International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

A Machine Learning Framework for Predictive Credit Risk Assessment and Loan Default Detection

Nilam J.Gade
Department of Computer Science
Dr. D.Y. Patil Arts Commerce Science College
Pimpri, India

Pooja L.Kunwar
Department of Computer Science
Dr. D.Y. Patil Arts Commerce Science College
Pimpri, India

***Abstract*- Loan default is still an issue that banks and financial institutions seriously face as it results in major financial losses and a higher credit risk exposure. It is important that high, risk borrowers are identified fast to not only improve loan approval decisions but also to retain financial stability. Conventional credit risk evaluation methods are mostly based on the manual examination of borrower attributes such as income, employment history, and credit score. Nevertheless, these methods may miss complex behavioral patterns and even lead to biased or inconsistent decisions. The paper outlines the use of a machine learning model for the prediction of loan default based solely on the borrower's structured data. Income level, employment type, loan amount, repayment history, and credit score together with other important financial and demographic features form the dataset on which the classification into defaulters and non, defaulters is done. A well, planned data preprocessing step followed by feature selection is performed to improve the accuracy and explainability of the model. Many supervised learning algorithms, Logistic Regression, Decision Tree, Random Forest, and XGBoost, are created and their results compared. To benchmark the performance of the developed models, standard classification metrics such as accuracy, precision, recall, F1, score, and ROC, AUC are used. A web application is also developed to visualize the prediction process in real, time. The suggested method is a trustworthy and flexible tool for credit risk evaluation which fosters data, driven lending decisions and better management of financial risks.**

Keywords:

Loan Default Prediction, Credit Risk Assessment, Machine Learning, Financial Data, Classification Models, Risk Management.

I. INTRODUCTION

Loan default prediction is a key matter for the banks and financial institutions as the defaulted loans make the banks less profitable and unstable. The banks have been traditionally applying only manual assessments of loan applications by reviewing the applications of the applicant's income, credit history, employment status, and characteristics of the loan such as duration. This process is something that has been going for decades but is also very time, consuming, subjective, and various officers are doing it very differently/can get different results despite their knowledge of the process. Given that there are more and more loan applications and borrower profiles become complicated, the automation of the decision support system is a solution that is greatly required.

Machine learning has come out as a great credit risk assessment analytical tool. By analyzing the data of past borrowers, ML algorithms can understand the features of the borrower's loan repayment behavior and thus forecast whether a loan applicant of today can default the loan or not.

However, due to the confidentiality restrictions of banking, the real, world loan datasets of borrowers are usually not publicly available, which in turn impedes researchers and students in training and testing different models with real banking data. To tackle the issue, this paper employs a newly produced synthetically generated dataset that mimics compact, accurate real borrower characteristics and financial behavior to the greatest extent.

The aim of this project is to develop a straightforward but efficient loan default predicting system based on four machine learning techniques: Logistic Regression, Decision Tree, Random Forest, and XGBoost. The objective is to evaluate the performance of these models and find the best algorithm for binary classification: Default or Not Default.

Besides, this work involves creating a user, friendly web application based on Flask to enable users to enter borrower information and get a prediction immediately, thus making the system not only theoretically sound but practically useful for demonstration and academic purposes.

In general, the paper demonstrates that machine learning can take decision, making in the financial sector to the next level by allowing for quicker, more reliable, and data, based predictions. The system from the present study is a throwback model aimed at teaching the basics of credit risk modeling.

II. OVERVIEW OF LOAN DEFAULT DETECTION

This paper is outlining a comprehensive and systematic approach to predicting loan default through the use of supervised machine learning methods. Essentially, it is about conceiving, developing, and assessing a classification tool that can predict a loan default by analyzing the financial and demographic details of a potential borrower. The tool acts as a scholarly model to exhibit the application of machine learning in the domain of credit risk evaluation.

