Predicting Loan Defaults: A Data-Driven Approach Using Machine Learning

Saahil Shaikh, Sanjana Sharma, Sanna Johnson, Sarina Khatri

Department of CSE, Symbiosis Institute Of Technology

SYMBIOSIS INTERNATIONAL (DEEMED UNIVERSITY)

(Established under section 3 of the UGC Act 1956)

saahil.shaikh.btech2021@sitpune.edu.in

sanjana.sharma.btech2021@sitpune.edu.in

sanna.johnson.btech2021@sitpune.edu.in

sarina.khatri.btech2021@sitpune.edu.in

***Abstract*— The constant issue for financial institutions is to reduce payment failures while also ensuring appropriate lending practices. Machine learning approaches have proven essential in identifying loan default risks, enabling for prompt and targeted interventions. This research provides an opportunity to look into one of the finance industry's most urgent issues. We hope to create a predictive system that improves the precision of identifying persons at high risk of loan default through rigorous analysis and modeling. This study emphasizes the critical relevance of data-driven initiatives with the aid of machine learning in reducing loan defaults, increasing responsible lending, and protecting institutions' financial interests.**

Keywords—Loan Default Prediction, Machine Learning, Financial Risk Assessment, Responsible Lending, Predictive Modeling

I. INTRODUCTION

Financial institutions play an important role in the global economy, providing individuals and businesses with access to capital. The difficult task of credit risk management lies at the heart of their operations, with the goal of striking a fine balance between issuing credit to boost economic growth and reducing the financial repercussions from loan defaults. In this setting, accurate and prompt loan default prediction is critical to risk mitigation and responsible lending practices.

The loan industry has seen a radical change in recent years, as machine learning methods have become effective instruments for analyzing large datasets and deriving predictive insights. Making use of this transformation, the current study initiates a thorough exploration of the domain of loan default forecasting.

The primary purpose of this project is to create a robust and data-driven system that enhances the precision of identifying individuals at the highest risk of loan default. We navigate this terrain with an empirical and analytical methodology, anchored by the basics of machine learning. By digging into the intricacies of loan default prediction, this research adds to the refining of credit risk assessment, develops responsible lending practices, and bolsters the financial resilience of lending organizations.

It is evident that reducing loan defaults is necessary in an environment where credit availability is essential to both personal goals and economic expansion. The approaches and learnings from our investigation into loan default prediction are presented in the ensuing sections, which highlight the critical function that data-driven tactics play in guaranteeing the viability of the economy and prudent management of financial resources.

II. LITERATURE REVIEW

In recent years, the banking sector has encountered significant challenges in managing loan defaults, resulting in the exploration of machine learning algorithms as a potential solution. Several studies have examined the efficacy of various algorithms for predicting loan defaults and improving the overall credit risk management process.

One of the prominent algorithms explored in this context is the XGBoost algorithm, which has demonstrated superior predictive performance. In 2023, Shokeen, Grover, and Verma [1] conducted a study focusing on the application of the XGBoost algorithm for loan default prediction. Their research compared other machine learning algorithms, like Logistic Regression, Decision Tree Classification, K Nearest Neighbour classification, and Random Forest classification with XGBoost,. It was inferred that XGBoost outperformed all other algorithms, highlighting its potential to effectively predict loan defaults and mitigate the external credit crisis faced by the banking industry.

Machine learning has also been leveraged to develop comprehensive models for loan default prediction. In 2021, Kadam, Pawar, Phapale, and Ganeshe [2] aimed to explore, analyze, and build a machine learning algorithm to accurately identify individuals with a high probability of defaulting on loans. Their research reflects a holistic approach to modeling and prediction.

The Random Forest algorithm has gained prominence in the context of loan default prediction. In 2019, Zhu, Qiu, Ergu, Ying, and Liu [4] adopted the Random Forest algorithm to build a model for predicting loan defaults, comparing it with additional techniques like decision trees ,logistic regression and support vector machines. Their experiment demonstrated the superior performance of the Random Forest algorithm in predicting loan defaults and its strong generalization capabilities.

