Improving Loan Approval Prediction with K-Fold Cross-Validation and Hyperparameter Optimisation: A Study on Machine Learning Classifiers

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Abstract. Loan approval prediction is among the main areas of financial institution's decision-making processes, facilitating the assessment of individual's creditworthiness and risk management. Despite the influx of loan applications received daily, not all applicants are granted approval, leading to inconsistent decisions and increased default risks. The paper considers different machine learning classification methods, which include Random Forest, LGBM, Gradient Boosting, K-Nearest Neighbor and Adaboost to forecast loan approval. By using cross-fold validation and hyper-parameter tuning techniques, the study strives to enhance prediction accuracy. Evaluation measures such as Accuracy, F1 score, Precision, and Recall are used for the performance of classifier. The results highlight the Random Forest classifier's superiority, achieving an impressive accuracy of 96.15% when employing a k value of 15. Overall, this study contributes to advancing loan approval prediction methodologies by providing insights into effective machine learning techniques for enhancing decision-making processes in financial institutions.

Keywords: Cross-Fold, Hyper-Parameter Tuning, Classifiers, Loan Approval, Accuracy, Precision.

1 Introduction

Banks strongly depend on loans as a major source of income and while serving people from different backgrounds to meet their needs such starting ventures, getting educated or supporting agriculture. But the main issue on ensuring loan repayment needs addressing as there are a number of factors that can disappoint such ones as unpredictable events or borrowers moving to escape. Risk management measures undertaken by banks include carefully scrutinizing applications based on age, marital status, employment status and loan amount in question along with property location before approving loans. Aware of the intricacy involved in this whole cycle, banks have come to adopt machine learning algorithms facilitating enhanced loan approval accuracy and efficiency. Intelligent algorithms including Random Forest, Logistic Regression and Tree-Based Models like Decision Trees, LGBM, Gradient Boosting, Adaboost, GridSearch prove beneficial for the right decision-making process by helping in counter product'ones data imbalance. This shift towards the utilization of machine learning aids for is essential even taking into account the heavy number of loan applications on average every day. Profits for banks significantly depend on loan approvals, therefore; they seek to avoid granting risky loans. Yet, the Verification area is time wasting that forces banks to introduce state-of-the art technologies such as machine learning allowing them for improving decision making. These algorithms consider parameters such as age, marital status, dependents population rating of job market and loan purpose location to refine modelling for a justified assessment model. By formulating machine learning and using that, banks are faced with some challenges which is algorithmic bias in interpreting by the AI algorithms also model interpretability to have a fair process of decision making. Moreover, machine learning model increases operational effectiveness by reducing time and efforts needed for data handling as well as risk assessment. In turn this reduces the human burden on bank employees which supports faster decision-making process. It also promotes a dynamic risk-management approach, that responds to an economy's dynamism' and people's sensitivities. Thorough reviews guarantee that machine learning models obey the accepted standards of correctness, equity and effectiveness in their respective fields.

To conclude, despite the successful machine learning integrations that have already promoted advancements in achieving effective loan approval processes banks are striving to find other complimentary cutting age technologies and methodologies thus further enhancing resourcefulness efficacy accuracy risk management competence. Banks should use cutting-edge analytics, alternative data sources and blockchain solutions to help borrowers get adequate secure credit quickly, fasting ways of loan approvals usher in through technology.

2 Related Works

Machine learning has gradually become an important weapon within the scope of loan prediction helping people come up with complex algorithms and record borrowers' behaviors based on vast data to predict their efforts in repaying. The subsequent section presents a review of some recent papers that use machine learning methods in the process of conducting economical assessments. Saini et al. [1] in 2023 ICACITE conference dealt with loan approval prediction on which they compared various classification algorithms for credit risk assessment. Tumuluru et al. [2] focused on customer loan approval prediction at the 20IICAI conference and researched several reflect reinforcement learning algorithms' performance. Athreyas et al. [3] carried out a thorough study concerning predicting loan default and eligibility, addressing financial decision-making processes. In 2018, Vimala and Sharmili [4] concentrated on forecasting economical risk using Naive Bayes and Support Vector Machine algorithms. Loan prediction using ML based models was published by Supriya et al. [5] in March–April 2019. In the year

