Transforming Financial Lending: A Scalable Microservices Approach using AI and Spring Boot

Bhushan Chaudhari[1]; Santhosh Chitraju Gopal Verma[2]; Srinivasa Rao Somu[3]

[1,2,3]Independent Researcher

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Abstract

The financial services sector has seen substantial transformation in recent years due to the use of microservices architecture, artificial intelligence, and other modern frameworks. Loan default prediction and fraud detection problems in financial lending processes now receive solutions through the use of artificial intelligence (AI) and machine learning (ML) techniques, since lenders want more secure, scalable, and improved systems. The proposed method details the complete implementation of a financial lending system transformation through AI while supporting it with Spring Boot microservices infrastructure. The research utilizes the Lending Club Loan Dataset, containing more than 100,000 loan records, to apply ML models for loan default prediction while improving lending decision-making. The research design applies important preprocessing methods that use ANOVA feature selection alongside methods to impute missing values and eliminate outliers to guarantee data reliability. The model used Logistic Regression (LR) because of its straightforward nature as an effective tool for binary classification operations. The performance metrics of the LR model showed outstanding results, reaching 93% accuracy and equal precision and recall ratings at 93%, besides an F1-score value of 92%. The LR model provided better predictive capabilities than the competing alternatives, which included Boost, Decision Tree (DT), and Gradient Boosting. Microservices architecture combined with AI and ML demonstrates great promise in transforming financial lending operations because it enables better and faster decision-making as well as operational efficiency and scalability.

***Keywords**: Microservices Architecture, Spring Boot, Financial Services, Agility, Scalability, Modular Approach, Inter-Service Communication, Containerization, Distributed Transactions, Machine Learning (ML).*

I. INTRODUCTION

Implementing AI and DL technology has significantly changed financial systems today, revolutionizing algorithmic trading applications, fraud detection systems, and credit score analysis. Financial services need IT solutions that display adaptable characteristics along with scalable and resistant architecture because the industry evolves at a fast pace. Monolithic traditional application architectures face difficulties meeting modern business requirements of financial services since they need quick market adjustment coupled with strong performance and constant availability [1]. Financial companies may benefit from microservices design, which transforms big systems into deployable, autonomous, and managed services [2]. Through well-defined APIs these services grant enhanced flexibility and scalability in addition to higher resilience because they can be developed independently from deployment to scaling distributed across multiple servers [3][4]The development process and deployment steps become easier when developers use Spring Boot as a Java application framework to complement their microservices approach[5]. This architecture system functions best in finance institutions because it helps them quickly adapt to market changes while supporting operational excellence [6]. The subfield of AI known as ML helps financial institutions analyze large datasets through its mechanisms for better forecasting operations [7][8]. Financial institutions require AI and ML solutions consistently because ML models demonstrate high value in resolving loan defaults, alongside issues with money laundering, identity theft, and credit card fraud [9].

A financial lending system can be transformed through the application of a microservices architecture with AI capabilities running on top of the Spring Boot framework [10]. Financial organizations may improve their fraud detection systems and loan default forecasts while streamlining loan administration by combining ML models with a versatile Spring Boot microservices architecture [11] This approach improves operational efficiency and security, managing the expanding financial sector complexities and competitive challenges.

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➢ *Motivation and Contribution of the Paper*

This research project's primary goal is to use AI models in conjunction with a scalable microservices architecture to produce financial lending projections that are more accurate and efficient in terms of time. Traditional risk models in lending processes face two major challenges when dealing with big, varied datasets and applying advanced prediction analysis in field operations. The research uses LR, ML together with the microservices framework built on Spring Boot to develop a predictive solution set for loan defaults, which leads to both precise outcomes and smooth deployment possibilities in operational contexts. The method leads financial services to make efficient and dependable decisions at higher speeds while minimizing risks in digital lending operations. There are three main contributions within this work:

- *Effective Preprocessing Framework for Loan Data*

A full data preprocessing framework demonstrated in the study includes removing incomplete loan records with non-terminal decisions alongside managing missing data and outlier points, and using ANOVA to enhance data quality, which produces results applicable to additional financial information sets.

- *Balanced Classification Through Under-Sampling*

The study illustrates the effective handling of class imbalance by selecting under-sampling compared to oversampling methods in large datasets to retain authentic data while enhancing model practicality and stability.

- *High-Performance Logistic Regression Model*

An improvement over more complex models like Gradient Boosting, DT, and Boost by the suggested LR model (93% accuracy, precision, and recall) demonstrates that simpler, interpretable models are capable of producing top-tier outcomes in financial risk prediction.

- *Thorough Evaluation Using Multiple Metrics*

A complete model performance evaluation system that takes into account both Type I and Type II mistakes for financial decision making is made possible by a variety of performance metrics such ROC-AUC, F1-score, confusion matrix, recall, accuracy, and precision.

- *Integrated AI Deployment Pipeline*

The framework merges Python, which develops models, with Spring Boot for deployment, which provides practical guidelines to apply AI-based financial predictions in actual business applications.

➢ *Justification and Novelty of the Paper*

This project delivers novelty by using AI feature selection along with the Spring Boot deployment framework in a single integrated solution to modernize traditional lending operations in finance. Statistical significance plays a vital role in ANOVA-based feature selection methods, which improves both the accuracy levels and the computational efficiency of the model. The under-sampling technique resolves the class imbalance problem that often occurs in financial datasets. The implementation of the LR model, known for its transparency and ease of interpretation, aligns with the need for explainable AI in financial decision-making. Leveraging Spring Boot further enhances the practicality of the solution by enabling scalable and efficient deployment in real-world environments. This comprehensive and modular pipeline not only improves predictive performance but also supports automation and real-time decision support in lending systems, justifying its relevance and applicability in modern financial technology.

