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An ensemble machine learning based bank loan approval predictions system with a smart application

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ABSTRACT

Banks rely heavily on loans as a primary source of revenue; however, distinguishing deserving applicants who will reliably repay loans presents an ongoing challenge. Conventional selection processes often struggle to identify the most suitable candidates from a pool of loan applicants. In response to this challenge, we present an innovative machine learning (ML) based loan prediction system designed to identify qualified loan applicants autonomously. This comprehensive study encompasses data preprocessing, effective data balancing using SMOTE, and the implementation of diverse ML models, including Logistic Regression, Decision Tree, Random Forest, Extra Trees, Support Vector Machine, K-Nearest Neighbors, Gaussian Naive Bayes, AdaBoost, Gradient Boosting, and advanced deep learning models such as deep neural networks, recurrent neural networks, and long short-term memory models. The model's performance is rigorously assessed in terms of accuracy, recall, and F1_score. Our experimental analysis reveals that the Extra Trees outperforms its counterparts. Furthermore, we successfully predict bank loan defaulters through an ensemble voting model, which includes the top three ML models, achieving a remarkable 0.62% increase in accuracy compared to the Extra Trees. To facilitate user interaction, we have developed a user-friendly desktop-based application. Notably, our findings demonstrate that the voting-based ensemble model surpasses both individual ML models, including Extra Trees, and existing state-of-the-art approaches, achieving an impressive accuracy of 87.26%. This innovative system has the potential to significantly streamline and enhance the efficiency of bank loan approval processes, ultimately benefiting both financial institutions and loan applicants alike.

1. Introduction

The banking industry plays a pivotal role in ensuring a nation's financial stability, and as such, it is subject to comprehensive regulatory frameworks in most countries. Among the core activities of banks, lending stands out, with the interest income generated from loans forming a significant portion of their assets (Dansana et al., 2023). Nevertheless, the current loan approval process faces notable challenges, primarily concerning its efficiency and accuracy, as it heavily relies on manual procedures. These procedures entrust individual bank managers with the responsibility of assessing the eligibility and loan default risk associated with applicants. The implications of these manual processes are considerable, ranging from potential financial losses for banks to the extreme scenario of systemic disruptions that could adversely affect the broader economy.

Throughout the history of banking, the loan approval process has revolved around the challenge of distinguishing creditworthy borrowers from a vast pool of applicants (Khairi et al., 2021, Carlin & Mayer, 2003). The need for effective loan default prediction has grown more pronounced in modern banking systems. Failures in predicting loan defaults have had far-reaching consequences, including banking crises (Musdholifah et al., 2020). Identifying loan defaulters manually has proven to be an intricate task, given the complexity of the contemporary banking landscape and the ever-increasing demand for loans.

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Machine learning (ML) algorithms, which empower systems to autonomously decipher patterns and make data-driven predictions, have emerged as a promising solution to assess the likelihood of loan default (Talukder et al., 2022, Ma et al., 2023, Mustaffa & Sulaiman, 2023). These algorithms delve into clients' transaction histories and social profiles, uncovering behavioral patterns and common characteristics that yield insights into future repayment behaviors (Koulouridi et al., 2021). Additionally, deep learning techniques, such as deep neural networks, have gained prominence in this context, as they excel in capturing complex, non-linear relationships within the data (Talukder, Islam et al., 2023), further enhancing the evaluation of the probability of loan default for individual customers. Consequently, ML and deep learning-based approaches have been extensively explored to provide a comprehensive assessment of loan default risk.

Within this context, the role of banks in evaluating credit risk cannot be understated. Assessing the credit history of borrowers before granting loans is fundamental for distinguishing between potential defaulters and non-defaulters (Kadam et al., 2021). Given the multifaceted nature of this task and the burgeoning demand for loans, developing an accurate predictive system manually is a formidable challenge (Rawate & Tijare, 2017). While some prior research has ventured into machine learning models for predicting loan default, reliance on a single classifier is insufficient for real-world deployment (Kadam et al., 2021). Therefore, we introduce an ensemble approach utilizing top-performing machine learning algorithms to enhance loan approval systems.

Loan approval constitutes a critical operation for financial institutions, entailing a comprehensive evaluation of various factors, including income, social status, and citizenship, to determine loan eligibility. Ensuring timely loan repayment is paramount for the successful operation of banks, necessitating a precise assessment of borrowers' repayment capacity (Kadam et al., 2021). Several studies have explored machine learning for enhanced loan approval prediction. (Bhargav & Sashirekha, 2023) utilized Random Forest classifiers and found them to outperform traditional Decision Trees. (Wang et al., 2023) introduced a stacking-based model that significantly improved joint loan approval. (Dasari et al., 2023) developed an ensemble model, boosting prediction accuracy from 80% to 94%. (Abdullah et al., 2023) applied advanced machine learning techniques, particularly Random Forest, for nonperforming loan prediction with a focus on emerging markets. Existing research in this domain has proposed various models, yet a comprehensive analysis encompassing both machine learning and deep learning approaches has been lacking. Moreover, most existing solutions have not demonstrated the level of accuracy required for practical implementation in real-life scenarios (Kavitha et al., 2023, Demraoui et al., 2022).