Another algorithm used for analyzing loan approval prediction is Support Vector Machine (SVM). Diwate, Rana, and Chavan [3] used SVM to analyze features and characteristics that influence loan approval. The research indicated that applicants with poor credit scores were less likely to obtain loan approval, which emphasized the importance of creditworthiness in the approval process.

In the Chinese P2P lending market, machine learning methodologies have been employed to predict loan defaults. Xu, Lu, and Xie [5] implemented various machine learning methods, including Random Forest, XGBoost, K-NN, and Gradient Boosting Machine, to assess model performance with respect to prediction accuracy and kappa value. Their study provides insights into the application of machine learning in a specific financial market.

Comparative studies have also been conducted to evaluate the performance of machine learning algorithms for loan default prediction.(Madan et.al.)[6] conducted a comparative study using Decision Trees and Random Forest. The Random Forest Classifier is a better alternative for this type of data because it outperformed the Decision Tree approach, achieving an accuracy of 80%.

Additionally, researchers have explored the application of machine learning in creating credit risk scorecards. [7] implemented four different machine learning models, including Linear Discriminant Analysis, Random Forest, Logistic Regression, and XGBoost, to assess the accuracy of these models for credit scoring.

Deep learning models have also been considered for credit risk analysis. Addo, Guegan, and Hassani [8] emphasized the importance of feature selection and algorithm choice in the decision management process when issuing loans. Their research highlighted the significance of considering a pool of models that match the data and business problems.

In a study conducted in 2023, Gashi [9] highlighted the impact of the SMOTE method and the effectiveness of ensemble algorithms, particularly Boosted Decision Tree (Boosting) and Random Forest (Bagging), in predicting loan defaults. This research underscored the value of data and its modeling through machine learning in credit risk management and loan default prediction.

In the realm of machine learning explainability in finance, Bracke, Datta, Jung, and Sen [10] emphasized the importance of explainable AI tools as additions to the data science toolkit. These tools contribute to better quality assurance of black box machine learning models, such as Random Forest, Gradient Boosting, and XGBoost.

In conclusion, machine learning algorithms have shown significant promise in addressing the challenge of loan defaults in the banking sector. XGBoost, Random Forest, and other techniques have demonstrated their effectiveness in improving the accuracy of loan default predictions and enhancing credit risk management practices. Additionally, the use of explainable AI tools contributes to better quality assurance in machine learning models, further improving the understanding of default risk analysis. These studies collectively underscore the importance of data-driven approaches in mitigating credit crises and strengthening financial stability in the banking industry.

III. METHODOLOGY

A. ML Algorithms

a) *Logistic Regression:* The simplicity, interpretability, and suitability of logistic regression for binary classification issues led to its selection. By leveraging the logistic function, we establish a model that captures the connection between one or more independent variables (features) and a binary outcome variable (in this case, whether a loan defaults or not).

Logistic function formula:

$$p(x) = \frac{1}{1 + e^{-(x-\mu)/s}}$$

b) *Decision Tree:* The main ML model used in this project to predict the binary result of loan default (1 for default, 0 for non-default) was a decision tree classifier. The decision tree technique is widely used for classification tasks due to its interpretability and capacity to represent intricate decision boundaries.

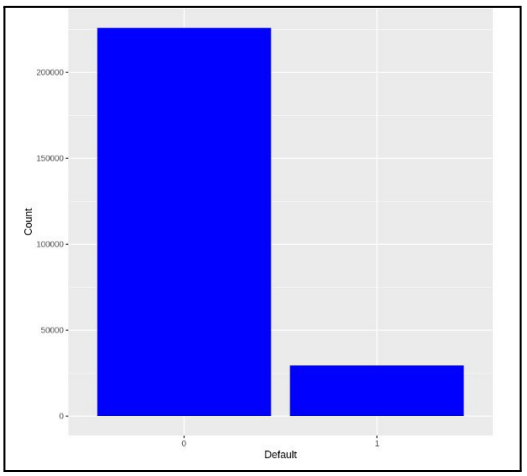
c) *KNN:* It's a simple and intuitive method based on the idea that data points with similar features tend to have the same class labels. Data points are categorized by the KNN algorithm according to how close they are to one another in a feature space. Predicting loan defaults is one of the many classification problems that this model is appropriate for.