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As the actual banking datasets cannot be revealed due to the confidentiality issue, the study is based on a synthetically produced dataset that represents the characteristics of borrowers in the real world. Among the variables in the dataset are yearly income, the amount of the loan, the credit score, the duration of employment, the ratio of debt to income, the number of credit accounts that are open, and the history of delinquencies. The wording synthetic is meticulously referring here to the data forged to resemble the pattern of real financial behavior so as to keep the privacy intact while providing the data for academic purposes. This strategy opens the door for conducting experiments and means the model in a controlled fashion without infringing on the protection of personal data.

The entire workflow for this research involves several well, defined steps. Initially, the data is created and preprocessed.

Preprocessing is the treatment of missing values, categorical variable encoding, numerical feature scaling, and dividing the dataset into training and testing parts. Then various supervised learning algorithms such as Logistic Regression, Decision Tree, Random Forest, and XGBoost are applied. The selection of these models is to cover both traditional statistical methods as well as advanced ensemble, based techniques.

The models are tested through the use of standard performance metrics such as Accuracy, Precision, Recall, F1, Score, and ROC, AUC. A comparative study is carried out to identify the algorithm that offers the most trustworthy and generalizable predictions for loan default classification. Particular attention is given to the aspects of model behavior, interpretability, and robustness.

The research goes beyond just model development and evaluation; it also covers the deployment of the best, performing model via a web application built with Flask. The application facilitates users in entering the borrower details and receiving the prediction result instantly (Default or Not Default). The deployment aspect here signifies the developed system's practical if not theoretical, usability.

On the whole, this work combines data creation, machine learning modeling, performance testing, and web deployment in one single integrated story. It is a holistic academic illustration of the role of predictive analytics in financial risk management, at the same time reflecting on issues like data shortage and privacy, which are typical of the real world.

III. OBJECTIVES OF THE RESEARCH

The primary aim of this study is to design a machine learning system that will be able to tell if a loan applicant is at risk of defaulting or not. It is intended to be a support tool for lending institutions in speeding up and standardizing their credit evaluation basing on applicants' data. Due to the lack of availability of actual banking data that is confidential, the research utilised a computer, generated dataset that depicts borrower characteristics and financial behaviors in a very realistic manner.

The study has outlined the following as its specific objectives:

1. Model Development and Evaluation: The goal here was to create and compare different machine learning models (Logistic Regression, Decision Tree, Random Forest, and XGBoost) to come up with the best algorithm that accurately predicts loan default.
2. Synthetic Dataset Creation: The purpose was to make a mock loan applicant dataset with plausible financial attributes which can be used instead of real confidential banking data.
3. Data Preprocessing & Transformation: The primary goal of this stage was to change the raw dataset into a clean and well, structured format that is fit for model training. Various preprocessing operations were done such as turning categorical variables into numerical form, standardizing.
4. Web Application Development: The plan was to create a user, friendly web application by utilizing Flask framework where users could conveniently enter their loan application details and get an instant prediction whether the loan would be Default or Not Default.
5. Performance Evaluation: The plan was to use accuracy, precision, recall, and F1, score metrics to compare the trained models and hence select the best, performing model.
6. Interpretability & Practical Use: The aim was that the whole system should be straightforward, clear, and helpful not only for academic purposes demonstration but also practical financial decision, making via explainable ML.

IV. LITERATURE REVIEW

A. *Machine Learning and Ensemble Models for Loan Default Detection*

Some recent articles have revealed that machine learning methods are very successful at forecasting loan defaults if they have access to both structured financial and personal data.
For a long time, credit scoring has mainly been done through simple and interpretable models such as Logistic Regression or Decision Trees. However, a comparison of these methods regularly demonstrates that ensemble learning models are the best in terms of both their predictive accuracy and their ability to generalize [1], [5], [12].
Studies that contrast the performance of traditional models with modern boosting techniques point out that tree, based ensemble algorithms like Random Forest, Gradient Boosting, and XGBoost are the best choices for tabular credit data [1], [8], [10].
By capturing complex nonlinear interactions between various borrower features (e.g., income, credit score, debt, to, income ratio, and prior delinquencies), these models can correctly identify the risk of default. Studies using real, world datasets, including Lending Club and institutional banking data, indicate that XGBoost is the model that most often leads to the highest ROC, AUC and F1, scores, thus becoming a strong contender for credit risk modelling. [5], [10].
Different advanced frameworks implement stacking and hybrid ensemble architectures in order to mix several base

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learners, thus getting better generalization and lowering variance [5], [12].
A comparative study of conventional and participation banks also verifies that boosting algorithms like XGBoost, LightGBM and CatBoost will consistently beat standalone models if they are properly tuned [11]. These results taken together suggest that ensemble learning is the preferred method for loan default prediction tasks.