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2021, Srinivasa Rao et al. [6] examined a deep study of predictive models for loan risk assessment as compared to traditional methods used in banks because digital lending platforms such as PAL has started operations across India due to its convenience and rate convergence or By comparing machine learning methods, in 2023 Kumari et al. [7] advanced loan eligibility prediction work led to the significant feature of this particular aspect as appropriate credit In 2023, Végh et al. [8] offered a comparative study on the implementation of machine learning classification models for loan approval prediction. In 2023, Diwate et al. [9] studied loan approval prediction using machine learning methods. Mamun et al. [10] discussed the works of predicting bank loan eligibility and further developing machine learning models at 2022 it enriched literature in that particular field as well relevants earlier prediction capabilities were open to other fields and everyone can help him independently try their approach predictions between independent books on theories lack compared do they are approvals so mutual development correlate In 2021, Al Mamun et al. [11] compared machine learning models for predicting bank loan capability in this journal published by Emerald Group Publishing Limited In 2020, Alaradi and Hilal [12] concentrated on tree-based methods for loan approvement optimization. Other research conducted by Orji et al. [13] was the investigation of classifiers which help to estimate eligibility for bank loan in 2022 year. In 2023, Prasanth et al. [14] use Random Forest algorithm for the loan eligibility and approval systems implemented by them in that year.

Loan eligibility prediction in the banking sector was improved by Kumar et al. [15] through different machine learning approaches that were used as early as 2022. In the year 2017, Vaidya [16] used logistic regression to predict loan application. Gupta et al. [17] suggested a Machine Learning-based system for bank loan prediction using the said method. In September 2021, Dosalwar et al. [18] conducted machine learning analysis on the availability of loan using various survey techniques in their study in India. Machine learning was investigated for predicting loan amounts by Jawale et al. [19] in July 2021.In 2017, Garg [20] critically discussed the cardiovascular risk score calculators and their linkage. Meena Kumari et al. [21] analyzed application of ML for prediction accuracy score between target class (i-e ‘loan eligibility) that uses only In 2029, Singh et al. [22] concentrated on different techniques used for credit card fraud detection from various perspectives and models in their most recent work. Shaheen and ElFakharany [23] analyzed the use of predictive analytics for cases of loan defaults in 2018 banking sector. In 2020, Lai [24] employed machine learning methods to forecast loan defaults. Soni [25] and Singh et al. [26] proposed an updated loan prediciton system based on a machine learning approach. Khoei et al. [27] developed advanced models for identifying GPS spoofing strikes on UAVs in 2022. Yadav and Singh [28] utilized algorithms such as support vector machines and logistic regression to predict loan status in 2023. Choudhary et al. [29] focused on machine learning regression algorithms in 2022 and Panchal. [30] focused on future credit cards in 2019.

This is a review of literature on machine learning studies associated with financial analysis, covering loan approval prediction. It emphasizes the contribution of machine learning to accurate financial forecasting and optimization, which helps with risk management in the field.

3 Proposed Methodology

We started our analysis on Loan Approval Prediction dataset from the database of Kaggle. The dataset is composed of thirteen Independent and dependent Attributes such as Loan-Id, Gender, Dependents, Education, Self-Employed, Applicant-Income, Coapplicant-Income, Loan-Amount, Loan Amount-Term, Credit History, Property Area, Loan Status (Target Variable). The dataset contains nearly 952 Instances. The Analysis was started with Data Exploration Initially for each type of attribute in the dataset, later we applied various data preprocessing techniques such as the data cleaning, data reduction, data transformation and data integration using the NumPy and Pandas library. The overall methodology of our approach is depicted in figure 1. Once the preprocessing process is done, we have gone through the partition of the cleaned dataset into two datasets:75% of Training dataset and 25% of Testing dataset. We have developed five machine learning classifiers such as LGBM Classifier, Random Forest classifier, K Nearest Neighbor Classifier, Gradient Boosting Classifier and Adaboost classifier to get their accuracy to predict the loan approval. Subsequently, we applied cross-validation with different values of k (k=5,7,10,12,15) and computed the accuracy for each classifier accordingly, later we applied the Hyper Parameter tuning methods such as the GridSearchCV, RandomizedSearchCV for the optimal predicted Classifier as base Classifier. The overall study aimed to assess the effectiveness of cross-validation and hyper parameter tuning in improving the accuracy of classifiers compared to their non-cross-validation and non-Hyper parameter Tuning performance. The classifier with the highest accuracy was identified as the best predictor for loan approval across various scenarios.

Table 1. Description of dataset.

