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Machine Learning-Based Default Loan Prediction for Financial Risk Assessment in Digital Lending

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***Abstract*—In recent decades, the global financial system has undergone tremendous change. While capital markets play a crucial role in some situations and traditional banks and financial institutions continue to be the main source of funding for businesses and people in the majority of nations, new digital lending platforms have lately emerged. In this paper, the author introduces a viable machine learning-based approach to the estimation of financial risk in online lending on the Lending Club dataset. The suggested solution starts with an extensive data collection and exploratory analysis, followed by intensive preprocessing of data that includes outlier treatment, feature engineering, one-hot encoding, and normalization, as well as the class imbalance mitigation method of SMOTE. A systematic hyperparameter optimization is applied to creating an optimized Extreme Gradient Boosting (XGBoost) model that is used to ensure that nonlinear relationships between borrower and loan traits are learned. There are various performance measures that are used to evaluate the model; some of them include accuracy, precision, recall, F1-score, ROC curve, and confusion matrix analysis. The experimental outcomes are highly predictive with an accuracy of 97.70, precision of 94.78, recall of 93.30 and a near-perfect AUC of 0.9991. The fact that the proposed model is generalizable compared to the traditional machine learning models also justifies the superiority of the given approach and shows that it has power, can be scaled, and placed in the context of applying it into practice to evaluate financial risks in the digital lending model.**

Keywords—*Digital Lending, Credit Risk Assessment, Machine Learning, Financial Risk Modeling, Online Lending Platforms*.

I. Introduction

The banking industry is a risk-taking one. An intermediation role is normally played by banks who take the deposits of the people who are the savers and provide loans [1] to those who are borrowers. In this manner, they are faced with a lot of risks that directly and/or indirectly impact their financial performance. Proper and efficient risk management by financial institutions [2], particularly the banking industry, is central to the global financial system since they are crucial facilitator in the achievement and promotion of economic growth and development. Banks play a very important role in economic development[3] as most economies are affected by the banking industry. In all the undertakings of the mortal being there is risk. Human beings drive financial institutions and hence face such challenges due to a myriad of reasons [4], the main reasons why such problems arise still include but are not confined to lax credit standards [5] between a borrower and a counterparty, poor management of portfolio risks, and ignorance to changes in economic or other conditions which may result in a decline of the credit status of counter parties of a bank. Risk management is a constant issue within the financial markets which are characterized by uncertainty[6]. The economic context is full of a number of risks, such as credit risks, operational risks, liquidity risks and market risks, each posing distinct challenges.

In any situation where risk exists [7][8], risk management is necessary. Risk management involves identification, analysis and prioritization of risks, use of well-coordinated but economical resources to help mitigate, monitor and control the likelihood and impact of negative occurrences. Properly controlled risk have a positive impact on the stability of banks, on the other hand, poor control cause degradation in the stability of the banks i.e. the bank run out of business [9]. In other words, risk is a chance that when properly handled, can provide a big reward and therefore increase financial performance (FP). Risk disclosure plays a vital role in improving transparency and accountability since it makes stakeholders have vital information related to the risk exposures of a bank [10]. Maintaining a good risk disclosure promotes the confidence of investors and depositors, as well as the regulatory compliance and decision-making process. Consistent risk-evaluations and modifications of the risk-management system are suggested to keep up with the shifts in the market situation.

Digital transformation in the changing global economic environment has established itself as a key pillar of strategic revival among companies that are increasingly subject to competition, technological upheaval, and growing demands to stay afloat financially [11][12]. In emerging economies, especially where reforms in the institutional modernization and financial system are [13] are being actively implemented, companies are going online to maximize operational efficiency and financial performance. Although the topic of digital transformation is increasingly gaining attention, the empirical knowledge about the financial impact of digital transformation is still insufficient, particularly in regard to its effects on firm indebtedness and their exposure to financial risk [14]. Although the process of digitalization is generally believed to lead to increased performance, its general impact on capital structure and financial stability of a firm is unclear. This is a critical gap when companies usually operate in the context of limited financing conditions and unstable macroeconomic conditions. Knowledge of whether digital initiatives could enhance financial performance and, consequently [15], decrease financial vulnerability, is significant to firms and investors that seek to create resilient and sustainable financial ecosystems.

The financial industry is ever changing and the necessity to create new styles in the risk management has been all the more pressing. The development of artificial intelligence (AI) [16] has been growing over the last several years with a tremendous influence on society in general and all the spheres of activity. The issue of AI can be dated back to the late 1940s where researchers in the area noted that with the right code it would be possible to make computers do things that resembled human intelligence. Machine learning (ML) [17] is a potent instrumentation of risk modelling and risk prediction, which is particularly applicable to non-profit organizations that carry out large-scale public welfare projects. These organizations have high lending risk and it is necessary to have effective ways of controlling risk in order to guarantee the integrity of its operation. The use of artificial intelligence (AI), especially deep learning (DL), to enter the financial systems [18] has greatly changed the finance industry [19]. The capability of deep learning to process and analyze large sets of data has resulted in breakthroughs in credit scoring, fraud detection and algorithmic trading.