Our motivation stems from building on these studies to enhance loan approval prediction accuracy and efficiency. We aim to contribute by developing an ensemble machine learning model, addressing data imbalance, conducting comprehensive model evaluations, and comparing our approach with existing methods, ultimately streamlining the loan approval process for financial institutions and applicants. We endeavor to construct an ensemble voting model using top-performing machine learning algorithms, a robust approach that holds the potential to revolutionize the loan approval process and expedite loan approvals for customers, ultimately benefiting both banks and loan applicants.

The contributions of this paper are as follows:

1. We have developed a loan approval prediction model using ensemble machine learning algorithms, which achieves higher performance than a single machine learning algorithm. The proposed model consists of nine machine learning algorithms: Logistic Regression (LR), Support Vector Machine (SVM), Decision Trees (DT), Gaussian Bayesian (GB), Random Forest (RF), AdaBoost (AdB), Extra Trees (ET), K- Nearest Neighbors (KNN), and Gradient Boosting (GB). To compare the machine learning model with the deep learning model in the loan prediction system, we train and test three deep learning models: Dense Neural Network (DNN), Long Short Term Memory (LSTM), and Recurrent Neural Network (RNN).
2. We have performed Synthetic Minority Oversampling Technique (SMOTE) analysis on the dataset to make it balanced to fit well for the model.
3. The performance of each machine deep learning model, and ensemble learning model is evaluated in terms of accuracy, precision, recall, and f1_score. We have included a comparison of our proposed model with some of state of the art models.
4. Finally, we have included the trained ensemble model in a desktop application developed with a user interface for individuals and banking institutions to check their bank loan status.

The rest of the paper is organized as follows. In section 2, we review related works. The proposed methodology is described in section 3. The prediction system is implemented, and result analysis is conducted in section 4 before concluding the article in section 6.

2. Related works

In the realm of bank loan prediction, ML algorithms have demonstrated their efficacy, mirroring their success in diverse domains such as data mining, decision support systems, cybersecurity, traffic management, game theory optimization, natural language processing, agriculture, and medical applications, including leaf disease, brain tumor, breast cancer, human behavior analysis, etc. (Islam et al., 2023, Sharmin et al., 2023, Alzubi et al., 2022, Talukder, Hasan et al., 2023, Kakkar et al., 2022, Ahammad et al., 2021, Khan et al., 2019, Ahamed et al., 2021, Ahmed et al., 2021, Uddin et al., 2023, Akhter et al., 2023).

Bhargav and Sashirekha (2023) employed novel Random Forest classifiers to compare machine learning approaches for loan approval prediction. Loan prediction datasets from the Kaggle library were utilized for accuracy and loss testing. RF method achieved 79.44% precision and 21.03% loss, outperforming the traditional Decision Tree with 67.28% precision and 32.71% loss in a sample of 20 instances. Statistical analysis via an independent sample T-test resulted in a p-value of 0.33, indicating insignificant differences between the techniques at a 95% confidence level. This study suggested that RF was more accurate in predicting loan acceptance than Decision Trees.

Wang et al. (2023) introduced a stacking-based model to approve financial institution risks, selecting the best model by comparing performance. They also built a bank approval model using deep learning on imbalanced data, utilizing CNN for feature extraction and counterfactual augmentation for balanced sampling. Optimizing the auto finance prediction model based on bank model features led to around a 6% increase in joint loan approval, as demonstrated in experiments on real data.

An ensemble model designed by (Dasari et al., 2023) that combines diverse machine learning algorithms using techniques such as bagging and voting classifiers. The main aim was loan eligibility prediction. This model enhances accuracy and reduces human effort and processing time, outperforming existing methods. Experimental results indicate a boost in performance from 80% to 94% compared to the previous model.

Abdullah et al. (2023) applied diverse machine learning techniques to predict nonperforming loans in emerging countries' financial institutions. Analyzing data from 322 banks across 15 nations, advanced machine learning models, especially random forest, outperformed linear methods with 76.10% accuracy. Bank diversification emerged as the key predictor, outweighing macroeconomic factors in nonperforming loan prediction.

The performance of machine learning algorithms was examined for the goal of assessing bank loan risks using conventional methods, with higher accuracy. Alsaleem and Hasoon (2020) achieved higher accuracy for Multilayer Perceptron (MLP) compared to RF, BayesNet, Naive Bayes (NB), and DTJ48 algorithms for categorizing bank loan risks. The

Table 1
Comparison of Different Existing Work's Results.

Parameter	Models for Loan Prediction used in the Existing Work														Paper	Year
	ET	RF	CB	LGB	EGB	DT	KNN	SVM	DTAB	LR	NB	XGB	BN	MP		
Acc(%)	**86.2**	85.6	84.9	84	83.9										(Anand et al., 2022)	2022
Acc(%)		72				69	59	70	**84**						(Kumar et al., 2022)	2022
Acc(%)		77.3				66.2	61.9	65		**78.5**	77.9	77.3			(Dosalwar et al., 2021)	2021
Acc(%)		78.5				73.5					77.5		75	**80**	(Alsaleem & Hasoon, 2020)	2020
Acc(%)						71.9		65.3		78.9	**80.4**				(Blessie & Rekha, 2019)	2019

model's performance was evaluated using the conventional metrics on a dataset containing 1000 loans and their repayment status.