Variable Name	Description	Data Type
Loan_ID	Applicant's Identity	Categorical
Gender	Sex of Applicant	Categorical
Married	Marital status of Applicant	Categorical
Dependents	Number of dependents depended on Applicant	Categorical
Education	To know whether the Applicant is literate or not	Categorical
Self-Employed	Employment of Applicant	Categorical
Applicant-Income	Applicant Income	Numerical
Coapplicant-Income	Co-applicant Income	Numerical
Loan Amount	Loan amount	Numerical
Loan Amount -Term	To know the number of terms required for Loan in months	Numerical
Credit-History	To know the Credit Score History of Applicant	Numerical
Property Area	To know the Assets of Applicant	Categorical
Loan-Status	Loan (`Approved/Rejected)	Categorical

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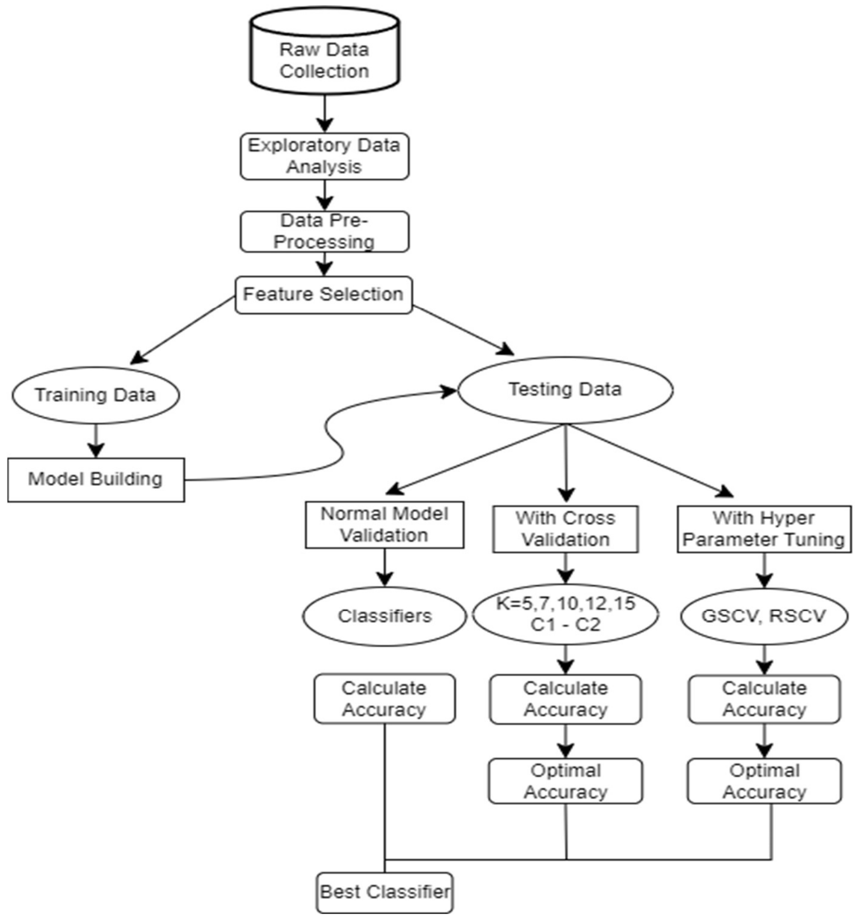

Fig. 1. Proposed Architecture

4 Experimental Analysis

In this section, we present experimental analysis and findings for our study on predicting loan approval. The study is then presented in its initial form without the use of Cross-validation and Hyper-parameter tuning. Now, with its cross-validation using k values of five, seven, twelve and fifteen while considering hyperparameter optimization for obtaining the best classifier. The experiment was carried out in a quad-core i7 machine with 16 GB RAM. Using the Google Colab web application development for libraries including Pandas, Numpy Scikit-Learn Matplotlib SciPy and Random from Python. We carried out our experimental analysis in two stages. To begin with, we focused on data cleaning in our first step through Panda's tool. To analyze the data, we employed various methods. Once we were done preparing the needed data, we headed for phase 2. In this step, we used five different machine learning classifiers to predict loan approval. But we did it in two ways. First, we evaluated how each of the classifiers performed without using cross-validation or hyperparameter tuning. This has enabled us to know how the software accurately predicts the dataset.

Table 2. Accuracies of Classifiers without Cross-Validation and Hyper-Parameter Tuning.