B. Data Preprocessing, Imbalance Handling, and Feature Engineering

Financial datasets are typically missing some values, contain outliers, have skewed distributions, and are severely imbalanced in terms of classes, in which non-defaulters considerably outnumber defaulters. There have been a number of publications that have pointed out how preprocessing is a key factor in the trustworthiness and the effectiveness of a model [1], [4], [9].

Imputation methods like mean/median imputation and other sophisticated methods are generally used to deal with incomplete financial records. Categorical loan features are converted to machine, readable formats by means of encoding methods such as one, hot encoding and Weight, of, Evidence (WoE) [9]. Besides, normalization and scaling help in the stable convergence of the model.

Class imbalance is still a very difficult problem in predicting credit defaults. Hybrid sampling schemes that first SMOTE and basically ENN for cleaning the data have given an improved minority default cases detection in these papers [2], [8]. A few of them also use class, weighted learning in boosting algorithms to alleviate the majority, class bias [4], [10]. Through feature engineering, ratio features such as loan, to, income and debt, to, income were found to drastically increase the predictive power of models, even being more influential in terms of accuracy improvement than changing the algorithm among the top performers [1], [12].

These research works provide evidence that strong preprocessing and imbalance treatment are the fundamental parts of dependable loan default prediction models.

C. Explainable AI and Interpretability in Credit Risk Models

Interpretability we consider financial decision, making, just having models that predict accurately is not enough; for regulatory compliance and stakeholder trust, the model needs to be transparent as well. A number of recent studies have incorporated explainable AI (XAI) methods such as SHAP and LIME to improve interpretability in credit scoring models [4], [7], [10].

One paper reported on the combination of XGBoost and SHAP findings and showed that the most important factors for default risk were a person's credit score, past delinquencies, debt, to, income ratio, credit utilization, and the size of the loan [10]. SHAP plots depict not only the overall importance of features but also the reasoning behind the classification of each individual borrower, thus enabling risk officers to get to the bottom of why a certain loan application is deemed risky.

In fact, some of the publications experimented with natural language and surrogate explanation models that provide a written account of the complicated boosting outputs in the form of risk categories like low, medium, or high risk [7]. These methods help to align AI credit systems with conventional decision, making processes, thus taking a step towards making AI, based credit scoring systems more acceptable in the real, world banking context.

In summary, explain ability toolkits are becoming more and more vital when it comes to being able to release machine learning models in the financially regulated environment.

D. Research Gap

Notwithstanding substantial progress, existing loan default prediction studies still have some limitations. Numerous models are built on single, institution datasets or data from specific lending platforms, which may not be representative of different economic contexts and borrower segments [1], [5], [11]. Several works have also been centred on the accuracy of the model, but have barely delved into aspects such as the deployment of the model or its integration into the lending systems workflow [6].

Ensemble methods invariably perform well in prediction, however, only a few studies have integrated synthetic data experimentation and structured comparative evaluation for ease of understanding by the academicians. Also, even though imbalance handling methods such as SMOTE and class, weighted training are very popular, comparative evaluation of different preprocessing strategies is still one of the inconsistencies in studies [2], [8].

Moreover, despite the fact that explainable AI approaches are widely recognized, their association with straightforward, educational prototypes, which could be used as teaching tools in the academic community, is still a rarity [7], [10].

Hence, there is a gap in the market for a systematic and reproducible framework of loan default prediction that encompasses synthetic data generation, a thorough preprocessing, a fair comparison of ensemble modelings, reliable evaluation metrics, and real, world deployment via a web, based interface. This disparity serves as the basis of this research.

