrfm19030210.
- [14] P. Anirudh, "Business Intelligence in ERP ML-Based Comparative Study for Financial Forecasting," *ESP Int. J. Commun. Eng. Electron. Technol.*, vol. 2, no. 4, pp. 17–26, October, 2024, doi: 10.56472/25839217/IJCEET-V2I4P103.
- [15] R. Abi, "Machine learning for credit scoring and loan default prediction using behavioral and transactional financial data," *World J. Adv. Res. Rev.*, vol. 26, no. 3, pp. 884–904, Jun. 2025, doi: 10.30574/wjarr.2025.26.3.2266.
- [16] V. Varma, "Security Compliance and Risk Management in AI-Driven Financial Transactions," *Int. J. Eng. Sci. Math.*, vol. 12, no. 7, pp. 107–121, 2023.
- [17] H. Kohli, R. Rajamani, M. R. Reddy Deva, and S. A. Pahune, "Improving Prediction of Credit Risks Based on Advanced Machine Learning and Feature Engineering Techniques in Banking Sector," in *2025 5th International Conference on Artificial Intelligence and Signal Processing (AISP)*, IEEE, Nov. 2025, pp. 1–5. doi: 10.1109/AISP68263.2025.11396116.
- [18] S. Singamsetty, "Accelerating data engineering efficiency with self-learning AI algorithms," *Int. J. Comput. Artif. Intell.*, vol. 6, no. 1, pp. 195–199, Jan. 2025, doi: 10.33545/27076571.2025.v6.i1c.154.
- [19] S. R. Kurakula, "Designing Enterprise Systems for the Future of Financial Services: The Intersection of AI, Cloud-Native Microservices, and Intelligent Data Processing," *Eur. J. Comput. Sci. Inf. Technol.*, vol. 13, no. 20, pp. 91–103, Apr. 2025, doi: 10.37745/ejsit.2013/vol13n2091103.
- [20] S. Gupta and R. Q. Majumder, "Integrating Explainable AI in Financial Fraud Detection Systems for Enhanced Decision Transparency," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, 2025, doi: 10.63282/3050-922X.IJERET-V6I4P113.
- [21] S. Garg, "Intelligent Tutoring Systems: The Future of AI-Powered Personalized Learning," *Int. Sci. J. Eng. Manag.*, vol. 01, no. 03, pp. 1–6, Oct. 2022, doi: 10.55041/ISJEM00114.
- [22] S. B. Shah, "Advancing Financial Security with Scalable AI: Explainable Machine Learning Models for Transaction Fraud Detection," in *2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, IEEE, Apr. 2025, pp. 1–7. doi: 10.1109/ICDCECE65353.2025.11034838.
- [23] M. R. Mathibela and D. Maposa, "Predictive Modelling of Credit Default Risk Using Machine Learning and Ensemble Techniques," *Math. Comput. Appl.*, vol. 31, no. 2, p. 45, Mar. 2026, doi: 10.3390/mca31020045.
- [24] S. Gupta SATI, "Design and Analysis of Advanced Machine Learning Methods for Financial Fraud Identification in Credit Card Activities," 2025. [Online]. Available: <https://saanvipublications.com/journals/index.php/jgrms/index>
- [25] D. Gajdosikova and J. Michulek, "Artificial Intelligence Models for Bankruptcy Prediction in Agriculture: Comparing the Performance of Artificial Neural Networks and Decision Trees," *Agriculture*, vol. 15, no. 10, p. 1077, May 2025, doi: 10.3390/agriculture15101077.
- [26] B. S. Shaikh, "Using LLM Chaining for Enhanced Fraud Detection in Credit Card Transactions: A Multi-Stage Approach," 2026, *Seattle, USA*. doi: 10.2139/ssrn.7534478.
- [27] S. Tarakampet, "Real-Time Fraud Detection at Scale: An Architectural Framework for FinTech Big Data Systems," *J. FinTech Digit. Assets*, vol. 1, no. 1, pp. 45–55, May, 2026, doi: 10.34900/jfda.v1i1.1380.
- [28] K. M. R. Seetharaman, "Predicting Cryptocurrency Price Movements Using Leveraging Machine Learning Algorithms," in *2025 International Conference on Networks and Cryptology (NETCRYPT)*, IEEE, May 2025, pp. 1497–1502. doi: 10.1109/NETCRYPT65877.2025.11102487.
- [29] S. Singh, "Performance Evaluation of Machine Learning Regression Models for 5G Network Resource Allocation Optimization," in *2025 International Conference on Multimedia Computing, Networking and Applications (MCNA)*, IEEE, May 2025, pp. 47–52. doi: 10.1109/MCNA65829.2025.11124374.
- [30] R. Dattangire, D. Biradar, R. Vaidya, and A. Joon, "A Comprehensive Analysis of Cholera Disease Prediction Using Machine Learning," in *Fifth Congress on Intelligent Systems*, 2025, pp. 555–568. doi: 10.1007/978-981-96-2697-7_39.
