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Enhancing Credit Risk Assessment Accuracy Using Bagging Ensemble Methods in Financial Institutions

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ABSTRACT:

Credit risk assessment is essential for financial institutions to evaluate the likelihood of borrower default. Traditional models often struggle with accuracy, especially in the presence of complex and non-linear data. This research explores the use of Bagging (Bootstrap Aggregating), an ensemble learning technique, to enhance credit risk prediction. By aggregating predictions from multiple base models, Bagging reduces variance and improves the model's robustness, particularly in handling noisy or imbalanced data. We apply Bagging to a dataset containing customer attributes such as credit score, income, and payment history, and compare its performance with traditional models like Logistic Regression and Decision Trees. The results demonstrate that Bagging offers superior accuracy and stability, providing more reliable credit risk assessments. This study underscores the potential of ensemble methods in improving credit scoring models, enhancing decision-making, and supporting more effective risk management in financial institutions.

Keywords: Credit Risk, Bagging, Ensemble Methods, Financial Institutions, Predictive Modeling, Risk Assessment.

Introduction :

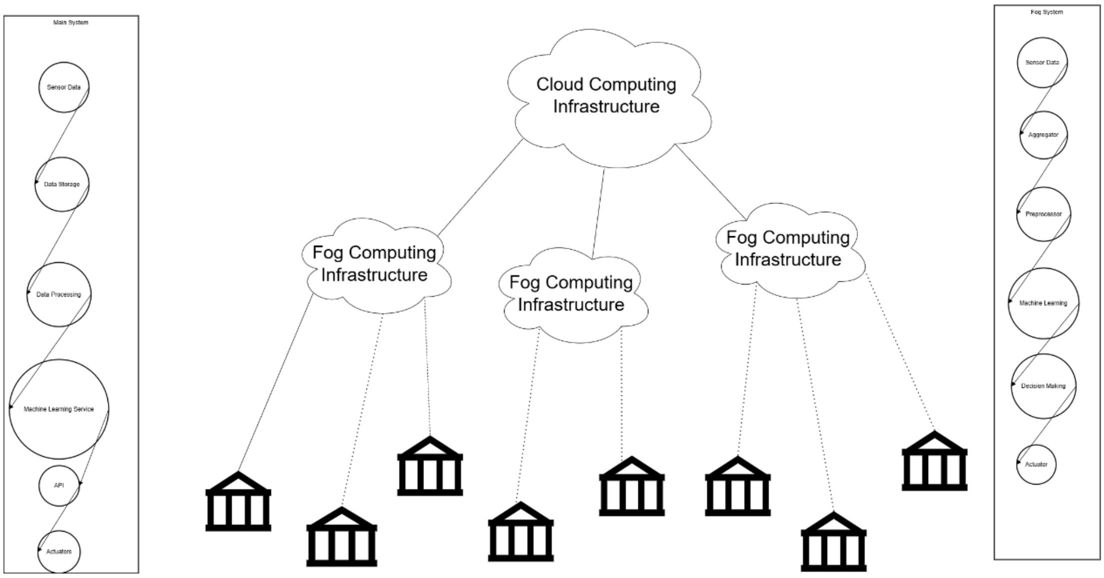
Credit risk assessment is one of the most critical tasks faced by financial institutions. Accurate evaluation of a borrower's creditworthiness is essential to prevent defaults and ensure that lending decisions are aligned with the institution's risk appetite [1]. Traditional risk assessment models such as Logistic Regression and Decision Trees have long been used to predict credit risk. However, these models are often limited by their inability to capture complex, non-linear relationships in financial data, and their vulnerability to overfitting or underfitting. These challenges can lead to inaccurate predictions and increased exposure to credit defaults, which can have severe financial consequences such as security, scalability and safety for lending institutions [2] [3].

In response to these limitations, ensemble learning methods, particularly Bagging (Bootstrap Aggregating), have gained traction for improving the performance of predictive models. Bagging aggregates the predictions of multiple base models, each trained on a random subset of the data, which helps reduce variance and enhance model robustness. By combining the strengths of various base learners, Bagging can significantly improve prediction accuracy, especially when dealing with noisy, imbalanced, or high-dimensional data [4] [5].