A. Motivation and Contribution

The banks have a significant part in the development of the economy, and weak management of credit risk in the relaxation of their lending criteria, and unstable economies continue to threaten the financial stability. The traditional risk evaluation methods had issues in the inability to model the complex and non-linear connection in a large, non-changing type of financial information, and the actual efficiency of digitalization and artificial intelligence in reducing credit risk was not known. To address this gap, the paper shall construct a robust, data-rich credit risk assessment system on the foundation of advanced ML tools to improve the quality of predictions, provide sound lending behaviors and make the modern digital banking systems even stronger. The contributions of the study are framed below:

- Fully detailed data collection and exploratory analysis of the Lending Club data as well as correlation analysis, distribution of loan grades and visualization of imbalances to extract meaningful information about credit risk characteristics.
- Elaborate data preparation structure that includes mistakes removal, outlier detection during Z-score analysis, feature engineering, an encoding of one-hot, and normalization to improve the quality of information and model preparedness.
- Effective handling of class imbalance through the application of SMOTE, resulting in a balanced dataset that enhances fair learning and improves minority-class (default) prediction.
- Development of an optimized XGBoost-based classification model capable of capturing complex nonlinear relationships, with regularization to prevent overfitting and ensure scalability.
- Systematic hyperparameter tuning to enhance model generalization, stability, and predictive performance in financial risk assessment.
- Extensive performance analysis in terms of various measures, including accuracy, precision, recall, F1-score, ROC curve, and confusion matrix analysis, which provides a good measure of performance more than accuracy.

B. Justification and Novelty of the Study

This study is justified by the need to have accurate and reliable measure of credit risk in the lending systems in which misevaluating the loan may result in money loss or poor loan decision. Traditional methods are usually prone to inability to address high dimensions of data, skewed classes and not linear form of real financial data. What is novel about the presented work is that it employs the end-to-end solution, which includes robust data pre-processing, outlier control, the assumption of the imbalance between the classes through the application of the SMOTE algorithm, and a simplified XGBoost model with the hyperparameters optimization. The work provides a comprehensive and practical solution to assist in enhancing the predictive power, generalization and scalability through the evaluation of performance with the help of multiple measures such as accuracy, precision, recall, F1-score, and ROC that are utilized to predict loan default in the practical environment.

C. Structure of the Paper

The paper is organized into certain main sections: Section II discusses the literature that is currently available on Financing Risk Assessment in Digital Lending Loans, Section III deals with the process flow that includes data set, techniques and model implementation, Section IV presents the findings of the study, Section V is the conclusion of the research and indicates the future direction.

II. Literature Review

The present literature review provides a report on the new developments regarding Financial Risk Assessment in Digital Lending Loans in detail. A brief summary of the reviewed studies is depicted in Table I, indicating the approach, performance outcomes, key findings, identified limitations, and suggested avenues of future research.

R Patel and P. G. (2025) propose an artificial neural network (ANN) based DL method to enhance the accuracy of loan default prediction based on the Lending Club data that consists of close to 400,000 records of loans. Their ANN, in contrast to the simpler model of the previous studies, also uses Batch Normalization and Dropout layers to control data imbalance and overfitting, resulting in an AUC-ROC score of 0.904, which is much greater than that of XGBoost (0.734) and Random Forest (0.724). They are also the first to present a new approach to missing value imputation, which guarantees good feature representation [20].

Rahman et al. (2025) model was trained and tested on a consumer loan dataset, and it had an AUC-ROC of 0.92, outperforming isolated SAE (0.86), VAE (0.88) and isolation forest (0.84). The suggested hybrid scoring system combining reconstruction error on SAE with likelihood estimation on VAE further increased the F1-score of 0. 8 6 than those of SAE of 0. 7 8 and VAE of 0. 8 0. Sensitivity analysis of the dimension of the latent space showed that the best outcome was achieved with 32 latent dimensions and the best weighting factor 0.6 in the hybrid model was found. Also, tuning experiments also showed that threshold tuning that τ=0.15 made false positives to 8% and false negatives to 7% [21].

Konatham et al. (2025) presents Bayes Shield, a federated learning platform built to measure credit risk, and which is secure and scalable. Bayes Shield builds on the interpretability and fast performance of Naive Bayes and the high-performance and scalability of LightGBM to provide a hybrid ensemble classifier, which is optimally adapted to non-IID, heterogeneous financial data. Homomorphic Encryption (HE) is employed to keep the models private during the update in order to provide privacy; that is, when they want to safely aggregate the parameters without exposing the raw data, they can use the TenSEAL library. The experiments developed on credit risk dataset show that the proposed approach attains a better accuracy (93%) and F1-score, as compared to baseline classifiers, such as Naive Bayes, XGBoost, LightGBM, and Random Forest [22].

Zhuang and Wei (2024) study has the data on six sets of imbalance ratios that are provided by the Knowledge Extraction platform, which is founded on Evolutionary Learning as the means to experiment with the effectiveness of the GAN model at making classification. Also, the data of a consumer finance company's credit and 559 features are subjected to data pre-processing and feature extraction to check the usefulness of the LightGBM-GAN model in predicting credit risks. As shown in experiments, (1) GAN is much more effective in classifying the information on risks (the accuracy is 86.7%), which is better than the traditional oversampling techniques on various datasets, (2) The LightGBM-GAN model is more successful in Area Under the Receiver Operating Characteristic Curve and Kolmogorov-Smirnov statistics (average values are 0.86 and 0.87, respectively) [23].