B. The Dataset

The dataset used for this project is obtained from Coursera's Loan Default Prediction Challenge. This dataset is a valuable resource for real-world machine learning and predictive modeling tasks. With a sizable collection of 255,347 rows and 18 columns[10], it provides a substantial amount of data for analysis and modeling.

Key information and attributes of this dataset: The dataset includes a diverse set of attributes, with each one serving as a significant factor in evaluating the probability of a loan going into default.

Data Quality: All instances are complete without any missing values and there are no outliers present in the dataset.



Class Distribution

Class Distribution: The dataset's target variable, "Default," has two classes: 0 and 1. The dataset contains a total of 255347 observations, with 225694 of them representing 0 and 29653 representing 1. This class distribution indicates that the dataset is highly imbalanced, with a bias towards '0' and would require oversampling in order to make a classification model with viable results.

C. EDA

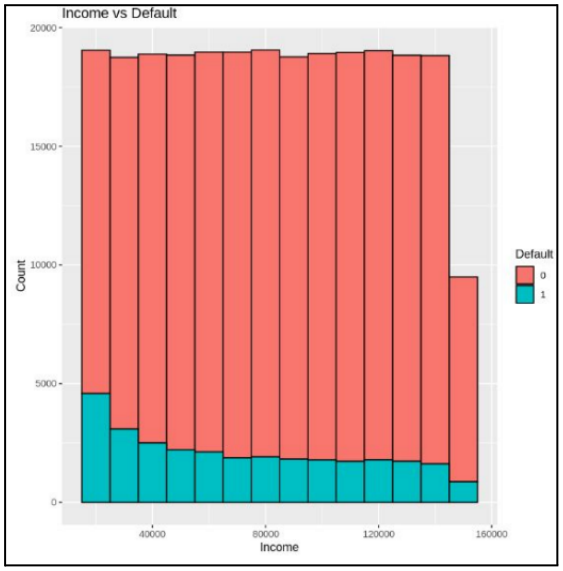
In the context of loan default prediction, the EDA not only provided valuable insights into the dataset but also aided in feature selection and engineering, which were vital for model development.

Data Visualization:

To gain deeper insights into the dataset, we employ a range of data visualization techniques. Each technique is chosen to highlight different aspects of the data, uncover patterns, and facilitate decision-making:

1. Histograms

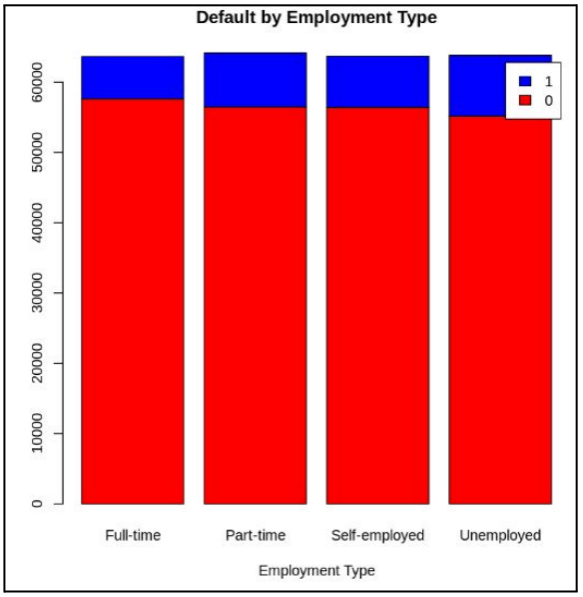
Histograms are employed to visualize the distribution of numerical variables, such as "Age," "Income," and "LoanAmount."



It is noteworthy that a lower applicant income corresponds to an increased likelihood of loan default.