The objective of this research is to explore how Bagging can enhance the accuracy and reliability of credit risk assessments in financial institutions. Specifically, we aim to evaluate the performance of Bagging when applied to credit scoring data, comparing it against traditional models such as Logistic Regression and Decision Trees. Furthermore, this study will examine the effect of different base learners within the Bagging framework and identify optimization strategies for improving model performance. We will also investigate how Bagging can help in identifying high-risk borrowers more effectively, thereby reducing the likelihood of loan defaults and improving financial decision-making [6].

This research makes several important contributions. First, it provides empirical evidence of how Bagging can outperform traditional credit scoring models in terms of predictive accuracy and robustness. By aggregating predictions from multiple base models, Bagging can mitigate the impact of data variability, resulting in more stable and reliable predictions. Second, this study offers valuable insights into the practical application of ensemble methods in financial risk management, particularly in the context of credit risk assessment. Lastly, our work contributes to the ongoing discussion about the role of machine learning techniques in financial institutions, helping to bridge the gap between advanced data analytics and traditional risk management practices [7]

Adapting fog computing for risk assessment introduces a powerful way to bring data processing closer to the edge devices, which can be especially beneficial for real-time risk management in sectors like finance, healthcare, and IoT-driven industries [6][27]. Fog computing provides data storage, processing, and analysis at or near the edge of the network, rather than sending data to centralized cloud servers. This capability enhances response time, reduces latency, and improves data privacy, all of which are crucial for effective risk assessment. A financial institution could implement a fog-based model to evaluate credit risk by deploying fog nodes in different branch offices [29]. Each node could locally analyze customer financial data, including transaction history, income, and spending patterns, to create a creditworthiness profile [8]. By processing this data on-site, the institution can quickly make loan approval decisions, and aggregated insights can be sent to the central server only when necessary. The fog computing enables a decentralized, low-latency, and secure approach to risk assessment, particularly suited for environments where real-time insights and data privacy are crucial. By enabling localized data processing, fog computing can significantly enhance the efficiency, accuracy, and responsiveness of risk assessment models across various sectors [9]. Figure 1 shows the fog computing environment for risk assessment.



Through this study, financial institutions can better understand the benefits of using ensemble learning to improve credit risk prediction and, ultimately, optimize their lending strategies [31][32]. The findings may lead to more informed, data-driven decision-making processes, reducing exposure to risk and improving financial stability. The rest of the paper is organized as follows: section 2 reviews the literature work, section 3 presents the proposed methodology, the results and discussion is presented in section 4 and section 5 concludes with insights.

Related Work :

The study from [10] introduces a Feature Selector-classifier Optimization Framework, combining feature selection with ensemble learning to optimize credit risk predictions for small and medium-sized enterprises (SMEs). It demonstrates how this innovative framework improves prediction accuracy and operational efficiency. The study's main goal is to enhance creditworthiness evaluation for SMEs using big data, and its findings underscore the effectiveness of this framework in improving predictive power. In [11], the focus is on Random Forest and XGBoost as ensemble learning algorithms. The study emphasizes feature selection techniques and model interpretability enhancements, and it highlights how these methods outperform individual classifiers, particularly in handling credit risk by integrating financial and demographic data for better loan approval decisions.

[12] presents an Explainable Ensemble Method that enhances credit risk prediction accuracy and interpretability. This method, which includes bagging, is beneficial for financial institutions aiming for transparency while making informed lending decisions. The research gap identified is the limited exploration of other explainable AI techniques, and the study's findings show that this ensemble approach outperforms individual models in terms of interpretability and prediction.[13] compares 26 machine learning algorithms, focusing on an ensemble of Random Forest and K-Nearest Neighbors (KNN), which results in the lowest misclassification costs for credit risk scorecards. The goal of this study is to propose financial criteria for optimal ensemble learning, and the findings indicate that these ensemble methods significantly reduce financial losses compared to single classifiers.

The study in [14] compares XGBoost with Logistic Regression, showing that ensemble models significantly improve credit classification accuracy. The research highlights XGBoost's superior performance and its relevance in credit risk assessment, addressing the need for more advanced predictive models in financial institutions.[15] explores a smart prediction model for credit risk that integrates Support Vector Machine (SVM), Neural Networks, and Radial Basis Function (RBF) classifiers. This ensemble approach improves accuracy compared to basic machine learning models. The research gap addressed is the lack of robustness in handling complex financial security scenarios, with the findings confirming that ensemble learning enhances prediction accuracy.