Sharmila et al. (2024) Selecting the decision tree classifier facilitates loan approval estimation. Despite these disadvantages, a decision tree classification system can be a helpful tool to forecast whether or not a bank loan application would be accepted. The experiment's findings demonstrate that the suggested model decision tree classifier achieves 95% accuracy with a 0.09% loss. This research provides a potentially useful method for predicting bank loan approval in today's hectic business environment [24].

Jain et al. (2023) explores the application of technology to credit risk management. The Scopus database was examined bibliometric ally. 86 papers were extracted from the Scopus database and visualized using VOS viewer version 1.6.19. The application of technology to credit management is of interest to researchers. Between 2019 and 2022, 46% of the materials were made available. The main research areas that arose were fintech credit evaluation, credit default learning algorithms, and the effectiveness of credit assessment employing technology. Using blockchain and artificial intelligence (AI) to evaluate credit risk removes human subjectivity and increases credit management transparency [25].

TABLE I. LITERATURE SUMMARY ON THE NEW DEVELOPMENTS REGARDING FINANCIAL RISK ASSESSMENT IN DIGITAL LENDING LOANS

References	Methodology	Dataset	Key Findings	Challenges	Future Scope
R, Patel & P G (2025)	Artificial Neural Network with Batch Normalization and Dropout	Lending Club dataset (~400,000 records)	Achieved AUC-ROC of 0.904, outperforming XGBoost and Random Forest; robust missing value imputation	Computational complexity; limited interpretability	Integration of explainable AI and testing on real-time lending data
Rahman et al. (2025)	Hybrid SAE–VAE deep learning model with threshold tuning	Consumer loan dataset	AUC-ROC of 0.92; improved F1-score (0.86); reduced false positives and negatives	Sensitive to latent dimension and parameter tuning	Adaptive thresholding and deployment on streaming data
Konatham et al. (2025)	Federated learning with Naïve Bayes + LightGBM and Homomorphic Encryption	Credit risk dataset	Achieved 93% accuracy and improved F1-score with data privacy preservation	High computational overhead due to encryption	Lightweight privacy-preserving models and cross-bank collaboration
Zhuang & Wei (2024)	LightGBM combined with GAN-based oversampling	KEEL datasets and consumer finance data (559 features)	Improved accuracy (86.7%), AUC (0.86), and KS statistic (0.87)	Training instability of GANs; model complexity	Stable GAN architectures and broader financial datasets
Sharmila et al. (2024)	Decision Tree classifier	Bank loan application data	Achieved 95% accuracy for loan approval prediction	Overfitting and limited generalization	Ensemble models and hybrid decision systems
Jain et al. (2023)	Bibliometric analysis using VOSviewer	Scopus database (86 documents)	Identified fintech, AI, and blockchain as key themes in credit risk management	Lack of empirical model validation	Empirical studies integrating AI and blockchain for credit assessment

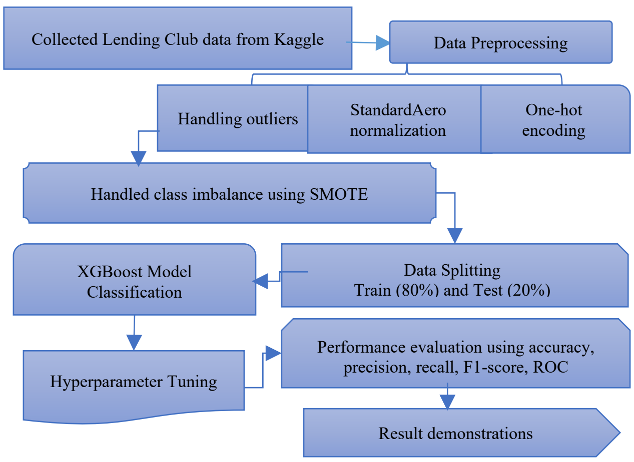

Fig. 1. Flowchart diagram of the Financial Risk Assessment in Digital Lending Loans

III. RESEARCH METHODOLOGY

The entire machine learning classification pipeline process of a lending dataset is shown in Figure 1. It starts by retrieving the Lending Club data on Kaggle, proceeds to data preprocessing involving the management of outliers, the use of one-hot encoding (categorical variables), and normalization of the features using StandardScaler. The SMOTE technique is used to deal with class imbalance. The processed data then be split to train (80%) and test (20%) sets. Hyperparameter tweaking is a technique used to enhance the performance of a classification model, such as XGBoost. Last but not least, the model is evaluated using accuracy, precision, recall, F1-score, and ROC. The outcomes are shown as result demonstrations.

A wide range of developments, such as the flowchart, are a necessary tool to underpin step-by-step processes:

A. Data Collection and Visualizations

This analysis based on the Lending Club data on Kaggle that contains historical records of peer-to-peer loans, borrower information, loan attributes, and loan repayment. It is a number of years old and is processed to predict credit risks and defaults, and one of the popular versions has about 887,379 records and 75 features.

