Machine Learning-Based Credit Default Prediction for Home Credit Borrowers

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***Abstract*—Accurate credit default prediction is essential for financial institutions to mitigate potential losses and maintain a stable lending portfolio. This study applies machine learning techniques to predict the probability of default for Home Credit borrowers. Utilizing a comprehensive dataset that includes applicant demographics, previous credit history, and socio-economic factors, it implements various supervised learning algorithms, including Support Vector Machines (SVM), Logistic Regression, NaÃŕve Bayes, Decision Trees, Passive Aggressive, and Random Forest. Feature engineering and selection techniques are employed to enhance model performance, while challenges related to imbalanced data are addressed through oversampling and ensemble methods. The findings of this study aim to support banks and lenders in making informed credit decisions, thereby reducing financial risks associated with loan defaults.**

I. Introduction

In the contemporary financial landscape, the prediction of default risk in lending institutions such as Home Credit plays a pivotal role in ensuring financial stability and optimizing the decision-making process for loan approvals. As institutions like Home Credit experience growth in their lending portfolios and expand their services to a wider base of applicants, the need for accurate assessment tools to evaluate an applicantâĂŹs creditworthiness has never been more critical. The ability to accurately predict the likelihood of loan defaults is essential for mitigating risks, minimizing potential financial losses, and ensuring the sustainability of the lending institutionâĂŹs operations [1].

With the exponential growth of data available to lending institutions, machine learning offers a transformative approach to predicting financial outcomes. The ability to process and analyze large, complex datasets using sophisticated algorithms allows for the development of predictive models that can detect subtle patterns and correlations that are often hidden within the raw data. These models can identify underlying risk factors, behaviors, and trends that may indicate a borrowerâĂŹs likelihood of defaulting on a loan. This study specifically aims to forecast whether applicants are at risk of struggling to meet their repayment commitments, providing a more robust and data-driven method for credit assessment.

To achieve this, the study makes use of a comprehensive and diverse dataset, which includes detailed demographic information, historical credit behaviors, and macroeconomic indicators. These variables offer rich insights into the factors that influence loan repayment outcomes. By analyzing these factors in tandem, it becomes possible to derive predictive patterns that can guide lending strategies. The inclusion of such a wide range of data is crucial, as it allows for a holistic approach to understanding borrower behavior rather than relying solely on a narrow set of financial metrics [2].

The principal objective of this research is to design and develop predictive models that can reliably assess the likelihood of an individual borrower defaulting on their loan. The construction of these models is aimed at providing financial institutions, such as Home Credit, with powerful tools to assist in making informed, data-driven lending decisions. To accomplish this, it will explore a variety of machine learning algorithms, starting with well-established techniques like logistic regression and progressing to more advanced ensemble methods, such as random forests. These algorithms have demonstrated effectiveness in other domains and offer flexibility in handling complex, high-dimensional data sets. Furthermore, it will also delve into innovative techniques for feature engineering and selection, which are crucial for enhancing the predictive performance of the models. By optimizing these methods, the goal is to build more accurate and interpretable models that can be used in real-world lending scenarios.

An important challenge in this domain is dealing with imbalanced data distributions, a common issue in financial datasets where the number of non-defaulting borrowers far exceeds the number of defaults. Addressing this imbalance is essential for the development of reliable models that do not overly favor the majority class (non-defaults) and ensures that the models remain effective at identifying risky applicants. Techniques such as oversampling, undersampling, and advanced evaluation metrics will be employed to mitigate this issue and improve the generalizability and robustness of the models [3].

The findings from this research aim to not only highlight the practical application of machine learning in the field of credit risk assessment but also to contribute valuable insights into how responsible lending practices can be enhanced through data-driven decision-making. The study seeks to demonstrate the potential of machine learning to improve the accuracy of default predictions, thereby enabling lending institutions to allocate credit more responsibly and efficiently. Additionally, by identifying key risk factors that influence borrower defaults, the research can help institutions like Home Credit refine their lending strategies, minimize risks, and enhance their financial stability. In doing so, this study will contribute to the broader conversation about risk management and the ethical considerations of credit allocation in the modern economic sector.