➢ *Structure of Paper*

Here is how the rest of the paper is structured. Sections I and II provide a background study on Transforming Financial Lending Prediction Using AI and Spring Boot. In Section III, the methodology is detailed. The findings, analysis, and discussion are contrasted in Section IV. The study's findings and future research ideas are presented in Section V.

II. LITERATURE REVIEW

A few significant studies on the topic of financial lending transformation. The present work is filtered and examined using AI and Spring Boot.

Sevidzem Simo Yufenyuy (2024) emphasizes using machine learning techniques to analyses credit risk. The Kaggle database was used to derive secondary data on borrower information that mirrored Credit Bureau data. This study used two ensemble models: gradient boosting and random forest. The results indicated that the income of the borrower, the proportion of income allocated to loan repayment, and the interest rates on loans are the most crucial factors in identifying defaulters. Additionally, the assessment findings showed that the gradient boosting technique and the random forest approach both performed well, with F1 scores of 93% and 92.9%, respectively. It was suggested that financial organizations give verification and completeness of data top priority since accurate data is necessary to create robust models [12].

Sharmila et al (2024). Although overfitting and underfitting restrict these algorithms, it has been proposed that Gaussian NB or LR affect bank loan acceptance. The decision tree approach also makes things easier to read and understand. The decisions produced by the DT classifier facilitate the likelihood that a loan will be approved. Despite these limitations, a DT classification system can be a helpful tool for predicting whether a bank loan application will be approved or denied. According to the trial results, the proposed model decision tree classifier achieves 95% accuracy with a 0.09% loss. In the busy corporate world of today, this study offers a potentially helpful technique for forecasting bank loan acceptance [13].

Lakshmanarao et al (2023) developed a method that employs ML and DL models to forecast loan default. Information on loan failures from Lending Club is used in this paper. Several data preparation techniques are applied to the dataset, and the resulting preprocessed dataset is produced. Later, four machine learning algorithms were proposed: feed-forward neural networks, DT, RF, LR, and K-NN. The suggested feed-forward neural network demonstrated an outstanding 99% prediction accuracy for loan defaults, according to the experimental data [14].

Paul (2022) aims to incorporate and leverage the banking ecosystem's IoT and ML business model using a neuro-fuzzy tool. Cybersecurity, digital marketing, offline customer interaction tactics, advisory boards, quality control, product research, and collaborative recruiting or external service outsourcing are all covered in the business model. To leverage the promise of IoT and ML, banks need to reconsider their business model. The bank makes money and discovers new methods to offer pre-approved loans with its products the use machine learning. Customers who can be provided with any financial product will be recommended by IoT and ML. Offerings of this nature will provide banks and their sister companies access to new revenue streams. It will also aid in the elimination of bad debt. 957 random data points are input into the machine learning model, which operates effectively on the Python platform with an accuracy level of 73.5% [15].

Ranjani (2021) examines key design principles that make it easier to create scalable microservices that are suited to the particular requirements of the financial services industry. The effectiveness of key patterns in maintaining system integrity during failures is examined, including the Circuit Breaker Pattern, which enhances fault tolerance, and Event-Driven Architecture, which permits real-time response to business events. Furthermore, by guaranteeing that every microservice maintains its own database, the Database per Service Pattern encourages loose coupling, which improves performance and lowers latency. In order to enhance user experience, the Backend for Frontend (BFF) pattern creates tailored APIs that exclusively support front-end apps, making it a crucial remedy [16].

Wu et al. (2022) The research study concentrated on agricultural supply chain finance (SCF) by conducting deep analysis of credit risk assessment. The research utilized GA in combination with BPNN and the SCRA framework. The accuracy of the Performance Comparison of Different Algorithms reached 70.1%. The GA-BPNN algorithm achieves better prediction results and faster computational speeds for agricultural SCF credit risk evaluation after being validated through experiments [17].

Li et al. (2020) A study evaluates XGB application as a solution for credit evaluation. The XGB model processes A realistic assessment of the Lending Club Platform's statistics for personal loans in the United States. The application of the XGB model was analyzed empirically to demonstrate its superior operations in choosing features, along with performance enhancements versus traditional analytics techniques, including LR and tree-based methods. The research obtained 0.9370 accuracy alongside Kappa at 0.7763 and AUC at 0.9481, and KS of 0.7700 [18].

Table I presents the background analysis of using AI and Spring Boot for Transforming Financial Lending, alongside its dataset information, along with performance assessment and contribution details.

Table 1 Overview of Recent Studies on Transforming Financial Lending Using AI and Spring Boot

Author	Proposed Work	Dataset	Key Findings	Challenges/Gaps
Sevidzem Simo Yufenyuy (2024)	Gradient Boosting and Random Forest are used in credit risk analysis	Kaggle - Simulated Credit Bureau data	Important characteristics include interest rates, borrowers' income, and income for loan repayment. F1 scores: 93% (GB) and 92.9% (RF)	Dependence on data quality; lacks real-world implementation
Sharmila et al. (2024)	Decision Tree Classifier for Predicting Bank Loan Approval	Kaggle Credit Bureau-simulated data	Decision Tree achieved 95% accuracy with 0.09% loss; overcomes overfitting/underfitting limitations of Linear Regression and Naive Bayes	Lacks comparison with more complex models; limited detail on dataset