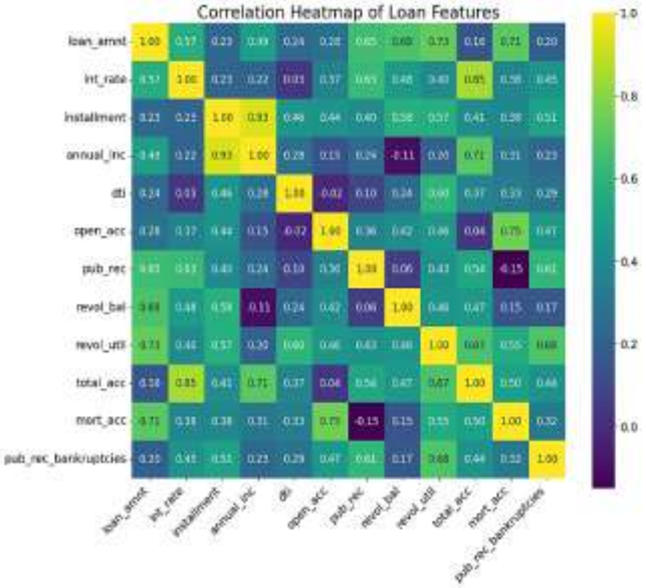

Fig. 2. Pearson Correlation Heatmap

The correlation heatmap of the important loan features, presented in Figure 2, indicates that there are strong associations between the features of loan amount, installment, and annual income, and moderate associations between different variables related to credit utilization and account. The correlation coefficient between most of the features is weak to moderate, which means that there is little multicollinearity between them and they offer valuable insights to use in the financial risks assessment model.

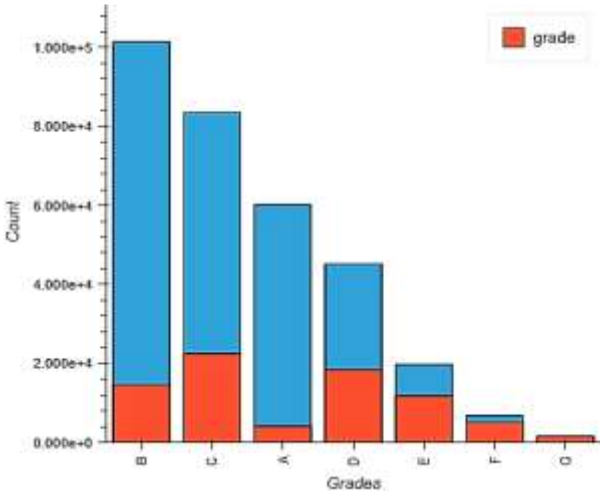

Fig. 3. Loan status by Grade

The distribution diagram of the loans in terms of the credit grade is given in Figure 3 with large percentage of loans being taken in the medium-risk classes including B and C with the lower credit grades being less common. This represents the total risk that the lending portfolio is composed of.

Identify applicable funding agency here. If none, delete this text box.

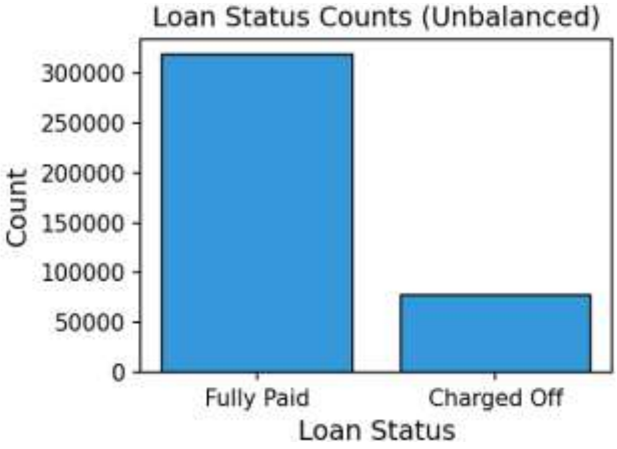

Fig. 4. Imbalanced data distribution

Figures 4 shows unequal distribution of the dataset's loan statuses, where completely paid loans make up a sizable majority as opposed to charged-off loans. This data imbalance suggests that in order to achieve an objective and successful model training in risk assessment of financial variables, data in models must be balanced.

B. Data Preprocessing

This stage is crucial for preparing the data required to construct the model. Observed errors were removed, outliers were managed, features were binned and merged to capture more information, and the results were normalized after categorical data were one-hot encoded and transformed to numerical data.

- **Handling Outliers:** It is necessary to deal with outliers since they are extraordinary values that differ from the rest of the data and may have an impact on certain models. The best way to deal with outliers was discovered to reduce their impact while maintaining the most data. provides information about the standard deviation (\sigma) and how much a data value (V) deviates from the mean (μ). When the Z-score (Z) exceeds 3, extreme values are shown. It is calculated as follows using Equation (1):

$$Z = \frac{(V-\mu)}{\sigma} \tag{1}$$

- **Data Normalization using Standard Scaler:** A few models may be impacted by features in a dataset having a distinct range. By utilising the normal scaler to scale the features, this issue was resolved. The new number (n) is scaled to conform to a normal distribution, albeit outliers may have an impact. Equation (2) is used to compute it:

$$n = \frac{n_i - n_{mean}}{\sigma} \tag{2}$$

- **One-hot Encoding:** One-hot encoding refers to a method of transforming a nominal variable into a dichotomous form. It generates additional columns for every category, with a 1 denoting the category's presence and a 0 denoting its absence. The main idea behind One Hot Encoding is to provide an opportunity to effectively use categorical data in machine learning models.