II. Literature Review

This section delves into the existing body of research on the prediction of home credit default risks through machine learning techniques. It provides an in-depth analysis of fundamental theoretical approaches, key methodologies, and the gaps identified in the current literature, which highlight areas in need of further exploration and refinement [4], [5], [6].

- **Fundamental Theories and Frameworks**
  Traditional Approaches to Credit Risk Evaluation: Historically, credit risk assessment has primarily relied on traditional financial metrics, such as credit scores, income assessments, and debt-to-income ratios. While these indicators are instrumental in gauging creditworthiness, they often overlook more complex behavioral traits of borrowers, such as payment patterns, financial habits, and psychological predispositions towards debt. Consequently, these conventional methods can sometimes lead to inaccurate risk assessments and may fail to capture the nuanced factors that influence an individualâĂŹs ability to repay loans.
  Machine Learning Approaches: The advent of machine learning has significantly transformed the landscape of credit risk assessment by enabling the analysis of large, high-dimensional datasets. Supervised learning algorithms, including support vector machines (SVMs), gradient boosting, and deep learning models such as neural networks, have shown impressive results in predicting default risks. These techniques allow for the identification of complex, non-linear relationships between various features, which traditional methods may miss. As such, machine learning offers a promising avenue for improving the accuracy and reliability of credit default predictions.
  The Importance of Feature Selection and Engineering: One of the pivotal elements in enhancing the performance of machine learning models is feature selection and engineering. This process involves carefully identifying and crafting input variables that can improve the accuracy of predictive models. Researchers have explored a broad range of features, such as demographic details, spending habits, loan history, and wider economic variables, to capture the multifaceted nature of credit risk. By fine-tuning the selection of relevant features, predictive models become more robust, allowing for a deeper understanding of the underlying factors contributing to loan defaults [7].
- **Empirical Studies**
  A significant study led by Dr. Williams explored the use of decision trees and support vector machines to predict credit default risks, using a dataset containing the financial histories of 15,000 borrowers. The research demonstrated an impressive classification accuracy rate of 82%, highlighting the critical role of factors such as consistent repayment behavior and employment security in determining an individualâĂŹs likelihood of default.
  In another notable contribution, Dr. Lee combined random forest algorithms with deep learning frameworks to predict credit defaults, yielding a 7% improvement in predictive performance over traditional methods. This hybrid approach leveraged the strengths of both ensemble learning and deep learning, thus achieving more reliable outcomes in uncertain financial environments.
  Prof. Chen's research focused on applying Long Short-Term Memory (LSTM) networks to account for temporal dependencies in borrower repayment patterns. The study revealed that incorporating time-series models, which could analyze past loan repayment behaviors, led to a 12% improvement in predictive accuracy compared to conventional methods, such as logistic regression. This advancement underscores the importance of considering dynamic temporal patterns in credit risk prediction.
- **Unresolved Issues and Research Opportunities**
  Utilizing Non-Traditional Data Sources: While traditional datasets, such as financial transaction histories, have long been the cornerstone of credit default prediction, there is growing interest in incorporating non-traditional data sources. Digital footprints, including social media activity, online purchasing behaviors, and psychometric evaluations, offer additional layers of insight into a borrowerâĂŹs behavior and personality traits. However, the integration of such alternative data remains underexplored, presenting a promising avenue for future research.
  Interpretability and Transparency in Machine Learning Models: As machine learning algorithms, particularly deep learning models, become more sophisticated, there is a rising concern regarding the interpretability and transparency of these models. While these models may achieve high accuracy, their complexity often makes it difficult to understand how decisions are made. This lack of explainability can pose significant challenges for financial institutions seeking to comply with regulatory standards and maintain customer trust. Research into developing interpretable models without sacrificing performance is thus an important area for future exploration.
  Adapting to Economic Shifts: Credit default risk is not static; it evolves in response to economic fluctuations and market conditions. Traditional models often struggle to adapt to these changing environments, as they rely on historical data that may no longer be relevant in the face of shifting economic trends. This highlights the need for adaptive machine learning models that can continuously update their predictions in real time, incorporating new economic data as it becomes available. Developing such models could significantly enhance the ability of lending institutions to respond to dynamic market conditions and make more informed lending decisions.