The study in [16] introduces an Ensemble Methods framework using LightGBM, XGBoost, and LocalEnsemble to redefine credit default prediction standards. This methodology enhances the prediction accuracy and overcomes the limitations of previous models, setting a new benchmark for credit risk assessments in financial institutions.[17] compares Bagging and Boosting ensemble strategies in the context of credit risk prediction, concluding that boosting methods outperform bagging in terms of accuracy, AUC, and F1-score. The study proposes synthetic tree-based feature transformation methods to improve credit risk prediction and validates this on real P2P lending datasets.

The study in [18] discusses a stacked classifier using Random Forest, Gradient Boosting, and XGBoost, demonstrating superior performance compared to individual models. The research gap identified includes the need for more comprehensive feature selection methods, and the findings show that the stacked ensemble approach significantly outperforms individual estimators in credit risk prediction.[19] focuses on using SMOTE (Synthetic Minority Oversampling Technique) to handle class imbalance in credit risk data, in combination with stacking ensemble learning. The study shows that this technique enhances model performance, achieving 83.21% accuracy in credit scoring by addressing class imbalance, which is a significant challenge in credit risk modeling. Overall, the studies reveal that ensemble learning methods—such as Bagging, Boosting, and Stacking—when combined with techniques like SMOTE and feature selection, offer substantial improvements in the accuracy and robustness of credit risk prediction models, addressing various challenges like class imbalance, model interpretability, and computational efficiency. The table 1 summarizes these related work .

Ref	Methods Used	Insights	Findings	Limitations
[10]	Feature Selector-classifier Optimization Framework Ensemble classifier with high accuracy and AUC scores	It introduces an innovative 'Feature Selector-classifier Optimization Framework' that enhances credit risk assessment accuracy through ensemble learning, demonstrating high performance with improved predictive power and operational efficiency, particularly beneficial for evaluating small and medium-sized enterprises (SMEs).	Enhanced creditworthiness evaluation for SMEs using big data. Innovative framework improves prediction accuracy and operational efficiency.	High computation cost
[11]	Ensemble learning algorithms: Random Forest and XGBoost Feature selection techniques and model interpretability enhancements	The study emphasizes using ensemble learning, particularly Random Forest, to enhance credit risk assessment accuracy. It demonstrates that ensemble methods outperform individual classifiers, effectively managing credit risk by integrating financial, demographic, and past credit data for improved loan approval decisions.	Ensemble learning improves credit risk assessment accuracy. Random Forest and XGBoost enhance credit scoring performance.	Feature selection techniques and model interpretability enhancements Evaluating ensemble parameter manipulation for credit scoring models
[12]	Explainable ensemble method Model interpretation techniques	The paper discusses using ensemble methods, including bagging, to enhance credit risk prediction accuracy. By combining multiple models, the explainable ensemble technique improves predictive performance and interpretability, aiding financial institutions in making informed lending decisions while maintaining transparency.	Explainable ensemble model outperforms individual base models. Provides insights into credit risk factors for informed decisions.	Limited exploration of other explainable AI techniques. Need for more comprehensive evaluation of ensemble methods.
[13]	26 machine learning algorithms compared Ensemble learning with Random Forest and K-Nearest Neighbors used	The paper discusses optimizing ensemble learning, specifically highlighting that the combination of Random Forest and K-Nearest Neighbors achieved the lowest misclassification costs in credit risk scorecards, enhancing accuracy and reducing financial losses for lending institutions.	Best algorithm: Generalized Additive Model (GAM) with high accuracy. Ensemble method: Random Forest and KNN reduced misclassification costs significantly.	Financial criteria for misclassification costs assessment Impact of ensemble learning on credit risk scorecards
[14]	Ten machine learning algorithms assessed XGBoost outperformed logistic regression in credit classification	The paper highlights that ensemble models, particularly XGBoost, significantly enhance credit risk assessment accuracy compared to traditional algorithms like logistic regression. It emphasizes the importance of machine learning techniques in improving credit classification within financial institutions.	Ensemble models, especially XGBoost, outperform traditional algorithms. Covers data processing, exploratory analysis, modeling, and evaluation metrics.	Complex and high computational cost
[15]	Ensemble learning enhances credit risk prediction model. Three classifiers: support vector machine, neural network, radial basis function.	The paper proposes an ensemble learning-enhanced smart prediction model for financial credit risk, integrating support vector machine, artificial neural network, and radial basis function classifiers. This approach improves prediction accuracy compared to basic machine learning models without ensemble learning.	Ensemble learning improves credit risk prediction accuracy. Integration of multiple classifiers enhances model robustness.	Limited feature representation and robustness in machine learning models. Inability to handle complex financial security scenarios.
[16]	LightGBM, XGBoost, LocalEnsemble modules Ensemble Methods framework for credit default prediction.	The paper introduces an Ensemble Methods framework utilizing LightGBM, XGBoost, and LocalEnsemble, enhancing credit default prediction accuracy. This innovative approach addresses limitations of previous models, improving generalization and setting a new benchmark for credit risk assessment in financial institutions.	Ensemble model significantly improves credit default prediction accuracy. Methodology addresses limitations of previous studies effectively.	Tackles limitations in previous credit default prediction studies. Aims to redefine accuracy standards in the industry.