Wang et al. (2019) utilized deep learning methods to assess consumer credit risk when e-commerce platforms provide unsecured loans to support customer purchases. Supriya et al. (2019) applied LR, DT, and GB to forecast loan risk. Khashman (2009) recommended a credit risk assessment system. They used a neural network trained using a backpropagation learning algorithm. They aimed to create a prediction system to assist the credit card issuer in modeling the risk of credit card delinquency. They also investigated the capability of deep learning (Movassagh et al., 2021, Sun & Vasarhalyi, 2021) in predicting credit card risks. Madaan et al. (2021) provided two machine learning models that analyzed particular attributes that are more useful to determine if an individual should be granted a loan. Their system might assist banking authorities in selecting appropriate people from a list of applicants who requested a loan.

Ghatasheh (2014) compared the performance of two algorithms: RF and DT. The RF algorithm was found to perform better for credit risk prediction in their research. Shoumo et al. (2019) performed a comparative analysis of popular machine learning models and showed that SVM outperformed other models among other models such as LR and RF. Their result demonstrated that the LR model can identify the optimal target consumers for loan approval. The model suggested that a bank should not only target affluent consumers for loan granting.

Bank authorities should also examine other customer traits that play a significant role in credit granting choices and forecasting loan defaulters (Kadam et al., 2021). Training and testing data sets had been created from the bank customer dataset. The training dataset comprises around 600 rows and 13 columns, while the test dataset has approximately 300 rows and 12 columns but does not include the target variable (Jency et al., 2018, Supriya et al., 2019).

Singh et al. (2021) used machine learning models trained on historical data to predict whether a new customer might be provided a loan or not. They created a model by feeding records and approval outcomes from past loan transactions into the system. Rath et al. developed models that can determine loan approval or disapproval (Rath et al., 2021). Their outcome showed that RF achieved a substantially higher accuracy (80%) than other algorithms, including LR (73%), DT (79%), and SVM (75%) (Zhu et al., 2019).

Supriya et al. (2019) employed DT to predict loan risk. They performed preprocessing of the data by applying missing value imputation and exploratory data analysis before model creation and assessment. Li (2019) compared the performance of the XGBoost algorithm with LR in their works. According to them, the XGBoost model has demonstrated substantially better outcomes than the LR model.

Anand et al. (2022) gathered a dataset of 850 records to forecast Loan behavior with machine learning models for secure banking. Their model included DT, RF, ET, CatBoost (CB), Light Gradient Boosting (LGB), and Extreme Gradient Boosting (EGB). Their finding showed that the ET and RF had higher accuracy in predicting loan approval.

Kumar et al. (2022) collected a dataset of 614 entries from a public repository to assess loan eligibility. They used a variety of machine learning algorithms, including RF, DT, KNN, SVM, and DT with AdaBoost. Their finding demonstrated that the ensemble model decision tree with the AdaBoost technique provided higher accuracy. Likewise, (Dosalwar et al., 2021) collected a loan prediction dataset from Kaggle. They trained and tested several models, including LR, DT, KNN, NB, RF, SVM, and XGB. The LR model was found to be more accurate in predicting loan eligibility.

Alsaleem and Hasoon (2020) used a dataset from the UCI repository that contains 1000 Instances, and 11 attributes to forecast loans. Five models, DT J48, Bayes Net (BN), NB, RF, and MLP, were used to forecast loans. MLP was found to be more accurate in predicting loan availability. Blessie and Rekha (2019) also collected loan data from a Kaggle source (Chatterjee, 2021). To forecast loans, they utilized four models: LR, DT, SVM, and NB classifiers. Their finding showed that NB produced more accurate accuracy in predicting loan availability.

Table 1 shows the detailed model performances of the existing works.

3. The proposed system for bank loan prediction

Fig. 1 depicts the overall design of the suggested model. This work aims to find the best model and integrate the model with the user interface to forecast loan receivers. We develop a web application that determines if a customer is eligible for a loan. Fig. 1 illustrates the pre-processing steps applied to the loan data, including data splitting into training and testing sets. Subsequently, nine machine learning algorithms are trained, and an ensemble model is constructed using the top three performing models. The model's performance is evaluated in terms of accuracy, precision, recall, and F1 score. Several features, including Gender, marital status, dependents, education, self-employed, applicant income, co-applicant income, loan amount, loan amount term, credit history meets, and property, are considered the most important for determining loan approval.

- **Data Collection:** In this study, a Kaggle dataset on the loan prediction (Chatterjee, 2021) is collected. The original dataset was imbalanced in nature. We have addressed this issue by employing two data augmentation techniques. One approach is SMOTE to balance the dataset. This approach is adopted to enhance the machine learning model's performance, as this tends to exhibit better results when trained on balanced datasets. To achieve dataset balance, we have also employed another technique wherein we trained a simple machine-learning model using the available data. After that, we utilized user-selected data, which closely resembled the available data, to evaluate the model and predict the corresponding class labels. Subsequently, we incorporated this additional data into the dataset. Once the dataset reached a state of near balance, we concluded the data augmentation process. The dataset contains 806 rows and 13 columns used to forecast loan receivers. Next, data preparation entails identifying relevant characteristics, dealing with missing information, and dealing with outliers. Finally, the data is divided into a training and testing set, with 75% training data and 25% test data.
- **Dataset Preparation:** Initially, the duplicate sample is checked to eliminate data redundancy. We ensured that there was not a single duplicate sample in the dataset. The cross-validation and testing approach are used to divide the data into 75% for training and 25% for testing. Data preparation includes data cleaning (manag-