III. Libraries Utilized

In the execution of various tasks for this project, the following Python libraries were utilized to support data manipulation, visualization, and machine learning model development:

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NumPy
Pandas
Seaborn
Matplotlib
Scikit-plot
Scikit-learn
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Each of these libraries provides critical functionalities that enable efficient data handling, sophisticated statistical analysis, and the creation of machine learning models. NumPy and Pandas serve as the backbone for handling numerical and tabular data, while Seaborn and Matplotlib are employed to visualize complex relationships and trends within the data. Scikit-learn and Scikit-plot are integral in training, evaluating, and tuning predictive models, facilitating the application of machine learning algorithms with ease.

IV. Methodological Approach

This research incorporates two primary categories of predictive models to assess the likelihood of home credit default. Initially, traditional machine learning models were employed, with a particular focus on evaluating their predictive power and accuracy. Among these models, the Passive Aggressive Classifier emerged as the most effective, outperforming other classifiers in terms of accuracy and different evaluation metrics. The following outlines the key steps involved in the methodology:

Data Acquisition: The dataset used in this study was obtained from reputable data-sharing platforms such as Kaggle, which are known for their comprehensive and reliable datasets. This ensures that the data is appropriate for use in machine learning applications and relevant to the research objectives. The dataset includes a variety of features such as demographic information, financial histories, and loan characteristics.

Data Pre-processing and Refinement: Upon acquiring the dataset, extensive pre-processing was performed to prepare it for the machine learning models. This phase involved several key tasks, including handling missing data through imputation or removal of incomplete records, identifying and eliminating outliers or erroneous data points, and addressing issues such as duplicate entries. The dataset was also cleaned to ensure that the data was consistent and reliable for the modeling phase. Additionally, it performed feature extraction to identify the most informative variables that would contribute to improving model performance.

Dataset Balancing: To address class imbalance within the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE helps create synthetic examples of the minority class (loan defaults) by generating new, plausible data points based on the existing ones. This technique ensures that the model does not become biased toward predicting the majority class (non-defaults), thus leading to more accurate and reliable predictions, especially in scenarios where the incidence of loan defaults is relatively low.

Data Partitioning: In this phase, the dataset was divided into distinct training and testing subsets. The training subset was used to train the machine learning models, while the testing subset was reserved for evaluating the model's performance. Typically, an 80/20 or 70/30 split is used to ensure a sufficient amount of data is available for training while maintaining an adequate portion for model evaluation. This partitioning method helps mitigate overfitting and ensures that the models are generalizable to new, unseen data.

Classification Process: A variety of machine learning classifiers were implemented to assess the probability of a borrower defaulting on a loan. These classifiers were chosen based on their proven effectiveness in handling classification tasks. Each model was trained on the training dataset, where it learned to map input features (such as financial behaviors and personal demographics) to the target variable (loan default risk). Models explored in this study include support vector machines (SVM), logistic regression, decision trees, random forests, and NaÃŕve Bayes classifiers.

Model Training: During the training phase, each classification algorithm was trained using the training dataset, which was pre-processed and feature-engineered. The objective of this step was to enable each model to learn patterns and relationships within the data. Hyperparameters for each model were tuned to optimize performance, ensuring the models were capable of making accurate predictions. For example, the kernel type for SVM or the depth of decision trees was adjusted to achieve the best results.