V. METHODOLOGY

1. Research Design*:*

This study uses a quantitative experimental research design to create and assess a machine learning based system for predicting loan defaults. The method combines synthetic data generation, preprocessing, training of supervised machine learning models, performance evaluation, and web, based deployment.

Due to the fact that real banking datasets are confidential and off, limits, a synthetic dataset was created to mimic valid borrower behavior while ensuring data privacy. The investigation adheres to a well, organized sequence of steps comprising data preparation, model implementation, evaluation, and deployment.

2. Data Collection Method

2.1 Nature of Data

This project is based on a fully synthetic financial dataset designed uniquely for loan default prediction.

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In the absence of knowledge of a real borrower's data, due to privacy and institutional restrictions, none was used or collected.

The dataset was created with Python from realistic financial distributions and behavioral patterns. To mimic real, world situations.

- Small amounts of missing values were introduced
- Random noise was added
- Mild class imbalance was incorporated

This method guarantees theoretical modeling experience while staying compliant with data protection laws.

3 Sources of Data

3.1 Primary Data

The research is based solely on internally simulated borrower data. It did not involve any external financial records or confidential datasets.

The dataset was produced by employing statistically plausible distributions for financial and demographic characteristics, such as:

- Age
- Income
- Loan amount
- Employment years
- Credit score
- Loan purpose
- Repayment history
- Debt-to-income ratio
- Previous defaults
- Default (Target Variable)

The data was generated by a combination of Gaussian, exponential, and categorical distributions to reflect the variability of actual borrowers.

3.2 Sampling Technique

The final dataset contains 5, 000 synthetic borrower records.

For model development:

80% of the data was used for training20% of the data was used for testing Stratified sampling ensured a proportional representation of the minority class (Default = 1)

5, fold cross, validation was utilized to minimize overfitting and maximize generalization

This structured sampling guaranteed sound and statistically reliable model evaluation.

3.3 Tools and Technologies Used

All development and experimentation were conducted in Python (Version 3.10) using Jupyter Notebook.

Libraries Used:

- pandas, numpy -Data generation and manipulation
- scikit-learn-Model training, preprocessing, and evaluation
- xgboost - Gradient boosting classifier
- imblearn (SMOTE) -Handling class imbalance
- matplotlib, seaborn - Visualization
- SHAP - Model interpretability
- Flask -Web deployment

3.4 Data Preprocessing

Model Data preprocessing was performed to ensure quality and model readiness.

The following steps were applied:

1. Handling Missing Values

- Median imputation for numerical variables
- Mode imputation for categorical variables
- KNN imputation (where required)

2. Encoding Categorical Variables

- One-Hot Encoding
- Label Encoding

3. Feature Scaling

- Standardization or normalization based on model requirements

4. Feature Selection Techniques

- Correlation analysis
- Mutual Information
- Feature importance using Random Forest and XGBoost

These preprocessing steps improved model stability and reduced classification bias.

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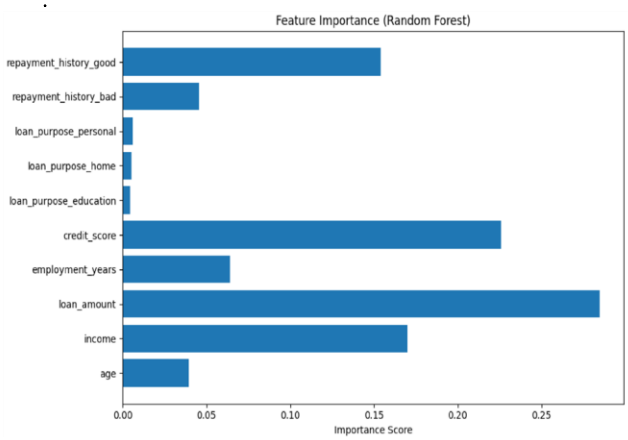

fig 1:-Feature Importance(Random Forest).