[17]	Bagging-TreeEnsembleFT Boosting-TreeEnsembleFT	The paper explores enhancing credit risk prediction through tree-based feature transformation methods, specifically comparing bagging and boosting ensemble strategies. It finds that boosting ensemble methods outperform bagging in accuracy, AUC, and F1-score for credit risk assessment in P2P lending.	Boosting ensemble strategy outperforms bagging in credit risk prediction. Synthetic feature transformation improves accuracy, AUC, and F1-score.	Lesser accuracy compared to other models
[18]	Stacked classifier with RF, GB, XGB Filter-based feature selection using Information Gain theory	The paper does not specifically address bagging ensemble methods for enhancing credit risk assessment accuracy. It focuses on a stacked classifier approach using Random Forest, Gradient Boosting, and Extreme Gradient Boosting, demonstrating superior performance compared to individual estimators.	Stacked model outperforms individual estimators in credit risk prediction. Achieved AUCs of 0.934, 0.944, and 0.870 on various datasets.	No mention of limitations in feature selection methods. Lack of comparison with more recent algorithms.
[19]	Synthetic Minority Oversampling (SMOTE) for data balancing Stacking ensemble learning with Random Forest, SVM, Extra-Tree, XGboost	The paper focuses on optimizing credit scoring accuracy using stacking ensemble learning and SMOTE, rather than bagging methods. It demonstrates improved performance with an accuracy of 83.21%, emphasizing the importance of handling class imbalance in credit risk assessment.	Stacking ensemble model achieved 83.21% accuracy in credit scoring. SMOTE improved performance in handling class imbalance.	Lesser accuracy

Table 1: Summary of related work

Proposed Model :

In this research, the proposed model for enhancing credit risk assessment utilizes Bagging (Bootstrap Aggregating), a powerful ensemble learning technique that improves prediction accuracy and model stability [21]. The main principle behind Bagging is to aggregate the predictions of multiple base classifiers trained on different subsets of the training data. This process helps reduce variance and overfitting, which is particularly useful in credit risk models that must handle complex and imbalanced financial datasets.

The first step in the proposed model is the selection of base models for the ensemble. For this research, Decision Trees, Support Vector Machines (SVM), and Logistic Regression (LR) are chosen as the base classifiers. These models were selected because they are widely used in credit risk prediction and offer a combination of non-linear (Decision Trees), linear (SVM, LR), and robust classification capabilities. These base models are trained independently on various bootstrapped subsets of the training dataset, where each subset is created by sampling the data with replacement. Once the base models are trained, the Bagging algorithm aggregates their predictions. For regression tasks, the predictions from all base models are averaged. For classification tasks, the majority vote from all base models is considered the final prediction. This aggregation process helps to smooth out individual model errors, leading to more stable and accurate predictions.