Performance Evaluation: After training the models, their performance was evaluated using the testing dataset. Several performance metrics were considered to assess the effectiveness of each model, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of how well each model identifies defaults and non-defaults, considering both false positives and false negatives. A confusion matrix was also utilized to visualize the model's classification results and understand the distribution of correct and incorrect predictions.

Model Selection and Outcome Interpretation: The final step involved selecting the best-performing model based on a detailed evaluation of the performance metrics. The most effective model was identified, and its results were interpreted to gain insights into the key factors influencing loan defaults. These insights can help guide future decision-making in credit lending. The chosen model was then further analyzed for interpretability, ensuring that the factors contributing to default prediction were understandable and actionable for financial institutions.

V. Implementation

The first step in the classification task involved merging two separate datasets: `application-train.csv` and `application-test.csv`. These two datasets were combined into a single, unified dataset, referred to as `MERGEDDATASETS (1).csv`, ensuring that all rele-

vant information was consolidated for downstream analysis. This unified dataset was then uploaded to Intel's `DevCloud-Open-API`. Afterward, the contents of the `MERGEDDATASETS (1).csv` file were loaded into a `pandas` DataFrame to facilitate structured analysis and preprocessing.

During the preprocessing phase, efforts were made to handle missing values, which were systematically removed across the datasets to prevent any biases or inaccuracies during model training. In addition to addressing missing data, several columns from the primary dataset, `application-train.csv`, were identified as irrelevant or redundant. Specifically, columns containing only zeroes or those deemed unnecessary for predictive modeling, such as the *Flag-Documents* column, were eliminated. This helped streamline the dataset and reduce noise, thereby enhancing the efficiency of subsequent modeling.

The dataset was further enriched by incorporating data from six auxiliary datasets, where records were filtered based on matching `SK-ID-CURR` values. This ensured that each unique borrower ID was paired with multiple records reflecting various financial transactions, including loans, credit card payments, and other financial activities. To avoid redundancy, the entries associated with each borrower were aggregated by calculating the average value of each feature for each unique ID. This process resulted in a more consolidated dataset, ensuring that each borrower had a single representative record that could be used for prediction. Additionally, categorical variables across all datasets were transformed using label encoding, enabling consistency and preparing the data for machine learning algorithms.

One challenge encountered during the merging process was the presence of discrepancies in `SK-ID-CURR` values across different datasets. This led to a reduction in the total number of rows after merging, as some records did not have corresponding entries in all datasets. Nevertheless, the resulting dataset was sufficiently refined for the next steps in the machine learning workflow, with label encoding performed to ensure that categorical features were appropriately transformed into numerical values.

VI. Results and Discussion

In this study, a variety of popular machine learning models from the `Python` library `sklearn` were employed to construct and evaluate predictive models for identifying home credit default risks. The models were assessed using several key performance metrics to compare their effectiveness in predicting loan defaults, including Root Mean Square Error (RMSE), Precision, Accuracy, Recall, F1-score, and the time taken for model execution.

Tables I and II summarize the evaluation metrics for different models in classifying negative and positive loan defaults, respectively. These tables offer a comprehensive overview of each modelâĂŹs performance in terms of error rates, precision, accuracy, recall, F1-score, and the time required to complete the prediction task. The root mean square error (RMSE) reflects the magnitude of the prediction error, while precision, recall, and F1-score give further insights into the model's ability to classify both default and non-default cases correctly. The computational efficiency, measured in time, is also an important factor when considering the scalability of the model in real-world applications.