3.5 Model Development

International Journal of Engineering Research & Technology (IJERT)
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The Four supervised machine learning models were implemented:

1. Logistic Regression
2. Decision Tree Classifier
3. Random Forest Classifier
4. XGBoost Classifier

Hyperparameter Tuning

GridSearchCV was applied to Random Forest and XGBoost to optimize parameters such as:

- Number of estimators
- Maximum depth
- Learning rate
- Minimum samples split

This improved predictive performance and reduced overfitting.

3.6 Experimental Setup

3.6.1 Evaluation Metrics

Models were evaluated using the following performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- Confusion Matrix

These metrics ensured balanced evaluation of both default and non-default classifications.

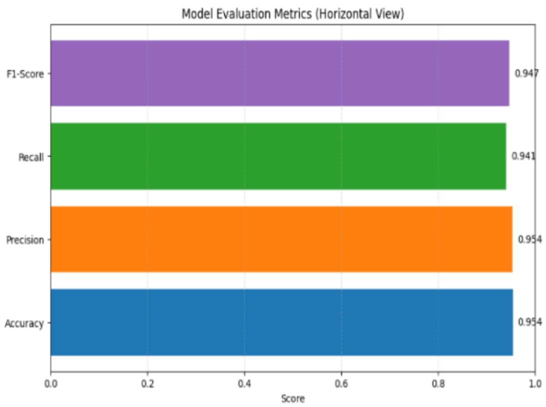

fig 2:-Model Evaluation Metrics.

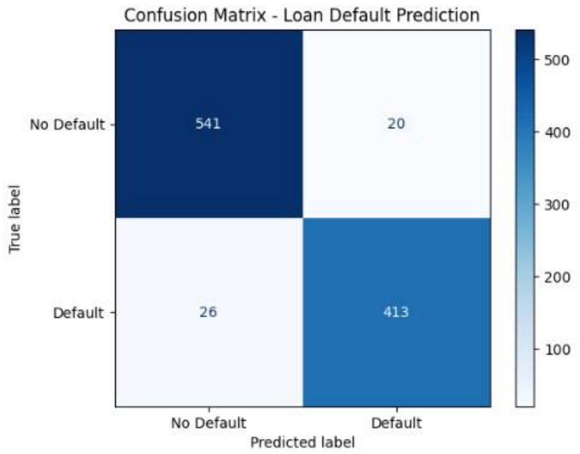

fig3:-Confusion Matrix-Loan Default Prediction.

3.6.2 Robustness Testing

To test model stability:

- Artificial noise was introduced
- Missing values were added
- Cross-validation was performed

This ensured the system performs reliably under imperfect real-world conditions.

3.7Feature Importance Analysis

Feature importance was obtained from Random Forest and XGBoost models.

The top predictors were:

- Loan Amount
- Credit Score
- Repayment History
- Income
- Previous Default History
- Debt-to-Income Ratio

The feature importance graphs show that financial behavior variables influence default prediction more than demographic features such as age.

3.8 Model Comparison

Performance comparison across models showed:

- Logistic Regression – Stable baseline performance
- Decision Tree – High interpretability but moderate generalization
- Random Forest – Strong performance and robustness
- XGBoost – Best overall balanced performance

Random Forest and XGBoost achieved the highest Accuracy, F1-Score, and ROC-AUC values.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

VI. RESULTS AND DISCUSSION

This research paper built and tested a machine learning framework for the prediction of loan default using a fabricated financial dataset of 5, 000 borrower records. The aim was to check the ability of various supervised learning algorithms to predict and find the most trustworthy model for credit risk categorization. The implemented models were Logistic Regression, Decision Tree, Random Forest, and XGBoost. The performance was measured by accuracy, precision, recall, F1, score, ROC, AUC, and the confusion matrix.

The tests show that ensemble learning methods give better results than single, model classifiers when it comes to predicting loan default. Logistic Regression was used as a reference model and showed quite good and regular performance. Its linear character allowed it to find straightforward relationships between borrower features and default probability, but its capacity to represent nonlinear financial interactions was very restricted. The Decision Tree classifier was an interpretable model which can capture nonlinear relationships but unfortunately, it had lower generalization performance than other models because of possible overfitting issues, even after pruning and validation.