C. Handling Class Imbalance using SMOTE

In predictive modelling, class imbalance is a major problem, especially in domains where the majority of data fall into the non-default class, such as credit risk prediction. By interpolating between the current minority class data samples and their closest neighbor, it generates synthetic data, adding new data points without generating duplicates. Additionally, because the minority class samples are expanded without duplication, it may avoid overfitting. This creates synthetic data (x_{new}) using Equation (3):

$$x_{new} = x_i + \lambda \times (x_{nn} - x_i) \quad (3)$$

where,

- x_i = minority class.
- x_{nn} = one of the nearest neighbours.
- λ = a random value between [0,1].

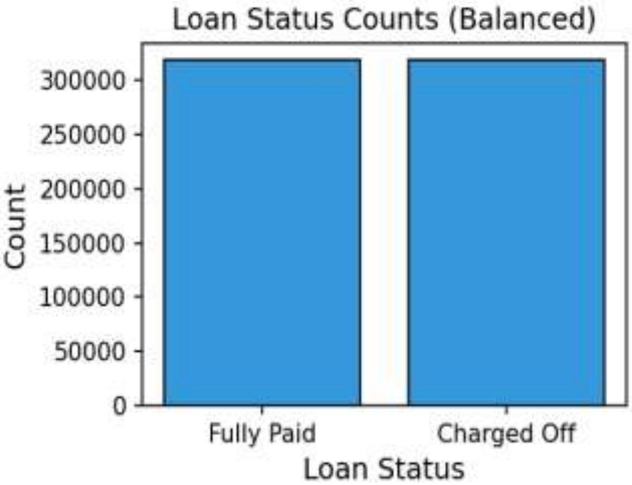

Fig. 5. Balanced Class Distribution

Figure 5 demonstrates that the balance in the loan statuses following pre-processing of the data is distributed evenly between fully paid and charged-off loans, with an almost equal share of each. This is a balanced representation in the classes that reduce bias in training the models and enhance more trusted and equitable classification results in financial risk assessment.

D. Data Splitting

Data balancing was followed by testing several divides to identify the optimal split. In order to ensure that the right characteristics were picked, an 80:20 split was ultimately established for the model development in the next step.

E. Classification Model: Extreme Gradient Boosting (XGBoost)

XGBoost, or eXtreme Gradient Boosting [26], is a tree-based algorithm. XGBoost has demonstrated remarkable performance and speed. Boosting is an ensemble method whose main objective is to lower variance and bias. The objective is to construct weak trees in a sequential fashion, with each new tree (or learner) addressing the defect (misclassified data) of the previous tree. The process of "re-weighting" involves readjusting the data weights each time a weak learner is introduced. Once convergence, the entire system creates a robust model due to this autocorrection once each new learner is added. To reduce the likelihood of overfitting, the model's loss function is described as penalizing the model's complexity with regularization. This method shows a solid capacity to handle sparsity by performing well even when there are numerous zero values or missing values. An approach known as the "weighted quantile sketch algorithm" is used by XGBoost to assist the classifier in focusing on erroneously labelled data. Learning how to categorize the wrong data is the goal of every new learner in each cycle. To categorize a particular example into its leaves, utilize the decision rules in the trees (q), and then add up the scores in the appropriate leaves (w) to determine the final prediction. The following regularized objective, which is provided in Equations (4) to (5), is minimized in order to determine the collection of functions utilized in the model.

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \quad (4)$$

$$\omega\eta\epsilon\rho\epsilon\ \Omega(f) = \gamma T + \frac{1}{2}\lambda||\omega||^2 \quad (5)$$

Here, l is a differentiable convex loss function that measures the difference between the objective y_i and the prediction $\hat{y}_i$. The second term Ω penalises the model's complexity (i.e., regression tree functions).

F. Hyperparameter Tuning

The hyper parameters of the ML models can be changed and determine the shape of the model and the learning algorithm. Because these hyperparameters are directly related to the model's learning and performance, it is crucial to make sure these hyperparameters are set appropriately. The XGBoost model was tuned with the hyperparameters in order to maximize its performance in terms of financial risk assessment. To enhance the potential for generalization and predictive performance, a number of handpicked hyper parameters were used to tune the XGBoost model. Column sampling ratio (colsample_bytree) was also experimented (0.7 to 0.9) to regulate the use of features at each tree level, and the maximum tree depth (max_depth) was also experimented (3, 6, 10 and 20) to obtain the feature of model complexity. A learning rate of 0.1 and 0.2 was tried to be in between convergence speed and stability. This was tested on 200, 300 and 500 trees (n estimators) to make sure that the learning capacity was adequate. To control the data sampling in the training process, subsampling values were also used, and the regularization parameters (reg_alpha and reg_ lambda) were used to reduce the overfitting. All these hyperparameter settings were used to optimize the XGBoost model to create a robust financial risk model.

G. Evaluation Parameters

In this study, primarily concentrate on the five performance evaluation parameters for classifier comparison: accuracy, precision, recall, F1-score, and ROC curve analysis.

The confusion matrix is a well-known method to see how a model of classification is good at predicting the true classes. The Confusion Matrix provides more than simply an eye-catching way to evaluate the model's classification accuracy. Additionally, other calculations may be made using the four values. As these are all goals for more targeted evaluations of the model, these calculations can be utilized to ascertain the model's advantages and disadvantages.

- **True Positive (TP):** This occurs when a positive result is predicted by the predictive model and the actual result is also positive.
- **False Positive (FP):** Is when a positive outcome is predicted by the model but the actual result is negative.
- **True Negative (TN):** Is a prediction of negative by the model and the result is negative.
- **False Negative (FN):** Is the model predicting negative but the actual value of the outcome is positive.