Classifiers	**Accuracy**
LGBM classifier	91.66%
Random Forest Classifier	95.83%
K Nearest Neighbor Classifier	83.33%
Gradient Boosting Classifier	95.58%
Adaboost Classifier	86.11%

In comparison of classifiers' performance without cross-validation and hyperparameter tuning, Random Forest looks to be approximately the best which has achieved higher accuracy at 95.83% on dataset that reveals better predictive features for this model. Gradient boosting did fine with a predictive power of 95.58%, thus being reliable on estimates Second, LGBM Classifier was not far behind with an accuracy of 91.66%, while AdaBoost got a middle level result which is equal to the somewhat notable value for its kind at 86.11%. However, the K-Nearest Neighbor had the lowest accuracy of 83.3% which indicates that this model might not suit such a dataset without additional calibration or reflection as Table 2 shows below references.

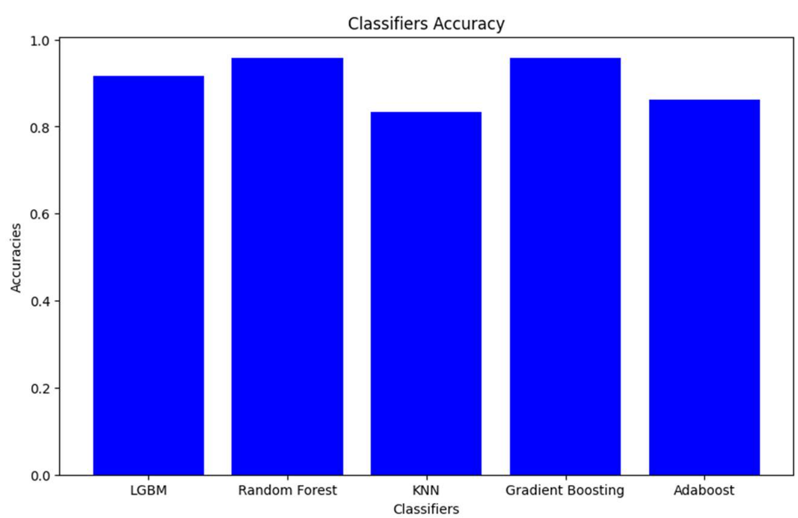

Fig. 2. Accuracy of different classifiers without Cross-Validation and Hyper-Parameter Tuning

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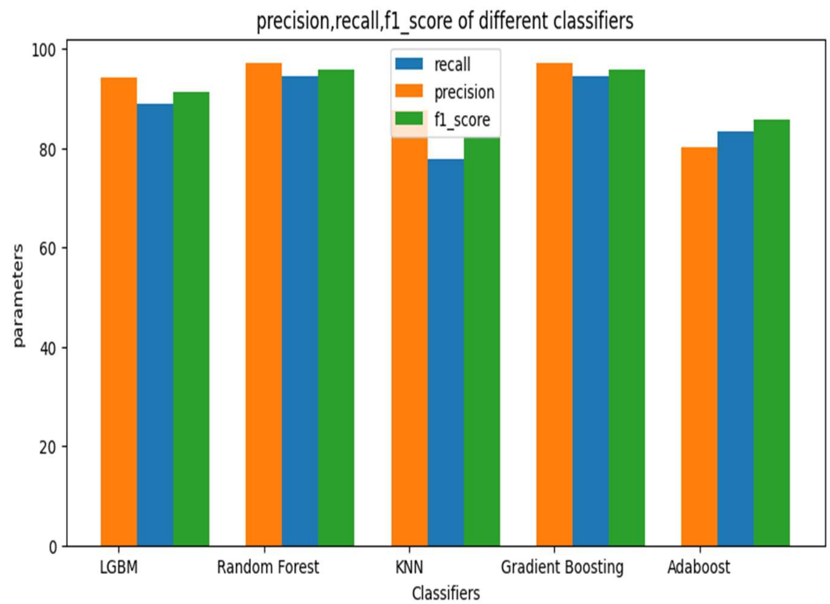

Fig. 3. Performance Metrics of Classifiers without Cross-Validation and Hyper-Parameter Tuning

In the cross-validation, each classifier was tested with various values of K (5,7,10,12,15), whereas Random Forest Classification always yielded the best scores recording highs as 0.96 at k =15. The LGBM classifier achieved high accuracy rates, with the result almost always exceeding 0.93. The K-Nearest Neighbor Classifier began with lower accuracy but went up to 0.77 at the value of k =15. The two algorithms, Gradient Boosting and Adaboost Classifier performed well as their accuracy scores ranged between 0.88 to 0.93, and from 0.81 to 0.86. Overall, Random Forest Classifier turned out to be a most stable classifier in this comparison being seconded by LGBM Classier but lagging behind when it came to KNN classifier first with low values of binary grouping before moving up following higher or greater k values.