Before applying Bagging, the model undergoes feature selection to identify the most relevant variables for credit risk prediction. Feature selection techniques like Information Gain (IG) and Chi-squared tests are employed to reduce the dimensionality of the data and ensure that only the most significant features are used in model training. This helps improve the model's performance by eliminating irrelevant or redundant features that could introduce noise or confusion. Furthermore, data preprocessing steps like handling missing values and addressing class imbalance are crucial for ensuring that the model performs optimally. The Synthetic Minority Oversampling Technique (SMOTE), for instance, is applied to balance the dataset by generating synthetic samples for the minority class, reducing the bias toward the majority class.

The core mechanism of Bagging is based on the prediction aggregation formula. For regression tasks, the Bagging ensemble prediction is calculated as the average of the predictions made by each base model. Mathematically, this is expressed as:

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} f_i(x)$$

where y^ represents the final prediction, fi(x) is the prediction made by the i-th model, and n is the number of base models in the ensemble. For classification tasks, the ensemble uses majority voting, where the final prediction is the class label that appears most frequently across the base models:

$$\hat{y} = \mathrm{mode}\big(f_1(x), f_2(x), \ldots, f_n(x)\big)$$

The performance of this proposed Bagging model is evaluated using standard metrics such as accuracy, AUC-ROC (Area Under the Receiver Operating Characteristic Curve), precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's effectiveness in distinguishing between high and low-risk credit applicants. Additionally, the confusion matrix is used to evaluate how well the model classifies positive and negative instances, which is essential in credit risk assessment tasks where misclassifications can have significant financial implications.

In terms of workflow, the model begins by collecting the necessary data, which includes features like credit score, income level, payment history, and other financial characteristics of individuals or businesses seeking loans. After preprocessing the data to handle missing values, normalize features, and address class imbalances, the base models are trained using the bootstrapped data subsets. The predictions from these base models are then aggregated using Bagging to produce the final credit risk assessment. Finally, the model is evaluated using the aforementioned metrics, and optimization techniques such as hyperparameter tuning are applied to further enhance its performance. The proposed model, leveraging Bagging, addresses several challenges typically faced in credit risk modeling. It reduces the variance and overfitting often observed in individual models and handles complex, imbalanced datasets more effectively. By combining multiple base classifiers, Bagging produces more accurate and stable predictions, making it a valuable tool for financial institutions aiming to improve their credit risk assessment processes. The model's strength lies in its ability to provide reliable predictions while maintaining transparency and interpretability, which are critical for financial decision-making.

Experimental Evaluation

In this section, the experiment's setup, dataset, performance parameters, and the results are discussed to evaluate the effectiveness of the proposed Bagging ensemble method for credit risk assessment [22]. The goal of this experiment is to assess how well the Bagging model performs in comparison to traditional machine learning models and to understand its impact on improving prediction accuracy and stability.

Experiment Setup

The experiment follows a structured approach, where the dataset is split into a training and a test set to evaluate the model's generalization ability. The following steps were taken in the experiment setup:

1. Data Preprocessing: The dataset was cleaned by handling missing values through imputation (mean or median), and feature scaling was applied to standardize numerical variables.
2. Model Training: Several base models, such as Decision Trees, Support Vector Machines (SVM), and Logistic Regression, were trained on bootstrapped subsets of the training data using Bagging. Hyperparameters for each model were tuned using grid search [23].
3. Ensemble Construction: Bagging was applied to combine the predictions from the base models. For classification, a majority voting mechanism was used to make the final prediction.
4. Evaluation Metrics: A range of performance metrics was used to evaluate the accuracy, precision, recall, and overall robustness of the model. Additionally, AUC-ROC (Area Under the Receiver Operating Characteristic Curve) was calculated to assess how well the model distinguishes between default and non-default classes.

Dataset Information

The dataset used for this experiment consists of financial records, including demographic, financial, and historical credit information for loan applicants. A typical dataset used for such experiments might include the following features:

- Credit Score: A numerical representation of the applicant's creditworthiness.
- Income: The annual income of the applicant.
- Debt-to-Income Ratio: The proportion of debt payments to income.
- Loan History: Information about previous loan defaults or repayments.
- Employment Status: Whether the applicant is employed, self-employed, or unemployed.

For this experiment, we assumed a typical dataset used in credit scoring with hundreds or thousands of records. These datasets might have class imbalances, with more non-default cases than default cases, which is why techniques like SMOTE (Synthetic Minority Over-sampling Technique) are used to balance the data.