Lakshmanarao et al. (2023)	Models using ML and DL to forecast loan defaults	Lending Club dataset	Achieving 99% accuracy, the Feed Forward Neural Network was evaluated alongside Decision Trees, Random Forests, Logistic Regression, and K-NN	Real-world generalization not validated; risk of overfitting
Paul (2022)	Business model using IoT and ML with neuro-fuzzy tool for banking	957 random data samples	Accuracy of 73.5%; ML helps pre-approve loans, reduce bad debt, and create new income sources	Modest accuracy; lacks large-scale validation
Ranjani (2021)	Design patterns for scalable microservices in financial services	957 random data samples.	Event-Driven, Circuit Breaker, BFF, and Database per Service patterns enhance responsiveness, fault tolerance, and system decoupling	No empirical model performance data; conceptual in nature
Wu et al. (2022)	Credit risk assessment in agricultural SCF using GA-BPNN and SCRA	Agricultural SCF dataset.	GA-BPNN achieved 70.1% accuracy; outperformed traditional algorithms in prediction speed and performance	Relatively low accuracy; needs broader dataset and context
Li et al. (2020)	Applying Extreme Gradient Boosting (XGB) to the assessment of personal loan credit	Lending Club platform data	XGB fared better than other tree models and logistic regression; 93.7% accuracy, 0.9481 AUC, 0.7700 KS, and 0.7763 Kappa	Comparisons limited to specific models; dataset scope may not reflect wider populations

III. RESEARCH METHODOLOGY

This project aims to construct an efficient ML model that will modernize financial lending processing operations. The system uses Spring Boot together with AI techniques to boost loan decision quality while optimizing procedures for loan approval. The first step of the financial lending transformation process starts by obtaining the Kaggle Lending Club Loan Dataset to create the analytical framework. The data collection phase takes place first before moving to a thorough preprocessing step to handle missing values and eliminate outliers in order to create consistent and quality data. ANOVA (Analysis of Variance) conducts feature selection to identify vital variables that influence the target outcome, which in turn improves model efficiency and reduces dimensionality of the data. A proportionate number of samples from the minority class are used through under sampling before separating the datasets for testing and training. The training data enables the creation of an LR model because of its interpretability and effectiveness for binary classification, including loan default prediction. The model's evaluation is based on a number of performance criteria, including the F1 score, which is used to determine prediction accuracy, recall, accuracy, and precision. The consolidation of results generates valuable information, which leads to enhanced financial lending decisions through intelligent decision-making practices. Figure 1 presents a flowchart that illustrates how AI with Spring Boot controls the implementation of the ML model to advance financial lending systems.

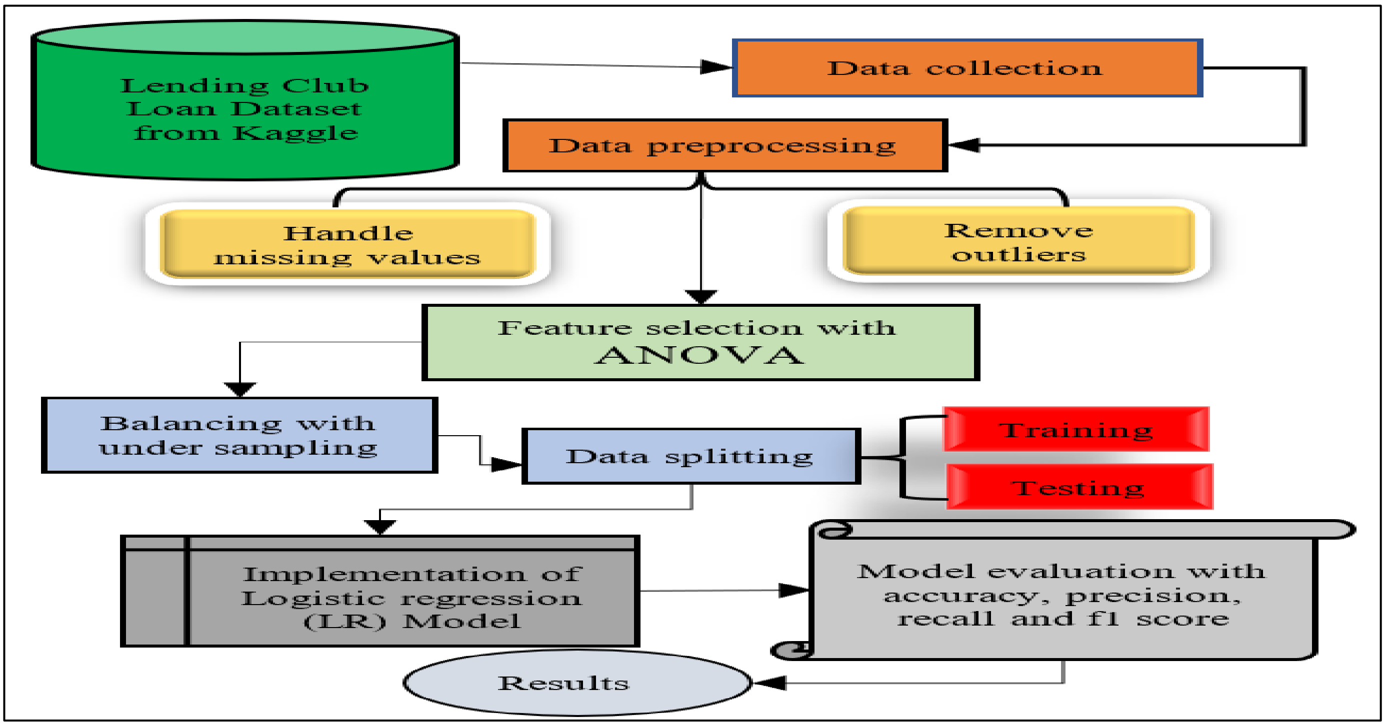

Fig 1 Proposed Flowchart for Transforming Financial Lending using AI and Spring Boot

Outlined below are the individual steps of the proposed flowchart for transforming financial lending

➢ *Data Collection*

This study utilized loan records from Lending Club, which initially included 100,000 records with a total of 151 features, consisting of 113 numerical and 38 categorical features. A thorough data cleaning and preprocessing process was applied, including the removal of irrelevant loan statuses such as 'Current' and 'Issued', which do not indicate final loan outcomes. Then, according to their repayment history, the loans were divided into "Good Loans" and "Bad Loans." Features with over 80% missing values, dynamically changing, or repetitive information were eliminated. Missing values in the remaining dataset were handled through imputation, and outliers were removed using customized thresholds to improve model accuracy, given the non-normal distribution of the data. The key target variable, 'loan condition', indicates loan quality, with 'Bad Loans' making up about 20% of the dataset, highlighting the precise default prediction's significance for financial lending risk management.