The evaluation metrics for individual classes were calculated using standard classification parameters:

Accuracy: The number of samples properly identified relative to the total number of samples for a test dataset is the definition of accuracy. Equation (6) provides the following

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (6)$$

Precision: It evaluates how many accurate positive predictions a model has produced by contrasting them with the actual positive guesses, and accuracy is calculated using the following Equation (7):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (7)$$

Recall: The function of all positive (default) cases that the classifier accurately classifies as positive is called recall. Recall is calculated as below in Equation (8):

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (8)$$

F1-Score: The balanced average of precision and recall is the F1-score, sometimes known as a balanced F-score. It is mathematically shown in Equation (9):

$$\text{F}_1 - \text{Score} = 2 \times \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (9)$$

ROC Curve: A two-dimensional graphical display called receiver operating characteristics (ROC) shows how well a binary classifier system is doing. Plotting the true positive rate (TPR) versus the false positive rate (FPR) at different threshold values yields the curve. The performance of a classifier may be intuitively represented by the ROC curve.

IV. Results and Discussion

The environment for this study has been obtained, and a Core (TM) i7-1065G7 CPU running at 1.30GHz and 1.50GHz is used for the experiments. Furthermore, Python 3.7.1 is used since it provides a number of models and modules for classification.

A. Result Demonstrations

Table II presents the performance of the XGBoost model for financial risk assessment in digital lending loans. The model shows excellent prediction skills with a high accuracy of 97.70%, indicating dependable overall classification performance. The model's accuracy in identifying risks and reducing false positive and false negative values is 94.78 and 93.30, respectively. A robust trade-off between accuracy and recall is demonstrated by the resulting F1-score of 94.03%, indicating the effectiveness and suitability of the XGBoost model for the financial risk assessment job in digital lending systems.

TABLE II. Model Performance for Financial Risk Assessment in Digital Lending Loans

Metrics	XGBoost
Accuracy	97.70
Precision	94.78
Recall	93.30
F1-Score	94.03

Figure 6 shows the ROC curve for the XGBoost classifier, which rises sharply towards the top-left corner and demonstrates exceptional classification performance. With a high AUC score of 0.9991, the model's ability to distinguish between classes is almost perfect.

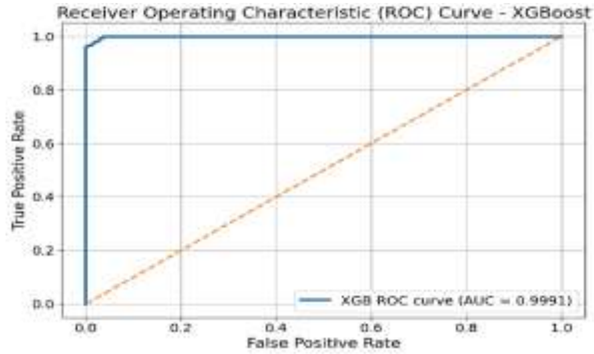

Fig. 6. ROC Curve Analysis

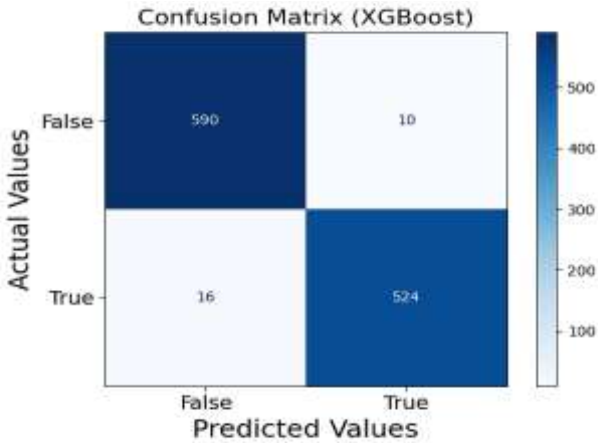

Fig. 7. Confusion Matrix of the XGBoost Model

The XGBoost classifier's confusion matrix is displayed in Figure 7, where the majority of examples are properly identified (590 true negatives and 524 true positives), with a small number of false positives (10) and false negatives (16), demonstrating high accuracy and efficient class discrimination.

B. Comparative Analysis

Table III, the accuracy of several models for evaluating financial risk in digital lending is contrasted. The accuracy of the Logistic Regression is 87.06, the accuracy of the Neural Networks is 89.4 and the Support Vector Machines is 75.0. XGBoost has the greatest accuracy of 97.70 compared to all the other models, demonstrating that it is the ideal model to apply for this purpose.

TABLE III. Comparison of Financial Risk Assessment in Digital Lending Loans

Model	Acc.	Pre.	Rec.	F1-Sc.
LR [27]	87.06	66.11	85.91	74.72
NN [28]	89.4	-	79.0	-
SVM [29]	75.0	-	74.0	75.0
XGBoost	97.70	94.78	93.30	94.03

Table IV presents a comparative analysis of financial risk assessment models using different datasets. The LGBM model achieves an accuracy of 79.61% on the Credit Risk dataset, while the Decision Tree model attains 94.08% accuracy on the Loan Default dataset. The proposed XGBoost model, evaluated on the Lending Club dataset, surpasses the rest with higher precision and the maximum accuracy of 97.70%, recall, and F1-score, highlighting its effectiveness for digital lending risk assessment.