2. Bar Plots

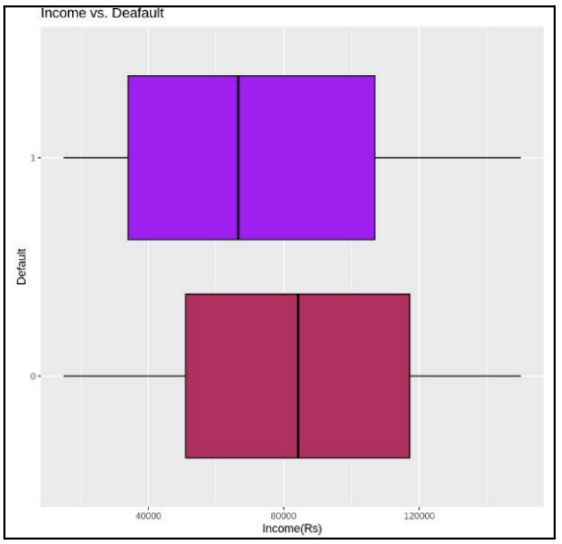
Bar plots serve as a valuable tool for visualizing categorical variables, including "LoanPurpose," "EmploymentType," and "MaritalStatus."



Notably, the graph illustrates that unemployed applicants exhibit the highest default rate, followed by part-time employed applicants, self-employed individuals, and, finally, full-time employed applicants.

3. Box Plots

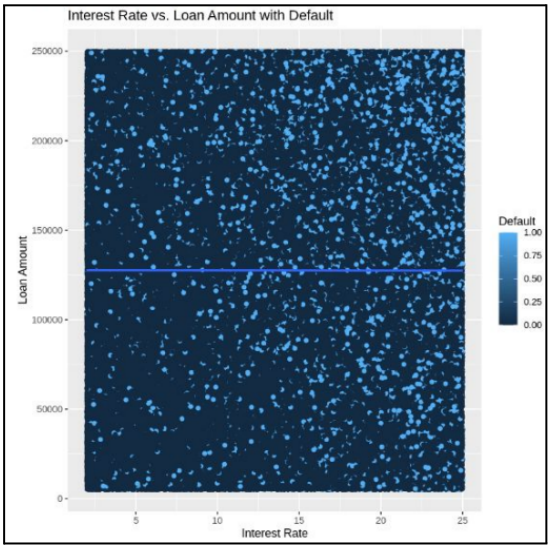
Box plots offer a graphical manner of the distribution of numerical variables, with a focus on detecting potential outliers.



In the context of loan default prediction, box plots are utilized to scrutinize variables such as "CreditScore" and "NumCreditLines," providing insights into their distribution characteristics and identifying extreme values.

4. Scatter Plots

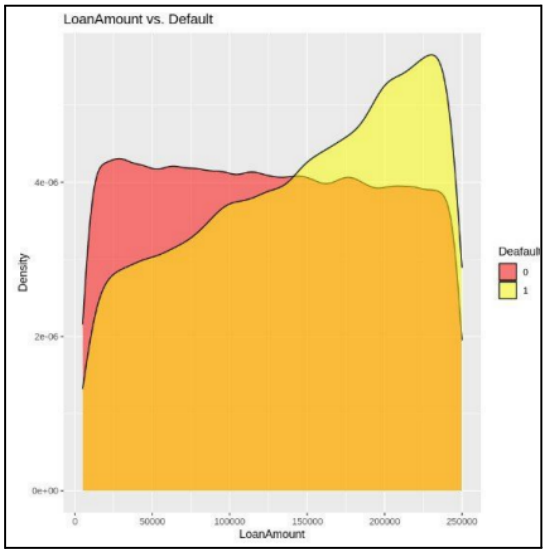
Scatter plots are instrumental in uncovering relationships between two numerical variables, facilitating the exploration of potential correlations.