Table 3 depicts the outcomes of various cross-validation runs (k = 5, 7,10,12, and 15) for different classifiers in terms of their capability to predict loan approval. They show metrics like precision, recall and F1 score, which gives information about the classifier's performance in various validation setups. Further, figures 5 to 9 provide insights into the predictive power of classifiers under identical cross-validation settings. These are important analyses as they play a key role of selecting the optimal classifiers that will estimate approval for a loan with high accuracy in realistic developments.

Table 3. Classifiers accuracies with Cross-Validation

With Cross-Validation Method					
Classifiers	**Accuracies at k = (5,7,10,12,15)**				
	K=5	**K=7**	**K=10**	**K=12**	**K=15**
LGBM	0.93	0.94	0.94	0.94	0.94
Random Forest	0.94	0.94	0.92	0.95	0.96
K NearestNeighbor	0.70	0.74	0.76	0.77	0.77
Gradient Boosting	0.88	0.91	0.92	0.93	0.91
Adaboost Classifier	0.81	0.86	0.84	0.84	0.84

Table 4. Performance Metrics of Classifiers with Cross-Validation

Performance Metrics of Classifiers with Cross-Validation						
Classifiers	**Metrics**	**K=5**	**K=7**	**K=10**	**K=12**	**K=15**
LGBM	**Precision**	0.9	0.91	0.94	0.93	0.93
	Recall	0.9	0.91	0.94	0.93	0.93
	F1-Score	0.9	0.91	0.94	0.93	0.93
Random Forest	**Precision**	0.94	0.94	0.95	0.95	0.96
	Recall	0.94	0.94	0.95	0.95	0.96
	F1-Score	0.94	0.94	0.95	0.95	0.96
KNN	**Precision**	0.7	0.74	0.76	0.77	0.78
	Recall	0.7	0.74	0.76	0.77	0.77
	F1-Score	0.7	0.74	0.76	0.77	0.77
Gradient Boosting	**Precision**	0.88	0.91	0.92	0.93	0.92
	Recall	0.88	0.91	0.92	0.93	0.91
	F1-Score	0.88	0.91	0.92	0.93	0.91
Ada boost	**Precision**	0.81	0.84	0.84	084	0.84
	Recall	0.81	0.84	0.84	0.84	0.84
	F1-Score	0.81	0.84	0.84	0.84	0.84

The accuracies of classifiers employing k-fold cross-validation at various k values (k=5, 7, 10, 12, 15) are illustrated in Figure 4, which shows the difference between the performance of classifiers.

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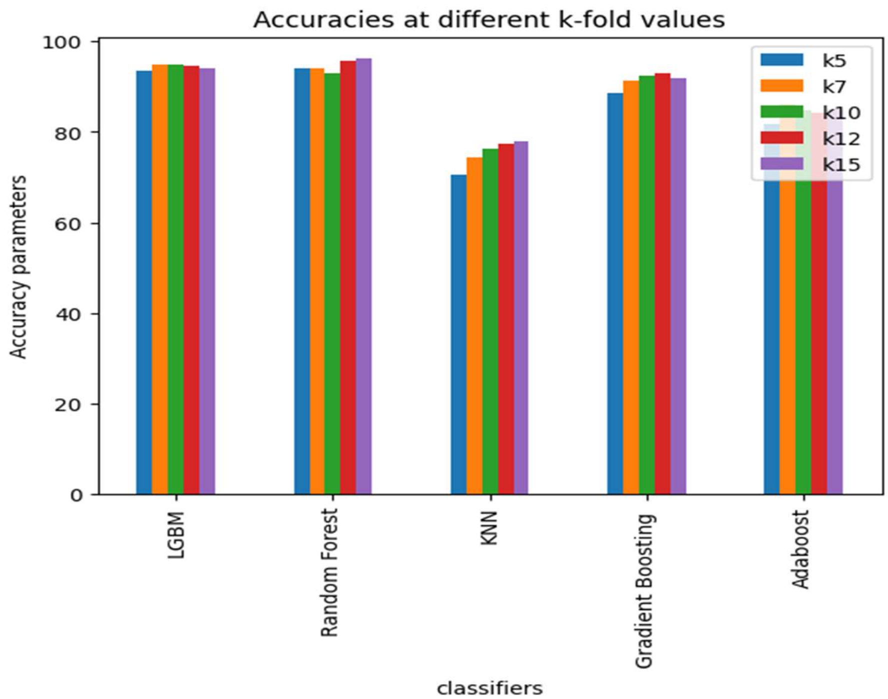