TABLE IV. COMPARISON PERFORMANCE OF FINANCIAL RISK ASSESSMENT MODELS USING DIFFERENT DATASETS

Ref.	Model	Dataset	Acc.	Pre.	Rec.	F1-Sc.
[30]	LGBM	Credit Risk Dataset	79.61	78.96	76.24	77.67
[31]	DT	Loan Default	94.08	86.72	89.39	88.04
Pro	XGBoost	Lending CLub Data	97.70	94.78	93.30	94.03

C. Discussion

This paper has identified the usefulness of XGBoost model on financial risk assessment in digital lending indicating good classification and good discrimination between risky and non-risky loans. Balanced error treatment is proven by the results of performance measures, ROC analysis, and confusion matrices, whereas comparative analyses of XGBoost with other models prove that it performs better on various data sets.

V. CONCLUSION AND FUTURE WORK

The method of lending credit allows banks to grow among individuals and businesses, also because they are going to pay it slowly, in the meantime, they can do large transactions that alone, maybe they could have never done. This paper shows that highly developed machine learning solutions have a high potential to improve loan default prediction in online lending settings. The results attest to the fact that the suggested method could be used to ensure a high level of predictive accuracy and equalized risk determination, which would allow making sure that the borrowers that would default and those that would not fail could be distinguished reliably. The high performance of XGBoost in the face of different metrics of evaluation and analysis comparing can demonstrate the suitability of XGBoost in the situation of complex financial data analysis and unbalanced risk situations. Besides technical performance, it is also shown that data-based risk assessment will be useful in helping to carry out the process of prudent lending, reduce financial losses, and ensure the stability of the institutions. The research will contribute towards the development of more open and sound banking practices since it will enhance uniformity and dependability of credit evaluations. All in all, the findings confirm the legitimacy of integrating intelligent analytics in the existing financial structure and generate useful information to the banks and other financial institutions that seek to strengthen risk management instruments in the continuously-digitizing and uncertain economic landscape.

As a way of making future work more dedicated, one may also think of deep learning and hybrid models that will help even more to predict credit risks. The flexibility of the model would be improved through incorporation of real-time data as well as other data sources such as transactional or behavioral data and experimenting the framework on different financial markets would improve the generalizability of the model.

REFERENCES

[1] S. K. Das, "Transforming Loan and Distribution Processing in Retirement Systems: A QA Automation Approach," *Int. J. Bus. Manag. Sci.*, vol. 05, no. 05, pp. 9–26, 2025.

[2] D. Patel, "Enhancing Banking Security: A Blockchain and Machine Learning- Based Fraud Prevention Model," *Int. J. Curr. Eng. Technol.*, vol. 13, no. 06, pp. 576–583, 2023, doi: 10.14741/ijcet/v.13.6.10.

[3] O. S. Ogundele and L. Nzama, "Risk Management Practices and Financial Performance: Analysing Credit and Liquidity Risk Management and Disclosures by Nigerian Banks," *J. Risk Financ. Manag.*, vol. 18, no. 4, 2025, doi: 10.3390/jrfm18040198.

[4] P. Chandrashekar, "Data-Driven Loan Default Prediction: Enhancing Business Process Workflows with Machine Learning," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, pp. 18–26, 2025, doi: 10.63282/3050-922X.IJERET-V6I4P103.

[5] E. C. Nwude and C. Okeke, "Impact of Credit Risk Management on the Performance of Selected Nigerian Banks," *Int. J. Econ. Financ. Issues*, vol. 8, no. 2, pp. 287–297, 2018.

[6] S. B. Shah, "Advanced Framework for Loan Approval Predictions Using Artificial Intelligence-Powered Financial Inclusion Models," in *2025 IEEE Integrated STEM Education Conference (ISEC)*, 2025, pp. 1–10. doi: 10.1109/ISEC64801.2025.11147327.

[7] R. Patel, "Automated Threat Detection and Risk Mitigation for ICS (Industrial Control Systems) Employing Deep Learning in Cybersecurity Defence," *Int. J. Curr. Eng. Technol.*, vol. 13, no. 06, pp. 584–591, 2023, doi: 10.14741/ijcet/v.13.6.11.

[8] V. Shah, "Managing Security and Privacy in Cloud Frameworks: A Risk with Compliance Perspective for Enterprises," *Int. J. Curr. Eng. Technol.*, vol. 12, no. 6, pp. 606–618, 2022, doi: 10.14741/ijcet/v.12.6.16.

[9] V. Verma, "Security Compliance and Risk Management in AI-Driven Financial Transactions," *Int. J. Eng. Sci. Math.*, vol. 12, no. 7, pp. 107–121, 2023.

[10] S. K. Chintagunta, "Enhancing Cloud Database Security Through Intelligent Threat Detection and Risk Mitigation," *TIJER – Int. Res. JOURNA*, vol. 9, no. 10, pp. 49–55, 2022.

[11] 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.

[12] A. Parupalli, "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, 2024, doi: 10.56472/25839217/IJCEET-V2I4P103.

[13] V. Verma, "Deep Learning-Based Fraud Detection in Financial Transactions: A Case Study Using Real-Time Data Streams," vol. 3, no. 4, pp. 149–157, 2023, doi: 10.56472/25832646/JETA-V3I8P117.