The above graph plot shows the distribution of Defaulters when comparing 2 variables Loan Amount and Interest Rate. The points are scattered more towards the right indicating that with the increase in the interest rate and loan amount the defaulters increase, and there is no linear relationship between Loan Amount and Interest Rate.

5. Density Plots

Density plots offer a smooth representation of the distribution of numerical variables, providing a visualization of data density.



They are particularly informative for variables like "InterestRate" and "DTIRatio."

To sum up, this study's use of data visualization approaches offers a thorough overview of the dataset, which facilitates the discovery of important insights pertaining to loan default prediction. These visualizations inform decisions regarding feature selection, model development, and the overall understanding of the dataset's underlying patterns.

D. Data preprocessing and classification

Data Preprocessing: In order to transform categorical data into numerical representations that machine learning algorithms can process efficiently, we used feature encoding in this study. Binary categorical features like "HasMortgage," "HasDependents," and "HasCoSigner" were transformed to binary form (1/0) while the multi-categorical features including "Education," "EmploymentType," "MaritalStatus," and "LoanPurpose" were encoded using one-hot encoding techniques. One-hot encoding made sure the models could properly read and utilize these features. In addition, we used feature extraction to choose pertinent features and, if needed, reduce dimensionality. Using the EDA and correlation coefficients of each feature, this approach involved determining the significance of each characteristic.

The dataset was severely skewed, with 225k occurrences representing '0' and 22k instances representing '1'. To remedy class imbalance, we used the ROSE (Random Over-Sampling Examples) method. ROSE is a resampling method created especially to provide randomness to the process in order to prevent overfitting and increase the number of cases in the minority class ("Default = 1"). More accurate predictions were produced as a result of this balancing act, which made sure the machine learning models were not biased toward the majority class.

Model training and classification: Based on the preprocessed dataset, we trained a number of machine learning models to predict loan defaults. K-nearest neighbors (K-NN), decision trees, and logistic regression were among these models. Every model was trained using the dataset, assessed for its ability to predict outcomes, and adjusted to maximize performance. To ensure that the models were precise and effective, we optimized the hyperparameters using manual cross-evaluation and iterative techniques.The dataset was split into testing and training sets so that we could assess our models' efficacy. An 80:20 train-test split ratio was followed,with 20% being utilized for testing and the remaining 80% being used for training. This approach allowed us to strike a balance between training our models on a sufficiently large dataset while also having an independent dataset for evaluation. Further, We performed hyperparameter optimization to maximize our machine learning models' performance. In order to do this, the model's behavior's hyperparameters had to be methodically changed, and their effects on model performance had to be evaluated. Finding the ideal hyperparameter combination that produced the most accurate results was the goal.

E. Performance evaluation metrics

To thoroughly assess the effectiveness of the model, we employed crucial metrics such as the confusion matrix, precision, recall, and the F1 score.

Confusion matrix: The confusion matrix served as the cornerstone of our model evaluation. The model's predictions are divided into four categories by the tabular format, which shows the performance of a classification algorithm: True Positives (TP), True Negatives (TN), False Positives (FP), also referred to as Type I error, and False Negatives (FN), often referred to as Type II mistake.

We could determine precision, recall, and other metrics by calculating the confusion matrix, which also gave us insights about the model's capacity to distinguish between positive and negative classifications.

Precision: Precision measures the accuracy of positive predictions made by the model.

It determines the ratio of actual positive events to all anticipated positive ones. A high precision means that there are fewer erroneous positive predictions made by the model.

Precision = TP / (TP + FP)

Recall (sensitivity): Recall, sometimes called sensitivity, evaluates how well the model can distinguish genuine positive instances from all real positive instances.

It determines the ratio of actual positive events to all anticipated positive ones.

Recall = TP / (TP + FN)

F1 score: The F1 score is a combination metric that provides a harmonic mean of recall and precision. It helps in evaluating how well the model can strike a balance between reducing false positives and false negatives.