Fig. 4. Accuracies of Classifiers with various k-values

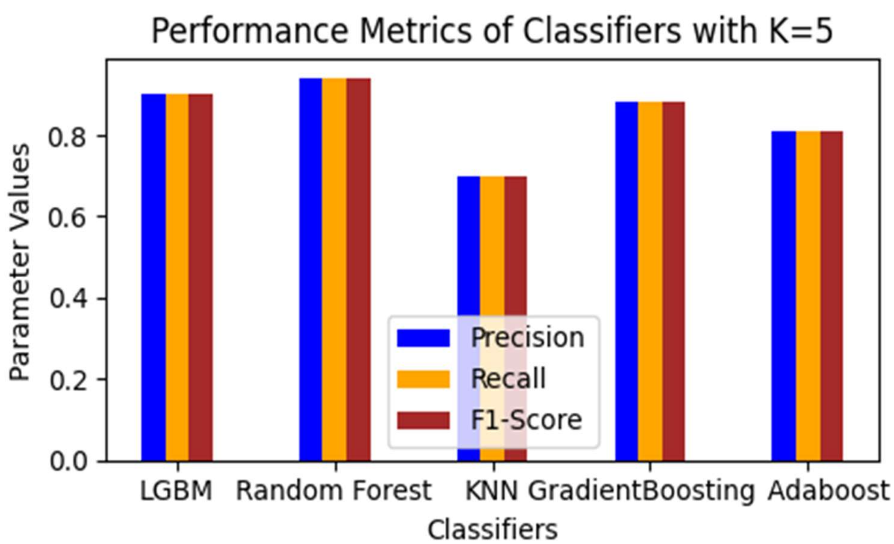

Fig. 5. Precision, Recall, F1-Score of Classifiers with K=5

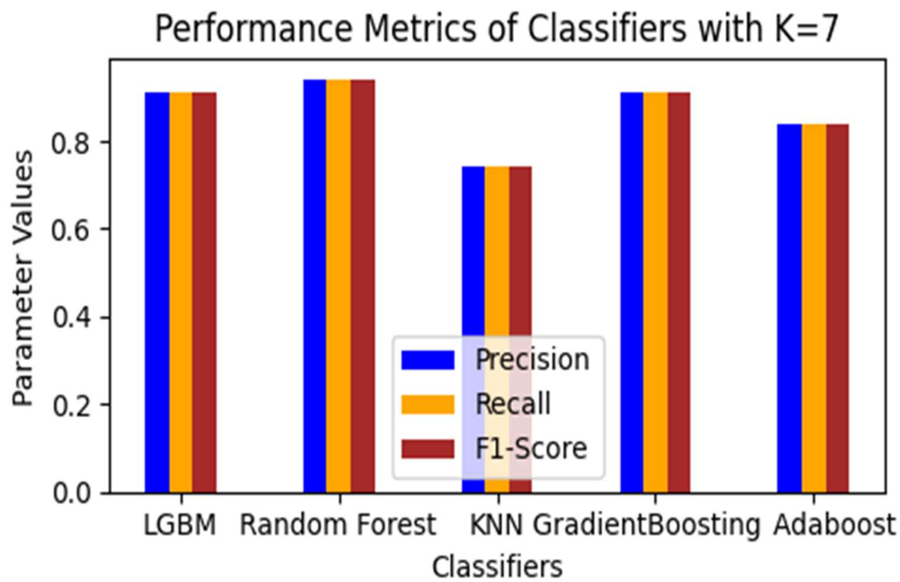