- [31] N. Prajapati, "Machine Learning-Based Efficiency Prediction of Computer Systems Based on Various Hardware Fault Configurations," in *2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON)*, IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/I2ITCON65200.2025.11210520.
- [32] X. Zhang *et al.*, "Data-Driven Loan Default Prediction: A Machine Learning Approach for Enhancing Business Process Management," *Systems*, vol. 13, no. 7, p. 581, Jul. 2025, doi: 10.3390/systems13070581.
- [33] S. Singamsetty, "Neurofusion: Advancing Alzheimer's diagnosis with deep learning and multimodal feature integration," *Researchgate.Net*, vol. 3954, no. 1, pp. 23–32, 2021, doi: 10.5281/zenodo.14889013.
- [34] G. Abbas, Z. Ying, and M. Iqbal, "From Binary Scores to Risk Tiers: An Interpretable Hybrid Stacking Model for Multi-Class Loan Default Prediction," *Systems*, vol. 14, no. 1, p. 78, Jan. 2026, doi: 10.3390/systems14010078.
- [35] V. Verma, "Deep Learning-Based Fraud Detection in Financial Transactions: A Case Study Using Real-Time Data Streams," *ESP J. Eng. Technol. Adv.*, vol. 3, no. 4, pp. 149–157, 2023, doi: 10.56472/25832646/JETA-V3I8P117.
- [36] S. B. Shah, "Advanced Machine Learning Models for Anti-Money Laundering (AML): Improving Detection Accuracy and Efficiency," in *2025 1st International Conference on Secure IoT, Assured and Trusted Computing (SATC)*, IEEE, Feb. 2025, pp. 1–5. doi: 10.1109/SATC65530.2025.11137255.
- [37] K. Wang, "A Comparative Analysis of Machine Learning Models for Credit Default Prediction," in *2026 IEEE 2nd International Conference on Electronics, Energy Systems and Power Engineering (EESPE)*, IEEE, Jun. 2026, pp. 1125–1129. doi: 10.1109/EESPE68405.2026.11649249.
- [38] S. Cahudhari, S. Manna, K. Vadivel, and L. K. S., "AI-Driven Credit Scoring Model in Smarter Lending Decisions for Farmers," in *2025 8th International Conference on Computing Methodologies and Communication (ICCMC)*, 2025, pp. 1429–1433. doi: 10.1109/ICCMC65190.2025.11139936.
- [39] H. Nagar and Sagar, "Bridging Tradition and Innovation: A Comparative Analysis of Credit Risk Models," in *2025 International Conference on Computing and Communication Technologies (ICCT)*, IEEE, Apr. 2025, pp. 1–5. doi: 10.1109/ICCT63501.2025.11018993.

- [40] P. K. Yemmanuru, J. Yeboah, and I. K. Nti, "Customer Credit Risk: Application and Evaluation of Machine Learning and Deep Learning Models," in *2024 IEEE 3rd International Conference on Computing and Machine Intelligence (ICMI)*, IEEE, Apr. 2024, pp. 1–5. doi: 10.1109/ICMI60790.2024.10585896.
- [41] T. Bhandari, P. Payne, M. K. Gourisaria, S. Shekhar Patra, and V. Petli, "Guardians of Credit: 'A Comprehensive Analysis of Machine Learning Models for Credit Risk Detection,'" in *2024 International Conference on Integrated Circuits and Communication Systems (ICICACS)*, 2024, pp. 1–6. doi: 10.1109/ICICACS60521.2024.10498659.
- [42] H. Yash, Affan, K. Saurav, and S. S. Dhanda, "Credit Card Default Prediction Using Machine Learning Models," in *2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT)*, IEEE, Sep. 2023, pp. 1–5. doi: 10.1109/CISCT57197.2023.10351316.
- [43] M. Hans, E. Hikmawati, and K. Surendro, "Predictive Analytics Model for Optimizing Carbon Footprint From Students' Learning Activities in Computer Science-Related Majors," *IEEE Access*, vol. 11, pp. 114976–114991, 2023, doi: 10.1109/ACCESS.2023.3324725.
- [44] K. Bisdoulis, "Assets Forecasting with Feature Engineering and Transformation Methods for LightGBM," 2024. doi: 10.48550/arXiv.2501.07580.
- [45] T. Chou and M. Lo, "Predicting Credit Card Defaults with Deep Learning and Other Machine Learning Models," *Int. J. Comput. Theory Eng.*, vol. 10, no. 4, pp. 105–110, January, 2018, doi: 10.7763/IJCTE.2018.V10.1208.
- [46] S. R. Islam, W. Eberle, and S. K. Ghafoor, "Credit Default Mining Using Combined Machine Learning and Heuristic Approach," pp. 1–7, Jul, Jul. 2018, doi: 10.48550/arXiv.1807.01176.