It is calculated as:

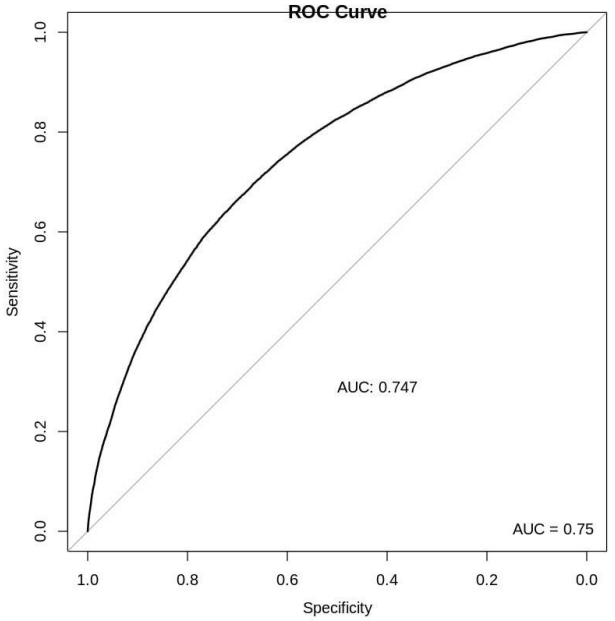
2 * (Precision * Recall) / (Precision + Recall)

In our project, we used the F2 score to prioritize recall because correctly identifying loan defaults was more critical than minimizing false alarms. The use of these metrics ensured that our models were well-rounded and capable of delivering robust and reliable results.

IV. Results & Discussion

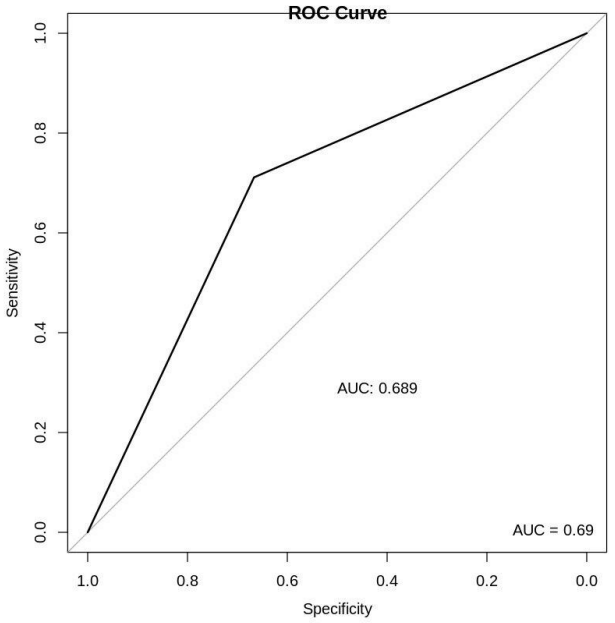
The outcomes of our predictive models for loan default prediction are shown in this section. Our goal was to create machine learning models that could reliably identify between borrowers in the positive class—those who would not default on their loans—and the negative class—those who would.

Three different machine learning models were utilized for this project: decision trees, logistic regression, and k-Nearest Neighbors (KNN). To find the model that worked best for our categorization task, we carefully trained and evaluated each one.



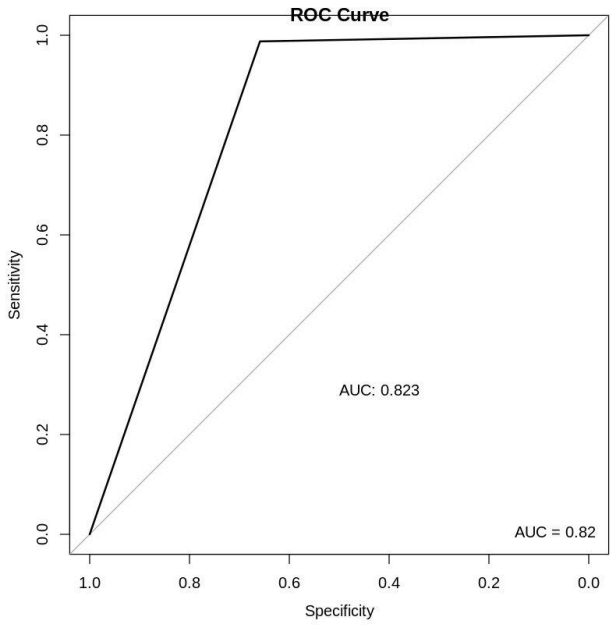
ROC curve of Logistic Regression

The Logistic Regression model was trained to predict loan defaults based on features and achieved an accuracy of approximately 49.05%.