Fig. 6. Precision, Recall, F1-Score of Classifiers with K=7

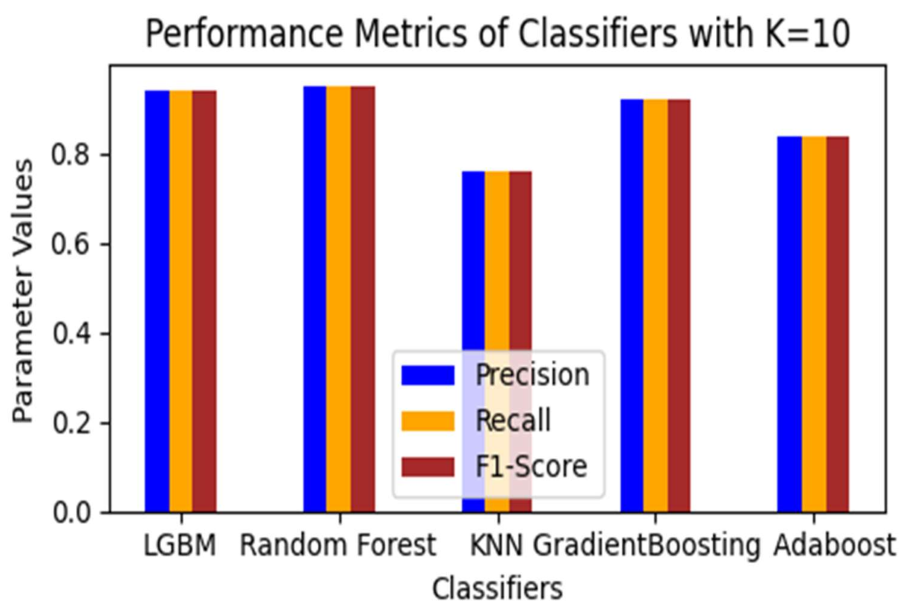

Fig. 7. Precision, Recall, F1-Score of Classifiers with K=10

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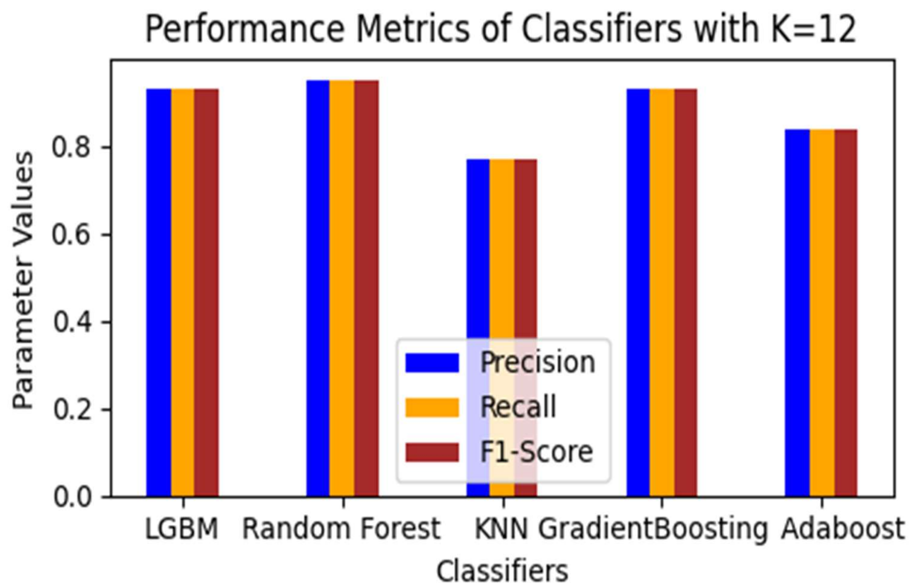