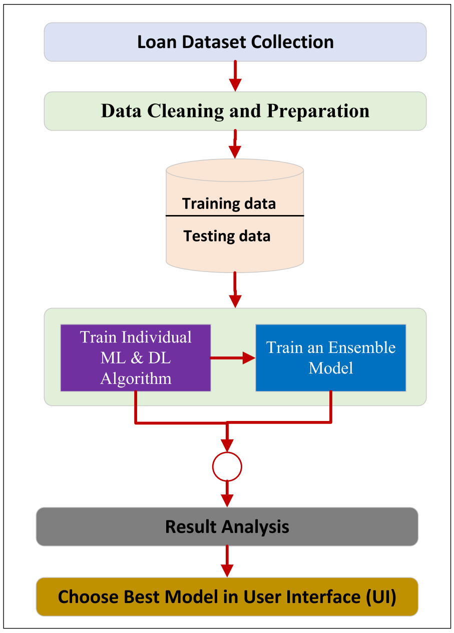


Fig. 1. Block diagram of the proposed system.

ing missing values), data transformation (normalizing the data), and data reduction (using just important features and removing duplicate values of less relevant characteristics). The first stage in preprocessing is data cleaning, which involves verifying for and removing any missing variables that may impair the model's accuracy. This is accomplished by either using a mean or mode function to fill in the missing values or removing all missing data. The missing values are discarded in this situation. After cleaning the data, log transformation was used to reduce or eliminate the skewness of our original data. Normalization aims to scale down features to a similar scale. This enhances the model's functionality and training stability (Singh & Singh, 2019). To make the dataset trainable for the machine learning model, categorical values are converted to numerical values using integer encoding, where each categorical value is mapped to a corresponding integer value. Equation (1) highlights the operation of the Integer-encoding approach. For e_i, it is a vector of the standard base, where e_i denotes the vector with the i^{th} coordinate.

$$e_i = I_A(x) = \begin{cases} 0, & \text{if } x \in A \\ 1, & \text{if } x \in A \\ 2, & \text{if } x \in A \end{cases} \tag{1}$$

Another technique for enhancing the capacity of machine learning models to identify patterns in data is normalization (Aljaaf et al., 2018). The Min-Max scale method is used to rescale the features further. Using the equation in (2), the features are rescaled from 0 to 1. In the equation below, χ denotes the real values whereas χ_{min} and χ_{max} are the minimum and maximum values of the feature f_i. The rescaled values are χ_v and $\chi, \chi_{min}, \chi_{max} \in f_i$.

$$\chi_v = \frac{\chi - \chi_{min}}{\chi_{max} - \chi_{min}} \tag{2}$$

3.1. Best model selection process

We developed a system that can forecast if a loan application might be a defaulter for a particular loan. Fig. 2 depicts the system architecture and selection process of the best model that is linked with a user interface.

1. First, we train nine different popular machine learning models and analyze their performance.
2. Secondly, we form two ensemble models: one consists of the nine classifiers, and another consists of the top three performing models. The performance of these ensemble approaches is evaluated.
3. Thirdly, the model with the highest accuracy is selected to include in a Desktop based application.
4. Finally, a user application is developed, and the best-performing machine learning model is adopted to forecast loan defaulters.

Ensemble approach: This involves combining multiple individual models to make more accurate and robust predictions. This aims to improve the performance and generalization of the overall model by leveraging the strengths of different individual models and reducing their weaknesses. Here, we use the voting ensemble technique, which is depicted in Fig. 3. In a voting-based ensemble, each model gives its prediction for a given input, and the final output is determined by the majority vote or weighted average of the individual model predictions.

4. Implementation and performance analysis

We have conducted the experiment on the hardware that includes a laptop with at least 4 GB of RAM and a Window. We use Anaconda Navigator (Anaconda3) for creating and debugging modern online and cloud applications. The machine learning and deep learning models are built on a Jupyter notebook with Python 3.9, and the following libraries: numpy, pandas, matplotlib, tkinter, pickle, message box, Keras, TensorFlow, and sklearn are used.

1. **Numpy** is a Python library that supports multidimensional arrays, linear algebra, and the Fourier transform.
2. **Pandas** is a Python-based data manipulation and analysis program technique.
3. **Matplotlib** is for creating static, animated, and interactive visualizations.
4. **Sklearn** is used for building machine learning and statistical models, such as clustering, classification, and regression.
5. **Tkinter** is a typical Python framework for generating graphical user interfaces for desktop applications.
6. **Pickle** is generally used in Python to serialize and deserialize Python object structures.
7. **MessageBox** Widget in Python Tkinter is used to show message boxes in Python applications.

4.1. User interface (UI) details

Fig. 4 shows the graphical view of the user interface we implemented. We have used a loan dataset with eleven independent attributes and one dependent attribute (Target attribute). Therefore, every independent attribute is to be filled for loan check availability in UI. Dependent attribute **Loan Status** depends on the following independent attribute: Gender, Married, Dependents, Education, Self-Employed, Applicant Income, Co-applicant Income, Loan Amount, Loan Amount Term, Credit History Meets, and Property Area.