Table II is a partial description of the characteristics.

Table 2 Data Variable Description

Feature	Description
last_fico_range_high	The upper limit of the borrower's most recent FICO score.
last_fico_range_low	The lowest range that the borrower's most recent FICO report falls into.
annual_inc	The annual income that the borrower self-reported upon registering.
acc_now_delinq	The number of accounts that the borrower has yet to pay.
delinq_amnt	The loan balance that the borrower has fallen behind on.
last_pymnt_amnt	The most recent total amount paid.
total_rec_prncp	The principal has been received thus far.

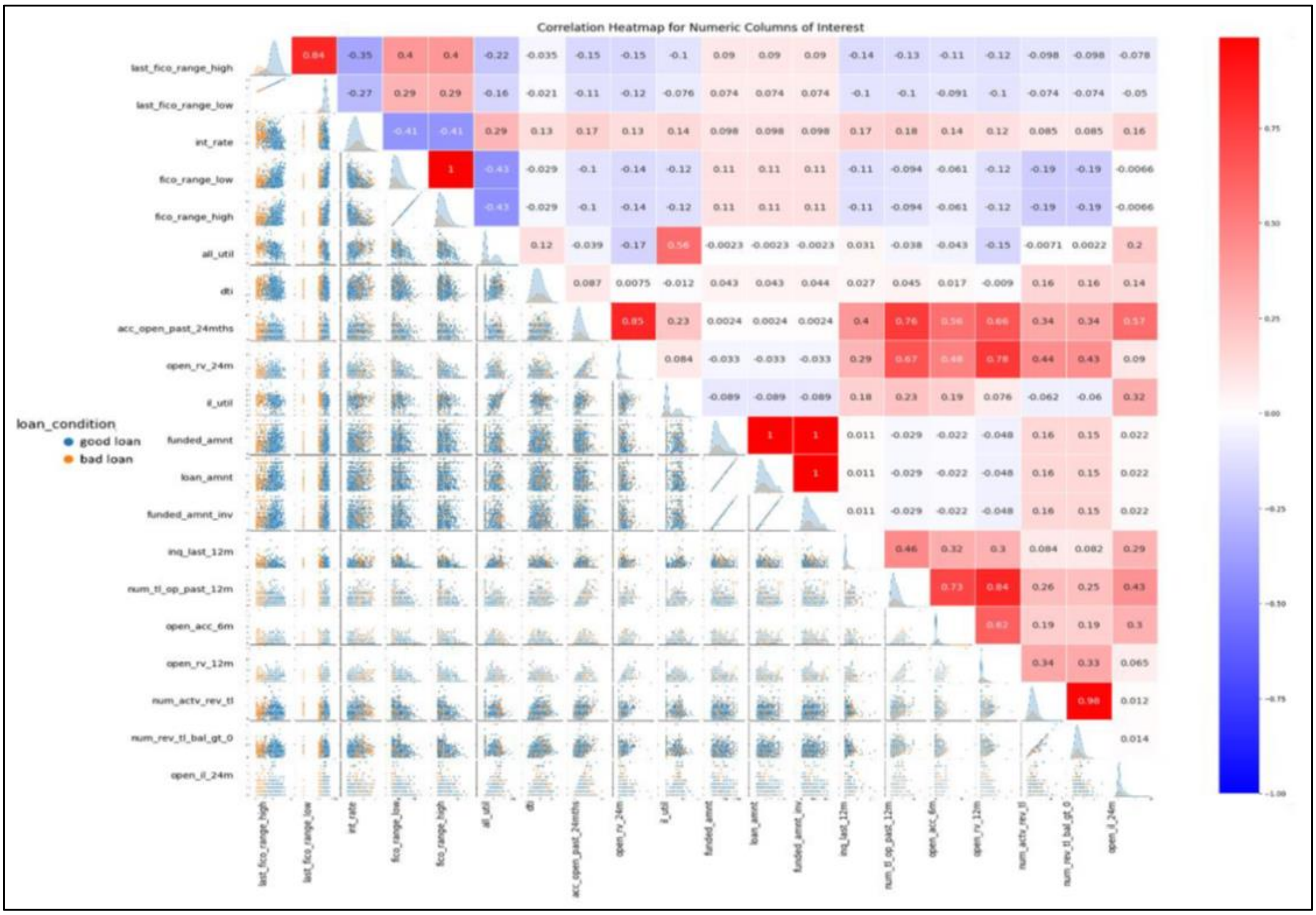

Fig 2 Correlation Analysis (Top 20 Variables)

Figure 2 depicts the Correlation heatmap with genomic data features plotted on both axes. It displays correlation coefficients through color intensity (red for positive, blue for negative) and includes small scatter plots in the lower portion to visualize relationships between variable pairs. Distribution histograms appear along the diagonal, creating a comprehensive visualization tool for identifying patterns and relationships across multiple genetic features.