Fig. 8. Precision, Recall, F1-Score of Classifiers with K=5

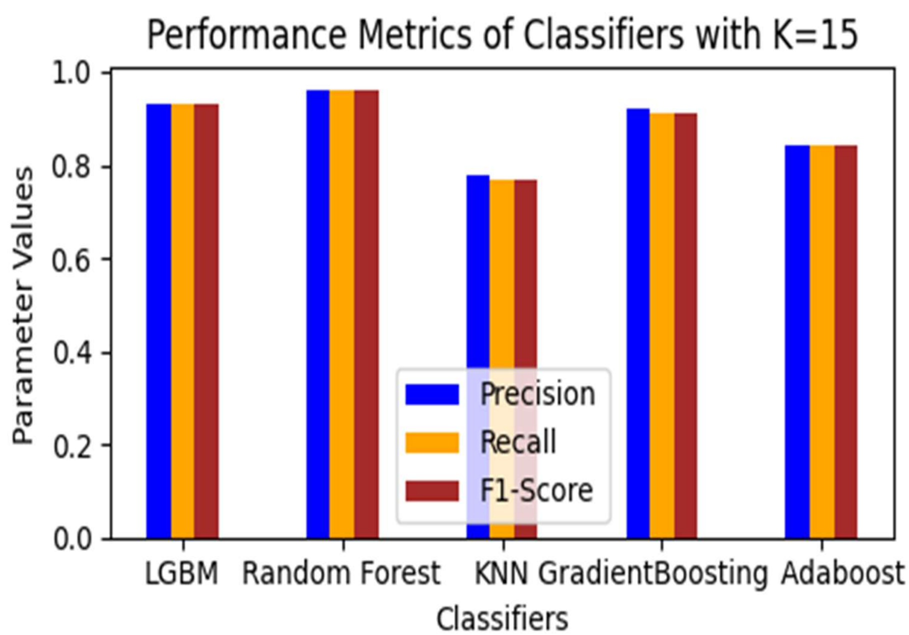

Fig. 9. Precision, Recall, F1-Score of Classifiers with K=15

Table 5. Hyper-Parameter Tuning for Optimal Classifiers

With Hyper-Parameter Tuning	
Classifiers	**Base Classifier: Random Forest**
GridSearchCV	95.83%
RandomizedSearchCV	94.77%

In Hyper Parameter Tuning, we have chosen two methods i.e. GridSearchCV and RandomizedSearchCV. We compared two methods for tuning the parameters of the Random Forest classifier since, it is the Optimal Classifier. GridSearchCV achieved a slightly higher accuracy of 95.83%, while RandomizedSearchCV resulted in a slightly lower accuracy of 94.77%. This shows that GridSearchCV might be a bit better than the RandomizedSearchCV and, it is represented in Figure.10 with their Accuracy Score. However, both methods are effective in improving its performance.

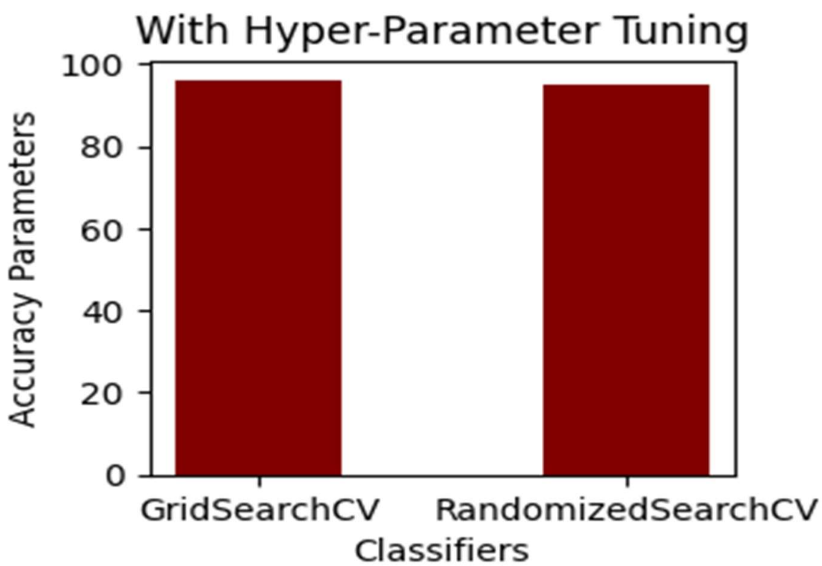

Fig. 10. Accuracy of Random Forest Classifier with Hyper-Parameter Tuning

5 Conclusion And Future Directions

Finally, the results of this research emphasize how critical machine learning classifiers are for predicting loan approvals and helping to improve decision making within financial institutions. By using a thorough appraisal involving cross-fold validation and hyperparameter tuning. The study revealed that the Random Forest classifier performed better, as it achieved an accuracy of 96.15% at K=15, While other classifiers performed adequately, Random Forest proved to be the best model for loan approval classification. Additionally, this research presented a similar analysis of the effectiveness comparison between GridSearchCV and RandomizedSearchCV tuning for accurate hyper-parameterization with respect to performance benches related to accuracy in predictive parameters among random forest classifiers.

In sum, this study provides valuable information about the application of machine learning techniques in optimizing loan approval prediction methodologies that can help institutions avoid default risks as well as enhance decision-making procedures. This research stresses the use of latest methodologies and measures, which are reported that include Accuracy F1 Score Precision Recall to inform sustainability risk assessment capabilities by machine learning. It would be suggested to further develop the selected classifier with respect to specific problem requirements to obtain improvements of predictive accuracy.

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