Connect Best Model With User Interface (UI): We developed the User Interface (UI) using the Tkinter Python library. This interface facilitates a visual representation of bank loan availability checks. The best model is connected with the UI according to the following (Fig. 5) process.

4.2. Performance metrics

Machine learning models can exhibit a diverse range of characteristics and behaviors, making it challenging to identify the optimal model

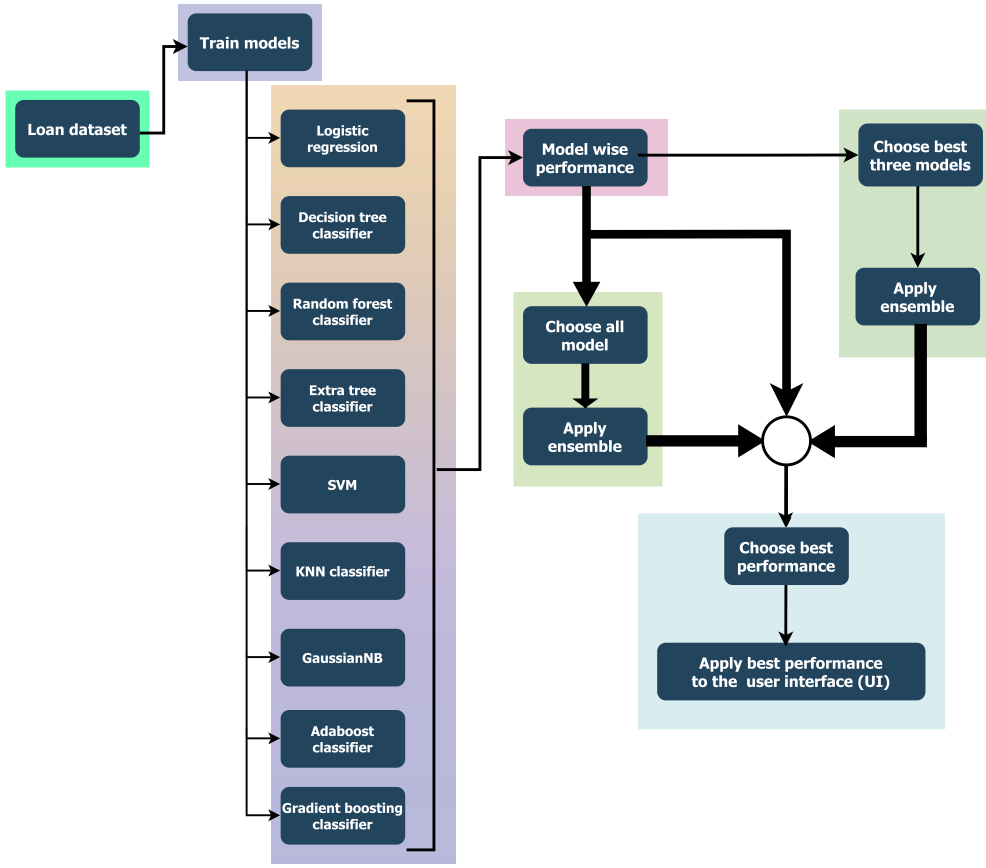


Fig. 2. Selection of the best model.

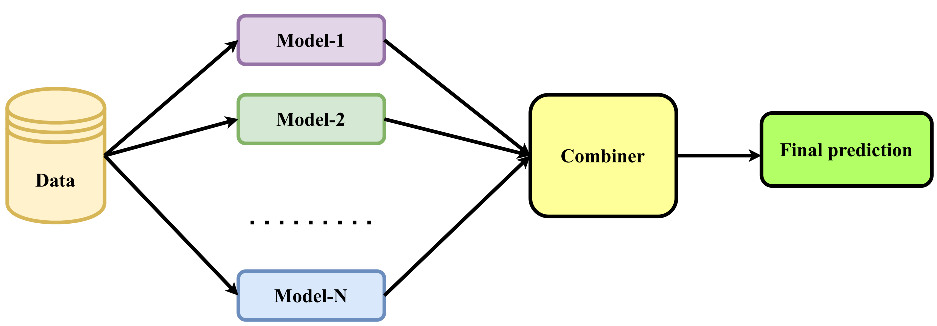


Fig. 3. Voting Ensemble Procedure.

for a given task. Consequently, it is crucial to possess a set of tools that can assess the performance of machine learning models effectively. Several commonly employed quality control measures in machine learning are outlined below. Among these measures, the accuracy, precision, recall, and F1-score stand out as the most widely used method for evaluating model performance. The confusion matrix for computing accuracy, precision, recall, and F1-score is presented below.

1. **True Positives** occur when the prediction is YES, and the actual output is YES.
2. **True Negatives** occur when the prediction is NO and the actual output is NO.
3. **False Positives** occur when the prediction is YES, but the actual output is NO.
4. **False Negatives** occur when the prediction is NO and the actual output is YES.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{3}$$

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

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

$$F1 - Score = \frac{(2 * precision * recall)}{(precision + recall)} \tag{6}$$

5. Results and discussions

We have selected the best model in two ways: i) training of individual model using random state data splitting and (2) Ensemble of the top performing model. Random data splitting means randomly dividing the dataset into two halves, with the training dataset =75% and the testing dataset = 25% to evaluate the model's performance.