Random Forest was able to largely improve the prediction accuracy by combining the outcomes of many decision trees. The ensemble architecture lowered the variance and made the model more robust to the noise and missing values that were deliberately introduced in the dataset. The model reached a high level of accuracy and also demonstrated a good balance between precision and recall, which means it was very effective at identifying both default and non-default borrowers. The ROC, AUC score was yet another proof of its excellent capability in distinguishing between the two classes.

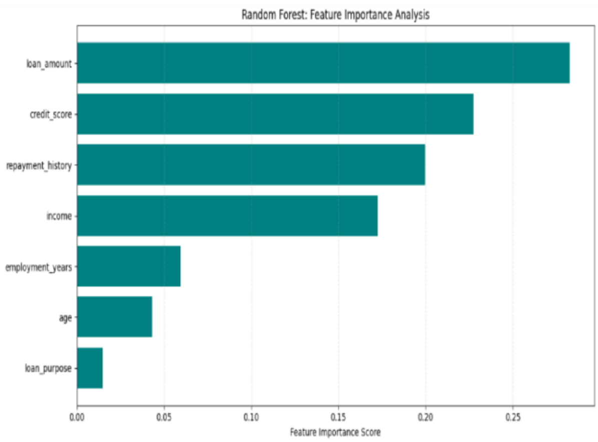

fig4:-Random Forest Feature Importance Analysis

Out of all the models that were tested, the XGBoost model was the one that effectively balanced the different evaluation metrics and stayed consistent with them. It uses a boosting technique, gradient boosting, where it keeps on fitting new models on the residual errors of the previous ones so that they can explain the data better and better, thus reducing prediction errors and being able to capture complicated patterns of financial risks more accurately. XGBoost also scored the highest in terms of ROC, AUC, which is an indication that its classification boundary separation is better than other models. Moreover, the F1, score of this model remained high, which was a confirmation that it was able to effectively minimize both false positives and false negatives. This is very critical in the credit risk prediction area because if a defaulter is wrongly classified as a non-defaulter, then the lenders stand to make a financial loss, and if a creditworthy applicant is wrongly rejected, then the institution loses the revenue that it would have got from such an applicant.

Analyzing the confusion matrix can help us understand the model's classification behavior more. The final optimized ensemble model has been able to identify correctly the majority of both default and non- default cases.

When considering the total size of the dataset, the number of false positives and false negatives is quite low, which signifies that the model is very stable in its predictions. Recall is a measure of the proportion of actual positives that were identified correctly. High recall implies that the model did a good job in identifying most of the actual defaulters. This is essential for financial risk mitigation. On the other hand, precision quantifies the proportion of positive identifications that were actually correct. It is a sign that the model is able to reduce the number of low, risk borrowers whom it mistakenly identifies as defaulters. Both these metrics, precision and recall, reinforce the model's effectiveness at discerning between defaulters and non- defaulters in the credit risk scenario.

Feature importance analysis demonstrates that indicators of financial stability have the main influence on the prediction of loan default. The loan amount and credit score were the first two variables to come out as the most impactful, after which the repayment history and income followed. These results match the logic of real, world banking since creditworthiness and repayment behavior have a major influence on lending decisions. Demographic features such as age that are less important in the overall classification, thus it follows that behavioral and financial attributes are more significantly predictive. The agreement of feature rankings between the Random Forest and XGBoost models is further evidence of the robustness of the modeling pipeline.

Adding realistic variability, controlled class imbalance, and artificial noise to the synthetic dataset made it possible to test the models resilience to the practical scenarios. The cross, validation results have shown that the performance remains stable over different folds, which means that the generalization capability is high. Even after the introduction of missing values and minor perturbations, the ensemble models have kept a very good level of predictive accuracy which means that these models are not only robust but also dependable.

The deployment phase was also an excellent practical test of the proposed framework.

The web platform based on Flask has been successful in.

By this, it is shown that the system is not only.