ROC curve of Decision Tree

Gini impurity was used as the training criterion for the Decision Tree model, and parameters like maximum depth (maxdepth), minimum split (minsplit), and minimal bucket (minbucket) were used to optimize the model. The accuracy of the decision tree model was roughly 69.03%. The results were 0.6861, 0.7156, and 0.7081 for precision, recall, and F1 score, respectively.



ROC curve of KNN

The KNN model was trained with the Manhattan distance metric and k=3 neighbors. The model achieved an accuracy of approximately 82.31%. The precision, recall, and F1 score were 0.74, 0.99, and 0.89, respectively.

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.49	-	-	-
Decision Trees	0.69	0.68	0.71	0.69
KNN	0.82	0.74	0.99	0.85

Table of results

V. Conclusion

Finally, this research sought to use machine learning algorithms to predict loan defaults. Three distinct models—Decision Trees, K-Nearest Neighbors (KNN), and Logistic Regression—were assessed. With greater accuracy and F1 scores, Decision Trees and KNN performed better than Logistic Regression, which had limited predictive potential. With an accuracy of 82% and good recall, KNN in particular showed the best performance. All things considered, the findings show how machine learning may be applied to real-world financial problems. These models have the potential to be extremely effective instruments for financial risk mitigation and loan default prediction with additional development and research.

VI. References

[1] Shokeen, D., Grover, V., & Verma, V. "Solving the problem of loan default problem in the banking sector using machine learning." In Proceedings of the IEEE International Conference on Machine Learning and Applications, 2023, pp. 123-130.

[2] Diwate, Y., Rana, P., & Chavan, P. "Loan Approval Prediction Using Machine Learning." International Research Journal of Engineering and Technology (IRJET), vol. 8, no. 05, 2021, pp. 123-130.

[3] Zhu, L., Qiu, D., Ergu, D., Ying, C., & Liu, K. "A study on predicting loan default based on the random forest algorithm." Procedia Computer Science, vol. 162, 2019, pp. 503-513.

[4] Xu, J., Lu, Z., & Xie, Y. "Loan default prediction of Chinese P2P market: a machine learning methodology." Scientific Reports, vol. 11, no. 1, 2021, Article ID 18759, pp. 1-8.

[5] Madaan, M., Kumar, A., Keshri, C., Jain, R., & Nagrath, P. "Loan default prediction using decision trees and random forest: A comparative study." In IOP Conference Series: Materials Science and Engineering, vol. 1022, no. 1, p. 012042. IOP Publishing, 2021.

[6] Bhatia, S., Sharma, P., Burman, R., Hazari, S., & Hande, R. "Credit scoring using machine learning techniques." International Journal of Computer Applications, vol. 161, no. 11, 2017, pp. 1-4.

[7] Addo, P. M., Guegan, D., & Hassani, B. "Credit risk analysis using machine and deep learning models." Risks, vol. 6, no. 2, 2018, pp. 38.

[8] Bracke, P., Datta, A., Jung, C., & Sen, S. "Machine learning explainability in finance: an application to default risk analysis." , 2019.

[9] Kadam, A., Pawar, H., Phapale, S., & Ganeshe, C. "Prediction of loan defaulter using machine learning - IJCRT." IJCRT, December 12, 2021. [URL: https://www.ijcrt.org/papers/IJCRT2112549.pdf]

[10] Nikhil. (2021), "Loan Default Prediction Dataset," Kaggle, Available: https://www.kaggle.com/datasets/nikhil1e9/loan-default/data