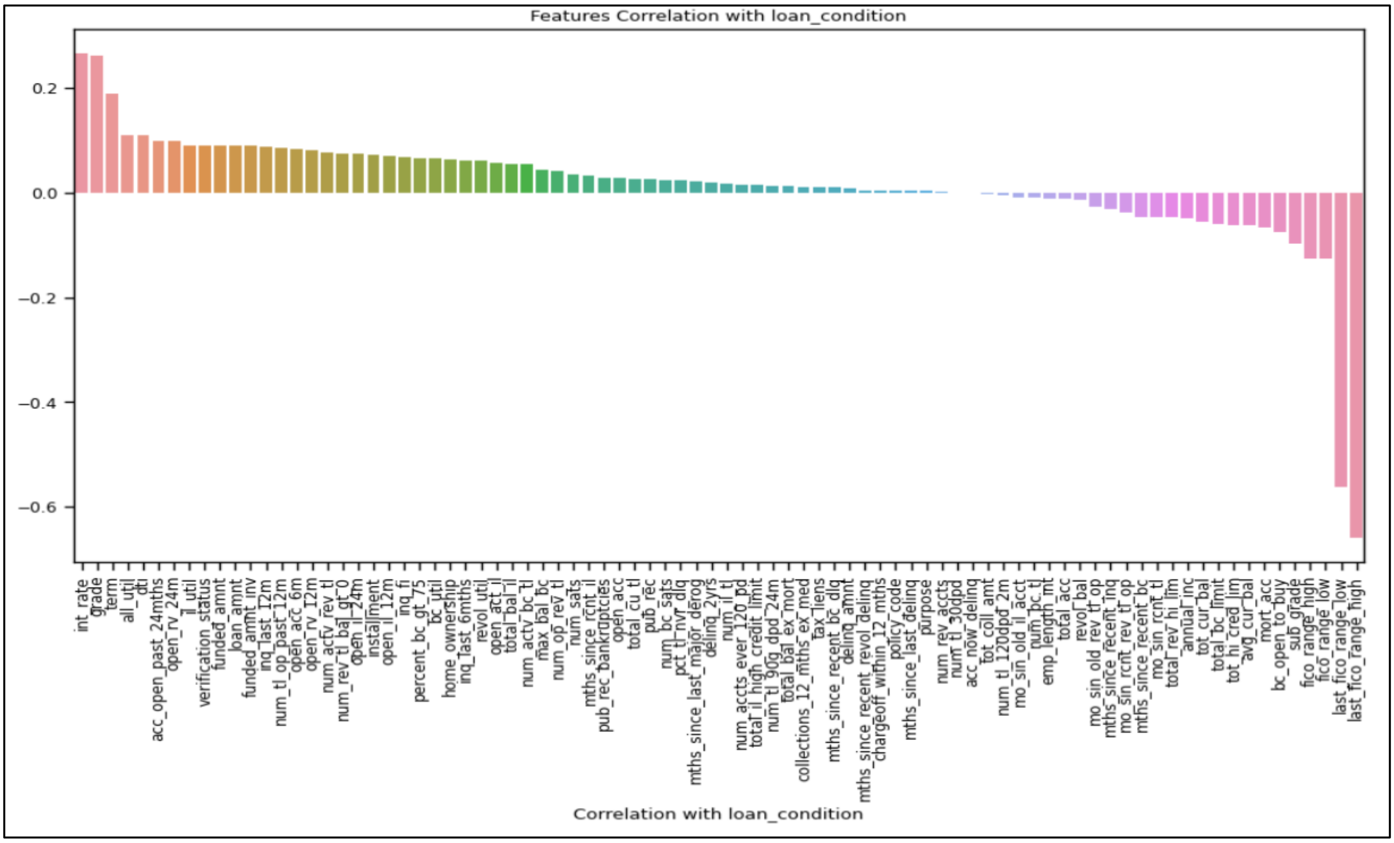

Fig 3Variable Importance to Loan Condition

Figure 3 shows a feature correlation bar chart displaying the relationship between various features and loan conditions. The chart uses color-coding (red to purple) to highlight correlation strength, with values ranging from approximately +0.7 (strong positive) to -0.6 (strong negative). Features are arranged in descending order of correlation, creating a visual ranking of which factors most strongly influence loan conditions.

➢ *Data Preprocessing*

A thorough data cleaning and preparation procedure was used to get the Lending Club dataset ready for analysis. This included eliminating exclusions, imputation of missing values, and outlier removal. The following steps of pre-processing are as follows:

- *Handle Missing Value:*

In order to handle missing values, one can use techniques such as KNN imputation or Instead, use the mode, median, or mean. An approach would be to remove rows or columns with an overwhelming amount of missing data. The method chosen depends on the data type and distribution to minimize bias.

- *Remove Outliers:*

The dataset contains several outliers, which might distort the results and alter the sample mean or variance.

➢ *Feature Selection with ANOVA,*

ANOVA-based feature selection requires ANOVA tests to investigate the relationship between features and categorical targets for choosing important attributes. The main aim of this process involves finding target-impacting features. ANOVA executes tests between different groups from a single feature by generating both F-statistic along with its p-value. Features that obtain p-values lower than 0.05 are considered statistically significant for model building. The model performance and interpretability increase when researchers employ this method to retain only key features which help decrease dataset dimensions.

➢ *Balancing with Under-Sampling*

Applying either under-sampling or oversampling processes will approach the data balance. When it came to measuring the model's correctness, random undersampling and SMOTE (oversampling) both worked similarly as data balancing techniques. Because under-sampling helps address class imbalances for big datasets and makes data understandable, it is the favored strategy.

➢ *Data Splitting*

A training portion utilizes 80% of the data in this collection, whereas a testing block uses 20% of the original data. This partition keeps one piece of data for measuring the model's efficacy and another for making sure the model learns from a large chunk of data.