[14] A. Parupalli, "The Evolution of Financial Decision Support Systems: From BI Dashboards to Predictive Analytics," *KOS J. Bus. Manag.*, vol. 1, no. 1, pp. 1–8, 2023.

[15] Y. Xue and X. Zhang, "Digital transformation and corporate capital structure: Evidence from China," *Pacific-Basin Financ. J.*, vol. 84, p. 102299, Apr. 2024, doi: 10.1016/j.pacfin.2024.102299.

[16] T. Shah, "Leadership in digital transformation: Enhancing customer value through AI-driven innovation in financial services marketing," *Int. J. Sci. Res. Arch.*, vol. 15, no. 3, pp. 618–627, Jun. 2025, doi: 10.30574/ijsra.2025.15.3.1767.

[17] S. B. Shah, "Evaluating the Effectiveness of Machine Learning in Forecasting Financial Market Trends: A Fintech Perspective," in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10968297.

[18] K. S. Hebbar, H. Parnerkar, and S. Gondi, "Ai-Driven Real-Time Fraud Detection Using Kafka Streams in Fintech," *Int. J. Appl. Math.*, vol. 38, no. 6s, pp. 770–782, Oct. 2025, doi: 10.12732/ijam.v38i6s.433.

[19] K. S. Hebbar, "Priority-Aware Reactive APIs: Leveraging Spring WebFlux for SLA-Tiered Traffic in Financial Services," *Eur. J. Electr. Eng. Comput. Sci.*, vol. 9, no. 5, pp. 31–40, Sep. 2025, doi: 10.24018/ejece.2025.9.5.743.

[20] H. R, M. S. Patel, and O. P. P G, "Predictive Analysis for Loan Defaults: A Deep Learning Approach," in *2025 Global Conference in Emerging Technology (GINOTECH)*, 2025, pp. 1–5. doi: 10.1109/GINOTECH63460.2025.11076632.

[21] N. Rahman, F. Mahmud, A. C. Das, M. S. Shak, S. R. Sultana, and R. Islam, "Hybrid Autoencoder-Based Anomaly Detection for Consumer Loan Default Prediction," in *2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN)*, 2025, pp. 1–6. doi: 10.1109/QPAIN66474.2025.11172016.

[22] M. R. Konatham, D. Priyadarshi Uddandarao, R. K. Vadlamani, and S. K. Reddy Konatham, "Federated Learning for Credit Risk Assessment in Distributed Financial Systems using BayesShield with Homomorphic Encryption," in *2025 International Conference on Computing Technologies & Data Communication (ICCTDC)*, 2025, pp. 1–6. doi: 10.1109/ICCTDC64446.2025.11158863.

[23] Y. Zhuang and H. Wei, "Design of a Personal Credit Risk Prediction Model and Legal Prevention of Financial Risks," *IEEE Access*, vol. 12, pp. 146244–146255, 2024, doi: 10.1109/ACCESS.2024.3466192.

[24] S. Sharmila, P. V. S. Sandhya, P. S. Kousar, P. Anuradha, and S. Deekshitha, "Bank Loan Approval using Machine Learning," in *2024 International Conference on Integrated Circuits and Communication Systems (ICICACS)*, 2024, pp. 1–5. doi: 10.1109/ICICACS60521.2024.10498192.

[25] V. Jain, R. Tiwari, R. Mehrotra, N. S. Bohra, A. Misra, and D. C. Pandey, "Role of Technology for Credit Risk Management: A Bibliometric Review," in *2023 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS)*, 2023, pp. 1–6. doi: 10.1109/ICBDS58040.2023.10346300.

[26] M. R. R. Deva and N. Jain, "Utilizing Azure Automated Machine Learning and XGBoost for Predicting Cloud Resource Utilization in Enterprise Environments," in *2025 International Conference on Networks and Cryptology (NETCRYPT)*, IEEE, May 2025, pp. 535–540. doi: 10.1109/NETCRYPT65877.2025.11102235.

[27] R. Yang, "Machine Learning-Based Loan Default Prediction in Peer-to- Peer Lending," *Highlights Sci. Eng. Technol.*, vol. 94, pp. 310–318, 2024.

[28] R. Sifrain, "Predictive Analysis of Default Risk in Peer-to-Peer Lending Platforms: Empirical Evidence from LendingClub," *J. Financ. Risk Manag.*, vol. 12, no. 01, pp. 28–49, 2023, doi: 10.4236/jfrm.2023.121003.

[29] L. Zhu, D. Qiu, D. Ergu, C. Ying, and K. Liu, "A study on predicting loan default based on the random forest algorithm," *Procedia Comput. Sci.*, vol. 162, pp. 503–513, 2019, doi: 10.1016/j.procs.2019.12.017.

[30] X. Zhang *et al.*, "Data-Driven Loan Default Prediction: A Machine Learning Approach for Enhancing Business Process Management," *Systems*, vol. 13, no. 7, 2025, doi: 10.3390/systems13070581.

[31] Z. Z. Kang, S. Y. Teh, S. Yong, G. Tan, and W. C. Ng, "Loan Default Prediction Using Machine Learning Algorithms," *J. Informatics Web Eng.*, vol. 4, no. 3, 2025, doi: 10.33093/jiwe.2025.4.3.14.