Fig. 4. Graphical view of User Interface.

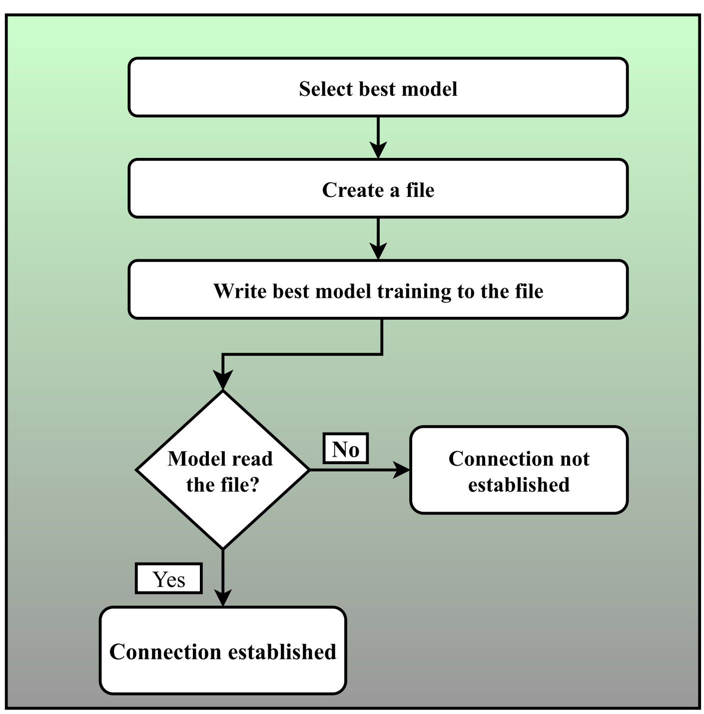
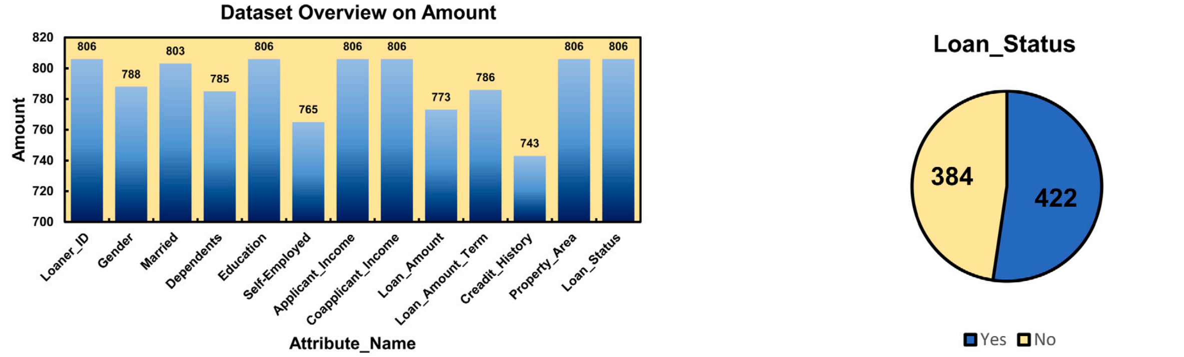
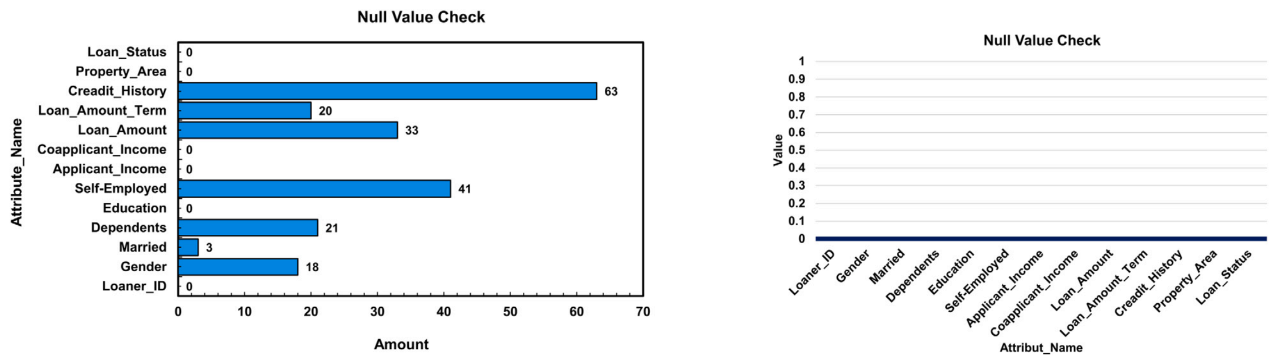


Fig. 5. Best Model Connectivity Process.



(a) Dataset Graphical View (b) Loan Status Graphical View

Fig. 6. Graphical view of dataset and loan status.



(a) Before Null Value Remove. (b) After Null Value Remove.

Fig. 7. Null Value Treatment.

Table 2
Dataset feature.