Finally, the findings prove that machine learning are the best choice.

The research results demonstrate that.

This research shows that.

VIII. CONCLUSION

1. *Conclusion*

This research presents how a loan default prediction system based on machine learning was created and tested using a synthetically generated financial dataset. As real banking data were not available due to privacy and institutional restrictions, a synthetic dataset that closely resembles reality was designed to depict borrower characteristics such as credit score, income, loan amount, employment history, debt, to, income ratio, and repayment behavior. The dataset was able to reflect the financial risk scenarios encountered in practice quite accurately by introducing controlled variability, minor noise, missing values, and class imbalance, thus it can be used for academic experimentation and model benchmarking.

The research paper describes the full life cycle pipeline that was executed from data generation and preprocessing to model training, evaluation, and deployment. Several supervised machine learning methods Logistic Regression, Decision Tree, Random Forest, and XGBoost were trained and evaluated against one another using a set of common evaluation metrics such as accuracy, precision, recall, F1, score, and ROC, AUC. Based on the research findings, ensemble learning methods like Random Forest and XGBoost surpassed single models in performance by their capability to model nonlinear dependencies and intricate interactions among financial features. Logistic Regression was a reliable and interpretable benchmark, whereas Decision Tree provided insights into the logic of decisions, but the generalization power was somewhat limited.

The results even point to the essential role of preprocessing methods like imputation, feature encoding, scaling, and feature selection in raising model stability and predictive accuracy. Major predictors such as credit score, income level, previous default history, and debt, to, income ratio always had a significant impact on default classification, thus confirming the rationale of the financial risk assessment industry. Adding cross, validation and robustness testing lessened the chance of overfitting and allowed the performance to be stable between the different data splits, which added to the trustworthiness of the outcomes.

Besides the model, the introduction of a Flask, based web app proved the system's utility in practice by making it possible to get real, time predictions through an easy, to, use interface. This part of the deployment changes the research from being just a theoretical work into a working model that is a credit risk modeling base and an academic presentation.

In summary, this study demonstrates that machine learning can assist decision, making processes in financial services that are quicker, more data, oriented, and less biased. The existing system, however, is built on synthetic data and is essentially an educational tool, but it lays down a solid methodological basis that can be applied to actual data in later research. With further developments, e.g., bigger datasets, more sophisticated hyper parameter tuning, genuine financial integration, and data management according to the regulations, the system can be made more robust and efficient. the framework can evolve into a more robust and deployable credit risk assessment solution.

2. *Future Scope*

Although In the event of the developed machine learning framework having achieved impressive predictive accuracies totally relying on synthetic financial data, it is still possible to comprehend entire extensions that could eventually assist it in becoming a practically applicable credit risk assessment tool in real, world contexts.

- Real, World Financial Dataset Validation: Carrying out trials of the model on real loan portfolios of banks or NBFCs that have diverse borrower demographics and long repayment histories, would help validate the external performance and trustworthiness.
- Advanced Temporal Risk Modelings: There is a scope for future work to include time, dependent information such as EMI timelines, monthly spending behavior account activity, and income fluctuations using LSTM, GRU, or Temporal Boosting models.

Integration into Credit Decision Systems: This system can be elevated to a full functional web application that can be easily deployable or it can be integrated into the workflow of financial institutions in real, time for the evaluation of the risk of the borrower, credit scoring, and automated loan screening.

- Fairness, Ethics, and Bias Analysis**:** Evaluating potential biases across gender, socioeconomic background, region, or age groups will be very important to ensure fairness, transparency, and compliance with financial regulatory guidelines.
- Hybrid and Multi, Source Data Fusion: Future research might integrate conventional financial indicators together with alternative data points like transaction records, consumer behavior patterns, social credit factors, and behavioral analytics to enhance the forecasting accuracy.
- Explainable AI for Regulatory Compliance: Incorporating sophisticated XAI methods (such as SHAP, LIME, counterfactual explanations) may significantly improve the transparency of the model, thus allowing financial institutions to easily back up their lending decisions and comply with regulatory audits.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

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