➢ *Logistic Regression (LR) Model*

As a foundational model for several classification problems, LR finds extensive use across numerous domains. In our study, the dependent variable is a discrete one, meaning it can take on just two possible values: 1 (the default) and 0 (the non-default). Consequently, this scenario does not lend itself to LR. Typically, in statistics, they apply probit or logit models to these types of problems. These models assume that there is a distribution in the probability of an event happening. A probit model is usually used when the cumulative standard normal distribution characterizes the probability of an event occurring. Employ a logit model, commonly known as LR, if the cumulative logistic distribution describes the likelihood of an event occurring. Taking the default probability as a linear combination of the independent factors allows us to forecast the event's likelihood of occurrence. This is mathematically represented in Equation (1)

$$P(y = 1|x_1, \dots\dots, x_k) = T(\beta_1 x_1 + \dots + \beta_k x_k + \varepsilon) \quad (1)$$

The dependent variable, y ($y \in [0,1]$), is mapped the logistic cumulative distribution function T, which ensures that the predicted value is within the range [0,1] in the real number space from 0 to 1. The independent variables, $x1$, …, xk, are also included. The error term is denoted as ε., as defined in Equation (2)

$$T(x) = \frac{e^x}{1+e^x} \quad (2)$$

- *Evaluation Metrics*

The evaluation of ML classifiers depends on multiple performance metrics to ensure accurate and meaningful comparisons. This phase marks the end of the prediction model. The prediction outcomes in this section may be assessed using a variety of assessment metrics, including classification accuracy, confusion matrix, and F1-score. Statistical values derived from the confusion matrix classes underpin all metrics. The following instances of the confusion matrix are:

- *TP - True Positive:*

Refers to the classifier's correctly detected positive tuples.

- *FP - False Positive:*

The classifier made a mistake by marking some positive tuples as false.

- *FN False Negative:*

The negative tuples that the classifier mislabeled are described.

- *TN True Negative:*

The negative tuples that the classifier successfully detected are referred to here.

- *Accuracy*

One parameter used to assess classification models is accuracy. Accuracy may be defined as the percentage of correct predictions their model generates. The better the model performs, the higher the accuracy. Equation (3) provides it.

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \quad (3)$$

- *Precision*

The precision measures how many positive class forecasts turn out to be true positive class predictions. It is computed by taking the total number of expected positive observations and dividing it by the number of accurately predicted positive observations, as shown in Equation (4).

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (4)$$

- *Recall*

The recall is determined by dividing the number of accurate positive samples by the number of correct positive predictions, as indicated in the related Equation (5).

$$Recall = \frac{\mathrm{TP}}{TP+FN} \quad (5)$$

- *F1 score*

The F1 score fully suggests that a positive true label is anticipated and is calculated as the harmonic mean of precision and recall. It is represented by Equation (6) in mathematics.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

- *ROC*

The ROC curve provides a visual representation of a classification model's performance. The FPR and TPR are represented by the x and y axes, respectively, in the ROC space.

These measurements, when combined, elucidate the precision and overall efficacy of the model in forecasting the target variable.

IV. RESULTS AND DISCUSSION

The transforming Financial Lending Predictions using AI and Spring Boot framework works, comprising 8 GB of RAM and an Intel® CoreTM i5-1035G1 CPU running at 1.19 GHz, provides the right setup for model training and application deployment. Python 3.9.13 and Jupiter® 3.2.1 were used to create ML models, and Spring Boot provided backend integration and API services. The proposed LR model delivers its performance metrics as shown in Table III when converting financial lending forecasts.

Table 3 Experiment Results of Proposed Models for Enhancing Financial Lending Predictions.

Performance matrix	**Logistic Regression (LR) Model**
Accuracy	93
Precision	93
Recall	93
F1-score	92