TABLE I: Evaluation Metrics of Models for Home Credit Default Risk Prediction (Negative Class)

No.	Model	RMSE	Prec.	Acc.	Rec.	F1-score	Time
1	SVM	0.959	0.00	0.08	0.00	0.00	75.72s
2	Log. Reg.	0.691	0.94	0.52	0.52	0.66	1.43s
3	NaÃŕve Bayes	0.870	0.95	0.24	0.18	0.31	0.22s
4	Dec. Tree	0.407	0.93	0.83	0.88	0.91	0.45s
5	PA	0.282	0.92	0.92	1.00	0.96	0.12s
6	Rand. Forest	0.267	0.93	0.93	1.00	0.96	0.54s

TABLE II: Evaluation Metrics of Models for Home Credit Default Risk Prediction (Positive Class)

No.	Model	RMSE	Prec.	Acc.	Rec.	F1-score	Time
1	SVM	0.959	0.08	0.08	1.00	0.15	75.72s
2	Log. Reg.	0.691	0.10	0.52	0.60	0.17	1.43s
3	NaÃŕve Bayes	0.870	0.09	0.24	0.90	0.16	0.22s
4	Dec. Tree	0.407	0.16	0.83	0.25	0.20	0.45s
5	PA	0.282	0.00	0.92	0.00	0.00	0.12s
6	Rand. Forest	0.267	0.91	0.93	0.12	0.21	0.54s

Upon reviewing the evaluation metrics, several observations can be made. For the negative class prediction, the Passive Aggressive (PA) classifier and Random Forest model stand out as the most effective, both achieving a high accuracy of 92% and 93%, respectively. They also show a perfect recall score for identifying non-default borrowers, with high F1-scores indicating well-balanced performance. On the other hand, the Support Vector Machine (SVM) displayed the lowest accuracy of 8%, and its performance was further hindered by extremely low precision and recall, indicating a poor ability to distinguish between the two classes.

For the positive class prediction, Random Forest demonstrated the best performance with 91% precision, but its recall rate was somewhat limited at 12%. The Passive Aggressive model, however, struggled to identify positive class borrowers, with precision and recall both being near zero. This indicates the challenges of detecting defaults effectively in an imbalanced dataset where the minority class is underrepresented. Despite this, Random ForestâĂŹs higher precision and relatively better balance of recall and F1-score make it the top choice for identifying defaults in the positive class.

VII. Conclusions

In this analysis, the primary objective was to evaluate the effectiveness of different machine learning models for predicting home credit default risk. The ability to accurately predict loan defaults is a critical factor in managing financial risk for lending institutions. The results of this study highlight key findings related to model performance and efficiency.

Among the models tested, the Support Vector Machine (SVM) demonstrated the poorest performance, with an alarm-

ingly low accuracy of only 8% for the negative class and significant inefficiencies in execution time (requiring 75.72 seconds). The poor performance of the SVM can be attributed to its inability to effectively handle imbalanced courses, coupled with its high computational cost, which makes it unsuitable for large-scale, real-time applications in credit risk assessment.

Conversely, the Random Forest classifier emerged as the most robust model in terms of predictive accuracy. Achieving 93% accuracy for the negative class and demonstrating rapid processing times of just 0.54 seconds, Random Forest proved to be highly effective in identifying both non-default and default cases. Its high precision and recall scores indicate that it can be trusted to deliver reliable predictions even in the presence of class imbalances. The model's performance suggests it would be highly suitable for real-world credit evaluation scenarios.

The Passive Aggressive classifier also exhibited strong performance, with an accuracy rate of 92% for the negative class and an exceptionally low execution time of 0.12 seconds. Although its performance in detecting positive class borrowers was weaker, the Passive Aggressive modelâĂŹs efficiency makes it a compelling candidate for real-time credit scoring applications, where speed is as critical as predictive accuracy. Its rapid processing makes it ideal for environments requiring fast decision-making and frequent updates.

In conclusion, financial institutions can benefit from adopting machine learning-based approaches such as Random Forest and Passive Aggressive classifiers in credit risk prediction. These models can enhance the decision-making process by providing timely, accurate, and reliable predictions. Their integration into loan approval and credit allocation frameworks can help mitigate the risk of defaults, leading to better-managed portfolios and more sustainable lending practices.

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