Attribute Name	Description of Attribute	Data Type
Loan_ID	Unique Loan ID	Integer
Gender	Male/ Female	Character
Married	Applicant married (Y/N)	Character
Dependents	Number of dependents	Integer
Education	Graduate/ Under Graduate	String
Self_Employed	Self Employed (Y/N)	Character
ApplicantIncome	Applicant income	Integer
CoapplicantIncome	Coapplicant income	Integer
Loan_Amount	Loan amount in thousands	Integer
Loan_Amount_Term	Term of loan in months	Integer
Credit_History	credit history meets guidelines	Integer
Property_Area	Urban/ Semi Urban/ Rural	String
Loan_Status	Loan Approved (Y/N)	String

5.1. Dataset

Table 2 shows the information of the loan dataset collected from the Kaggle source (Chatterjee, 2021). The dataset includes the following features presented in Table 2.

Fig. 6 shows the data visualization attribute, and the YES and NO Status of the loan dataset are target attributes.

5.2. Analyzing exploratory data (AED)

First, the dataset was cleansed. Next, we perform exploratory data analysis and feature engineering. Finally, the model was applied to predict if the applicant might return the loan. A bank usually analyzes the potential financial risks before deciding on lending money to a customer. Therefore, a thorough analysis is required to understand the customer's characteristics.

The AED includes handling missing values, Log Transform, picking critical columns using filtering, generating new columns, identifying target variables, and presenting the data in graphical format. To analyze and extract information from the loan dataset, this work utilizes Python's pandas package. The outcome of AED is presented in different graphs for better presentation and comprehension.

Fig. 7 shows the result of null value count and removal. Fig. 8 and 9 show the graphical presentation of log transmission of attribute numerical values. Fig. 10 shows the mutual dependency of data attributes.

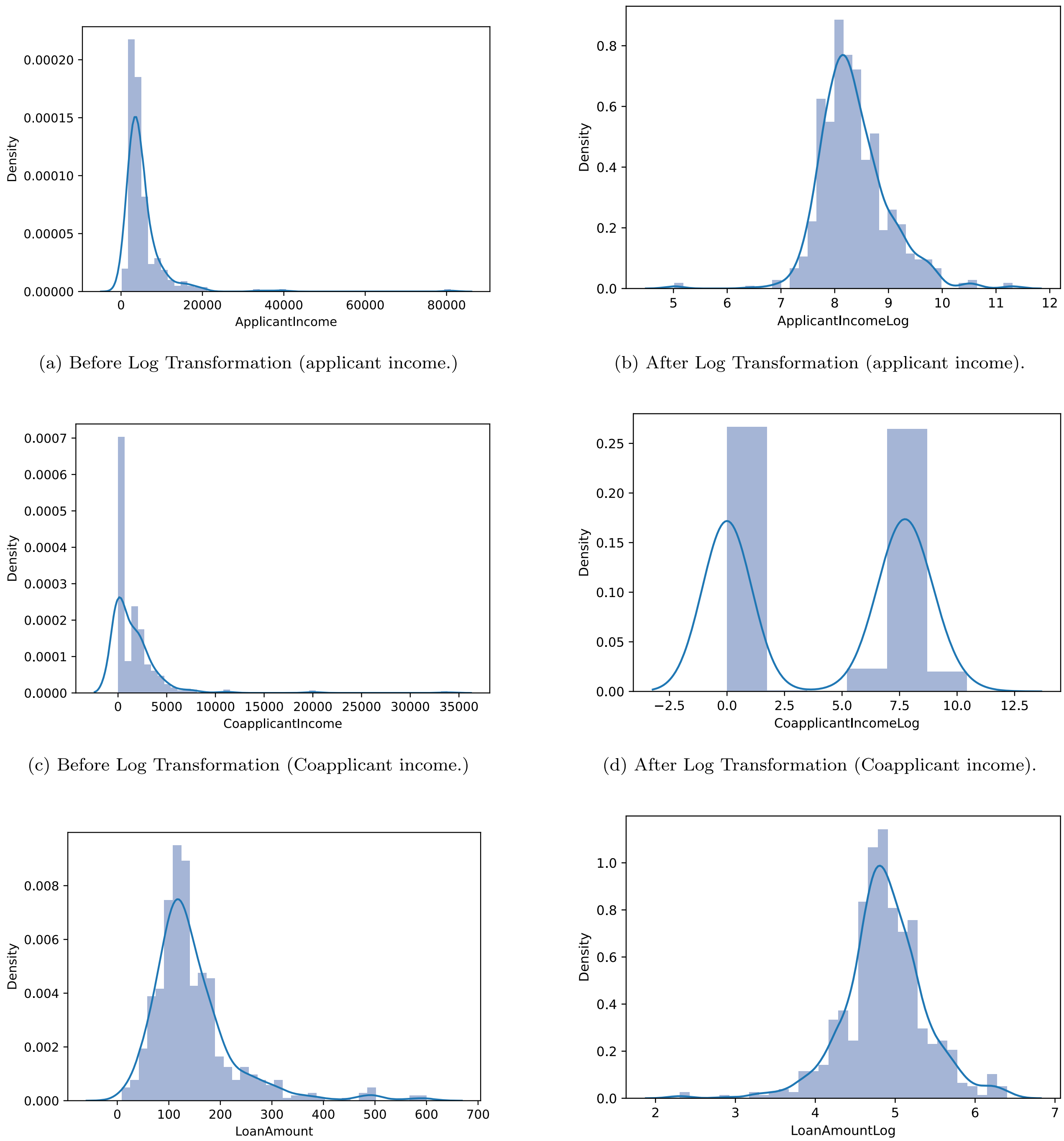
5.3. Model wise performance analysis

Table 3 presents the model-wise performance results. Table 3 presents the precision, recall, and F1-score performance for various models. Here is the analysis of the results.