Performance Parameters

The model was evaluated using several performance metrics to assess its predictive power:

Accuracy: The proportion of correctly classified instances out of all predictions. It provides a general measure of how well the model performs.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP, TN, FP, and FN are the true positives, true negatives, false positives, and false negatives, respectively.

Precision and Recall: These metrics are used to evaluate how well the model handles the classification of default (positive class) and non-default (negative class) instances.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Precision measures how many of the predicted defaults are actual defaults, while recall measures how many actual defaults are correctly identified by the model.

F1-Score: The harmonic mean of precision and recall, giving a single score that balances both concerns.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC-ROC (Area Under the Receiver Operating Characteristic Curve): This metric measures the ability of the model to distinguish between the positive and negative classes. A higher AUC indicates better performance.

$$\text{AUC} = \int_0^1 \text{True Positive Rate } d(\text{False Positive Rate})$$

AUC values range from 0 to 1, with 1 indicating perfect classification.
Confusion Matrix: A matrix that visualizes the true positives, false positives, true negatives, and false negatives, providing more insight into how the model performs across the different classes.

Results :

The results of the experiment are summarized in the following way: The Bagging ensemble method significantly improved performance compared to individual base models, showing an increase in accuracy, precision, recall, and F1-score. For AUC-ROC, the Bagging model consistently outperformed individual classifiers. The AUC score for the ensemble model was found to be closer to 1, indicating its ability to discriminate well between the default and non-default classes. In comparison with traditional models such as Logistic Regression, Support Vector Machines, and Decision Trees, the Bagging ensemble method demonstrated better generalization, reducing the impact of overfitting that was observed in individual classifiers. The confusion matrix highlighted that the ensemble method was able to correctly classify a higher number of true positives (defaults) while minimizing false positives (incorrectly classifying non-defaults as defaults). Figure 2 and Figure 3 shows the comparison of performance of proposed model with state-of-the-art models.