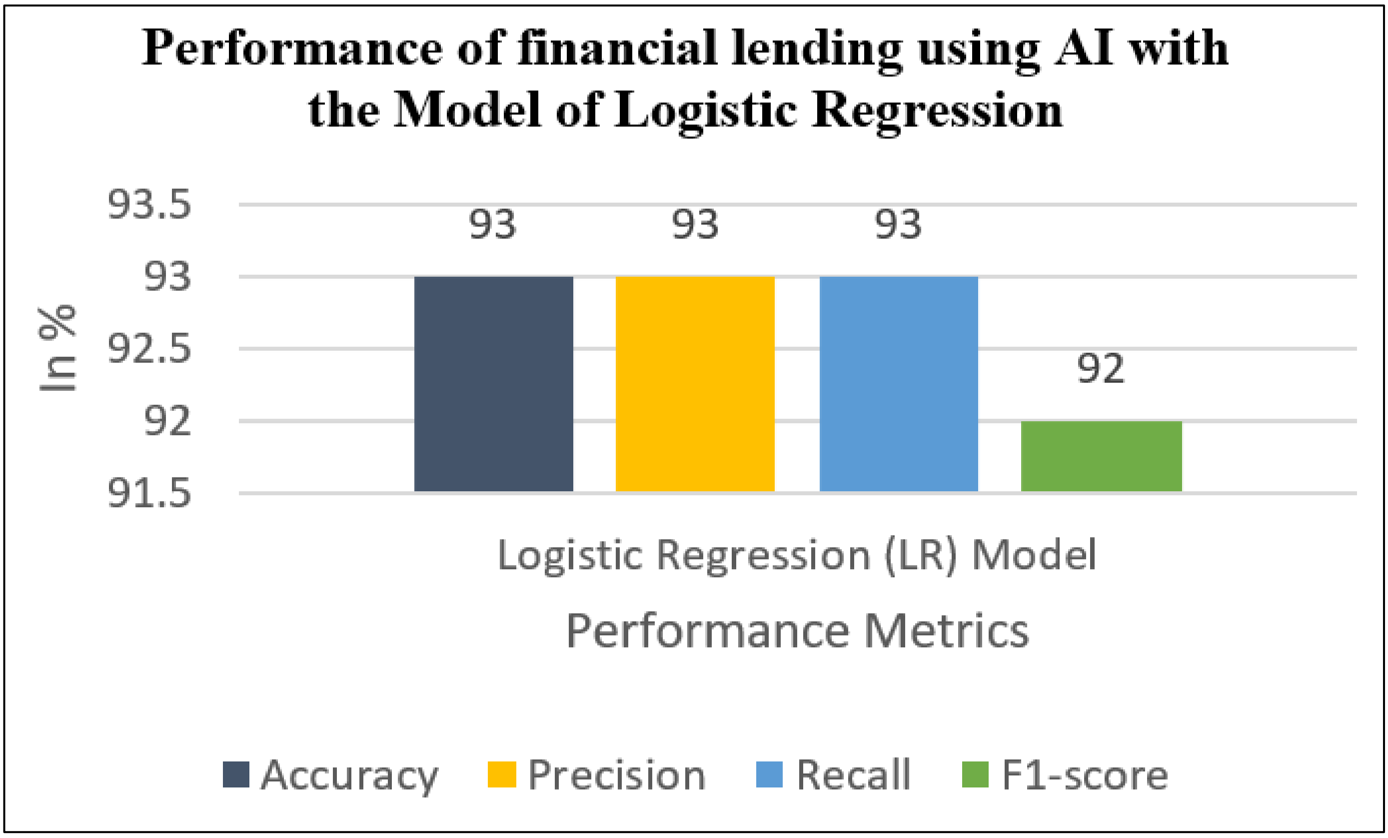

Fig 4 Model Performance of Logistic Regression using AI

Figure 4 with Table III reveals the LR model attained a 93% success rate in identifying loan repayment status, showing it predicted correctly in most cases. With both precision and recall also at 93%, the model is well-balanced in identifying true positives while minimizing FP and FN. The model's robustness is further confirmed by its 92% F1 Score, which successfully strikes a balance between recall and precision. Together, these measures demonstrate the LR model's dependability and efficiency in forecasting loan repayment or default.

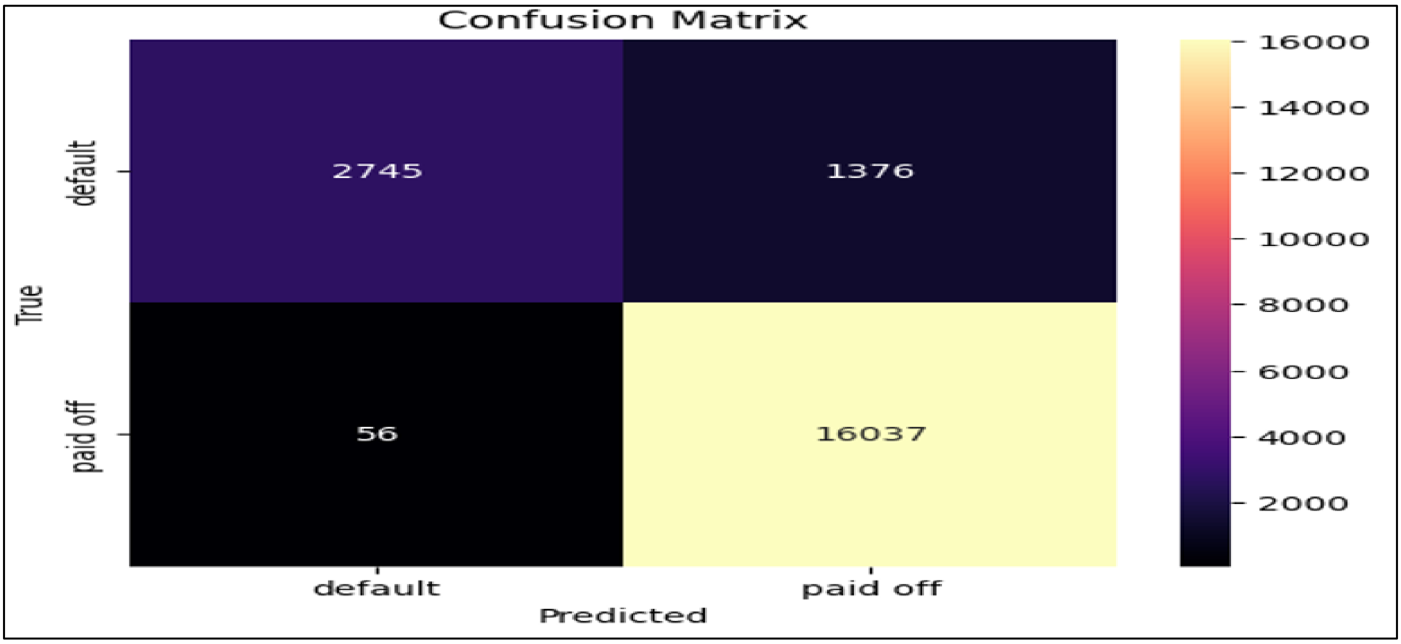

Fig 5 Confusion Matrix of Logistic Regression Model

The confusion matrix illustrates how well the LR model performs in identifying loan statuses as "paid off" or "default" in Figure 5. While the algorithm misclassified 1,376 defaults as paid off and just 56 paid-off instances as defaults, it accurately predicted 2,745 defaults and 16,037 paid-off cases. The overall distribution indicates high accuracy, particularly in identifying paid-off loans, as reflected by the large number of true positives in the lower-right quadrant. The concentration of correct predictions enhances the visualization of a strong classification capability of the model.