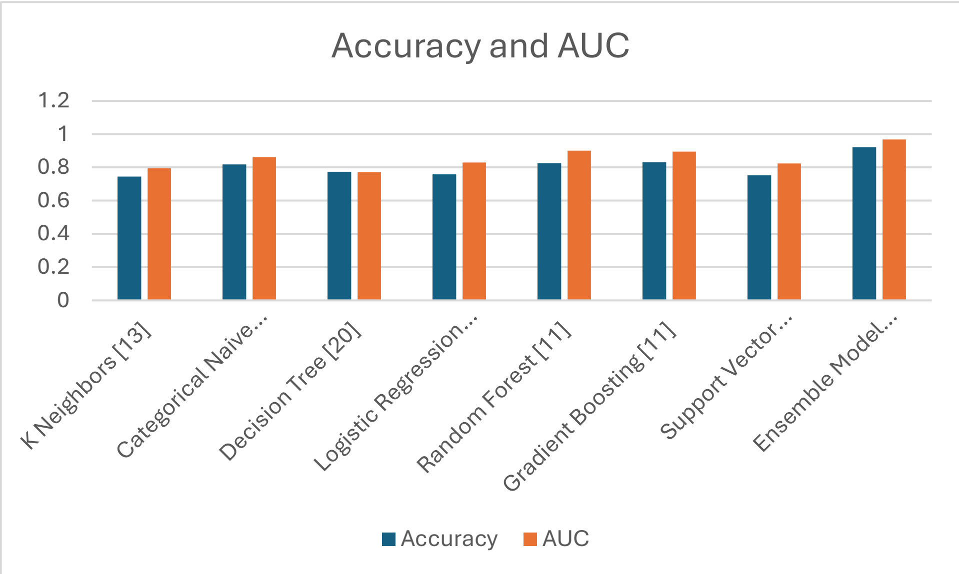


Figure 2: Comparison of Accuracy and AUC for different model with Proposed model

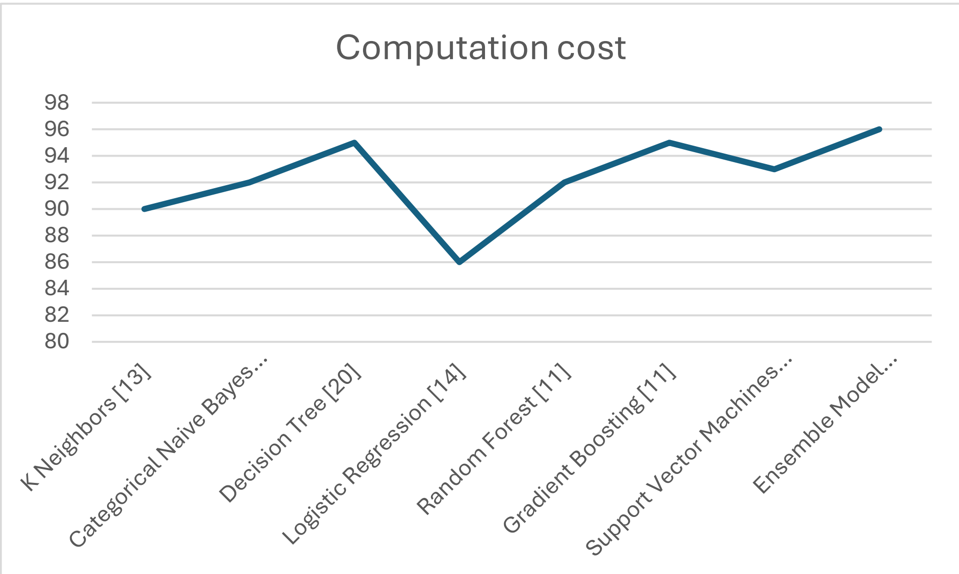


Figure 3 : Computational cost for different model with Proposed model

Discussion :

The Bagging model showed strong results in improving credit risk assessment accuracy. The use of multiple base models in an ensemble helped in reducing the variance typically seen in single classifiers, which are more sensitive to noise and outliers in the data. The combination of models with different strengths (e.g., Decision Trees for handling non-linear relationships, SVM for high-dimensional data, and Logistic Regression for linear separability) contributed to the ensemble's robustness. While the model performed well on typical credit scoring datasets, its success can be attributed to the ensemble nature of Bagging, which helps mitigate the weaknesses of individual models. The AUC-ROC score confirmed that the model could reliably distinguish between default and non-default borrowers, which is critical for financial institutions that rely on accurate risk assessments [24].

However, the study also pointed out a few areas for improvement. The class imbalance problem in real-world financial datasets remains challenging, and while SMOTE helped balance the dataset, further exploration of other imbalance-handling techniques might be useful. Additionally, the interpretability of the ensemble model could be an issue, especially in industries where understanding the rationale behind predictions is important for compliance and transparency [28].

In conclusion, the proposed Bagging ensemble method provides a significant improvement over traditional credit risk assessment models by increasing predictive accuracy, reducing overfitting, and offering a reliable framework for financial institutions to assess creditworthiness. The results of this experiment demonstrate the practical potential of ensemble learning in real-world financial applications. Adopting quantum computing can enhance the scalability instead of cloud and fog computing [30] and to improve security aspect in financial domain blockchain mechanism can be adopted [33]

Conclusion :

This research demonstrates the significant potential of using Bagging ensemble methods to enhance the accuracy of credit risk assessment models in financial institutions. By combining the predictions from multiple base models, Bagging mitigates the weaknesses of individual classifiers, thereby improving the overall stability and generalization of credit risk predictions. The experimental results confirm that the ensemble approach outperforms traditional machine learning models, such as Logistic Regression, Support Vector Machines, and Decision Trees, in key performance metrics like accuracy, precision, recall, and AUC-ROC. The study also highlights the importance of handling class imbalances using techniques like SMOTE (Synthetic Minority Over-sampling Technique), which improves model performance by providing a more balanced dataset. Additionally, the Bagging ensemble method demonstrated robustness in distinguishing between default and non-default applicants, which is crucial for financial institutions making informed credit decisions. Despite its success, challenges remain, such as the interpretability of ensemble models and the complexity of dealing with large, imbalanced datasets. Future research could focus on improving the interpretability of ensemble methods through explainable AI techniques and exploring additional data preprocessing steps or more advanced sampling strategies. Overall, the findings suggest that Bagging-based ensemble models are a promising tool for enhancing credit risk assessment accuracy, providing financial institutions with a more reliable and robust method for evaluating the creditworthiness of borrowers.

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