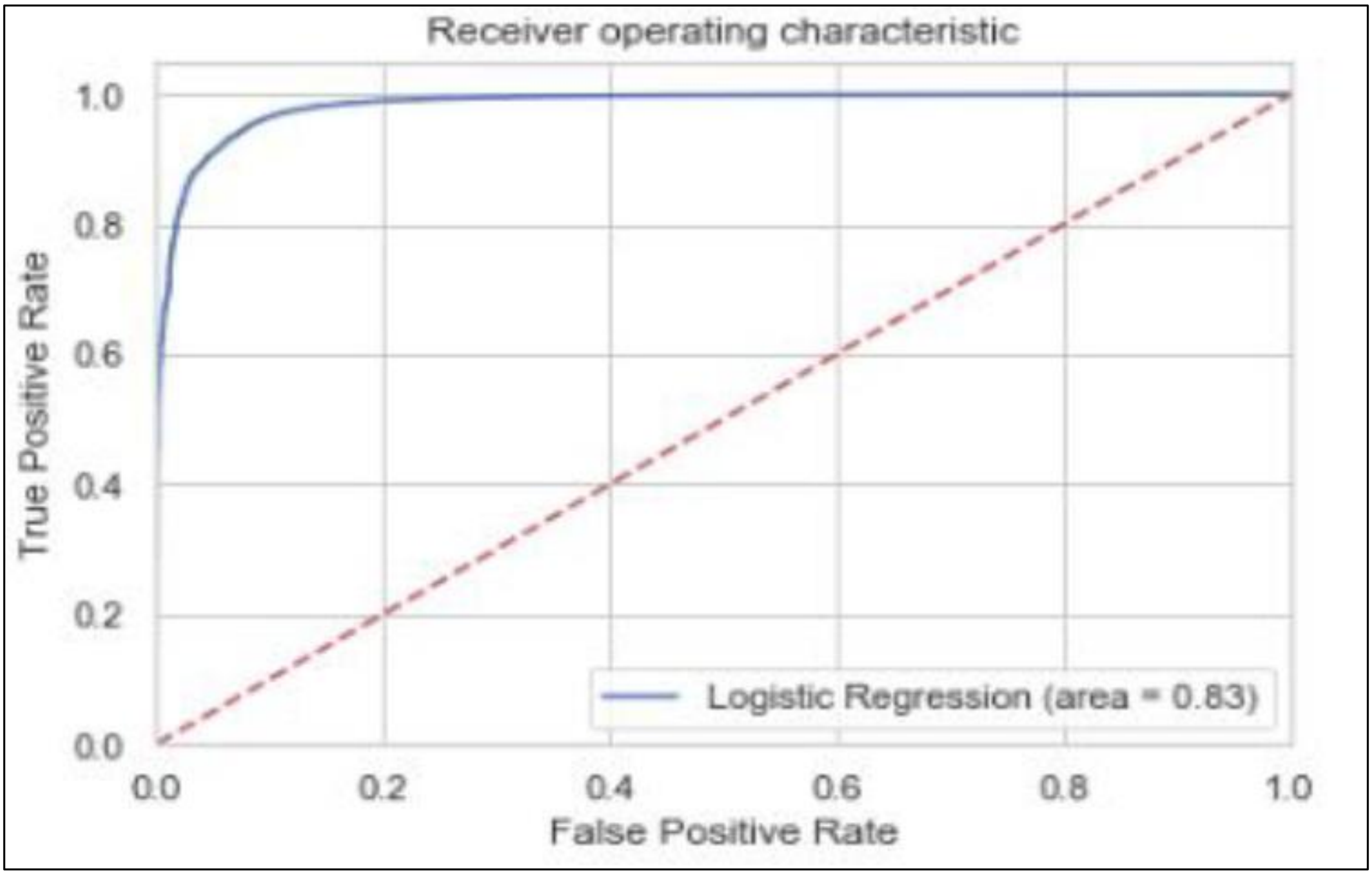

Fig 6 ROC Curve of Logistic Regression Model

The LR model's performance at different classification criteria is evaluated by looking at its ROC curve, which is shown in Figure 6. The curve has a high sensitivity (TP Rate) and a low FP Rate, suggesting strong discriminating capacity. Since the model's reported AUC is 0.83, It successfully differentiated between positive and negative classes. More than anything else, this curve deviates heavily from the diagonal red line, which is random guessing, further proving that the LR model is very accurate.

- *Comparison with Discussion*

This section compares the proposed LR model with other models such as the XGBoost model [19], DT Model [20], and GB model [21] and reveals that the proposed LR model outperforms the others in terms of prediction accuracy. These models are compared in detail in Table IV

Table 4 Comparison Between ML models for Transforming Financial Lending on Lending Club Loan Dataset

Models	**Accuracy**
Logistic Regression (LR) Model	93
XGBoost Model[19]	87.08
Decision Tree (DT) Model[20]	86.10
Gradient boosting (GB) model[21]	80.29

The LR model of Table III achieved the highest accuracy of 93% over all comparative models in the following Table. Among the alternatives, the accuracy of 87.08% attained by the XGBoost model is quite close to that of the DT model, which is 86.10%. The accuracy of the GB model was 80.29%, aside from this. These findings show that, in terms of prediction, the suggested LR model performs better than the other ML approaches studied.

V. CONCLUSION AND FUTURE STUDY

The possibility of deriving the financial lending systems optimization through the combination of AI, ML, and microservices architecture based on Spring Boot. Research was done on the Lending Club Loan Dataset by employing an LR to attain remarkable outcomes of 93% recall, accuracy, and precision, as well as an F1 score of 92%, demonstrating the efficacy of AI in loan default prediction. Microservices allow you to scale, be resilient, and develop as banks and financial institutions move in an ever-changing world. Future work towards improvement of the system's predictive capability would include the use of more advanced ML models like DL and ensemble methods, as well as real-time data integration for dynamic decision making, and NLP, enabling the use of unstructured data. Furthermore, the financial institutions equipped for the digital era will have to incorporate more powerful fraud detection mechanisms, as well as more scalable solutions to tackle bigger datasets and ever-changing regulations.

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