We achieved the highest precision value of 0.94 from the classification report for "No" loan status for the LR model. In contrast, the highest recall achieved for "Yes" loan status is 0.97, and the highest f1-score value was 0.77 achieved for "Yes". DT achieved 0.81 for "Yes" and the highest f1-score (0.80) for "No". On the other hand, the highest recall value of 0.82 is achieved for "Yes". We obtained the highest precision value of 0.85 for "No" loan status in the case of the RF model. In contrast, the highest recall for "Yes" loan status is 0.82, and the highest f1-score value of 0.84 was found for both "Yes" and "No".

In ET algorithm, the highest precision value of 0.88 is found for "No" and the highest f1-score for "Yes", the value is 0.86. On the other hand, the highest recall value of 0.89 is obtained for "Yes".

In the SVM model, the highest precision value of 0.94 is obtained for "No", and the highest f1-score for "Yes" is 0.75. On the other hand, the highest recall value, 0.97, was achieved for "Yes". Again, we achieved



(a) Before Log Transformation (applicant income.)

(b) After Log Transformation (applicant income).

(c) Before Log Transformation (Coapplicant income.)

(d) After Log Transformation (Coapplicant income).

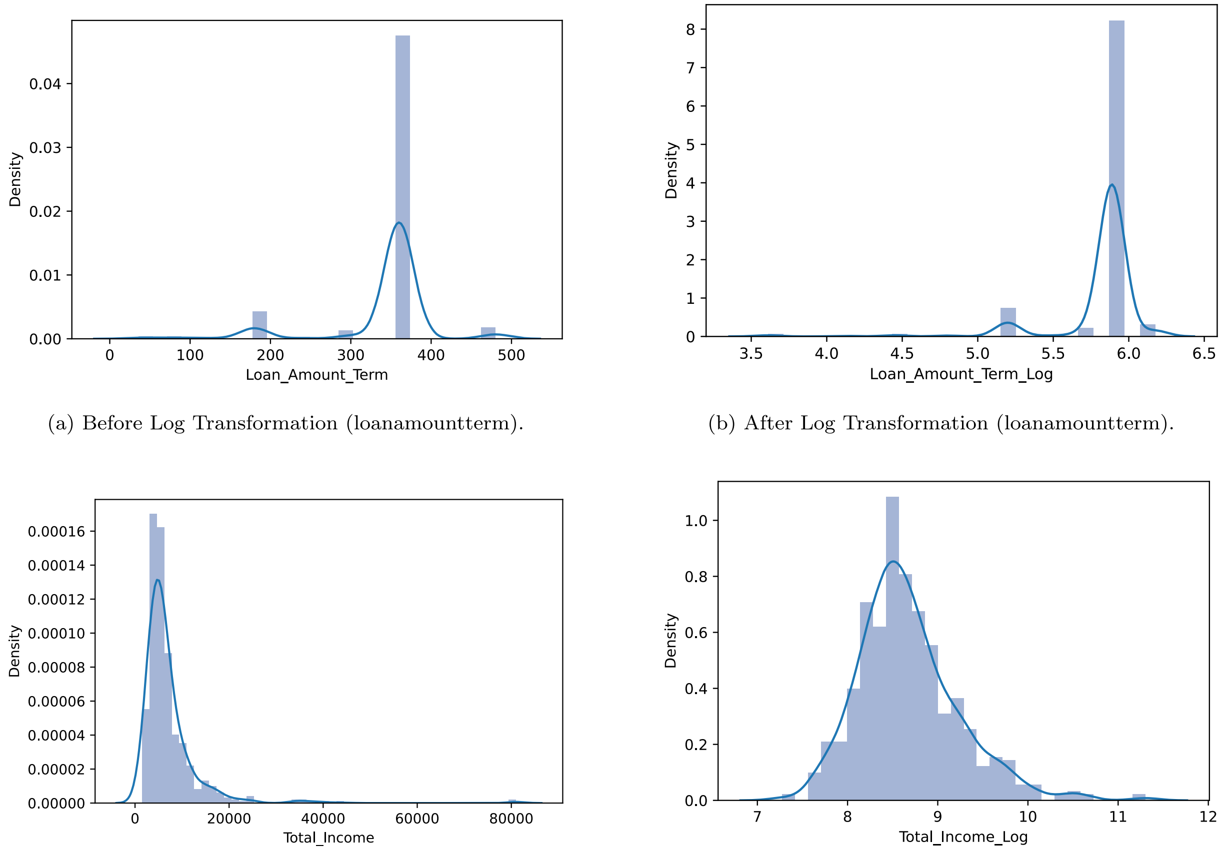
(e) Before Log Transformation (loan amount).

(f) After Log Transformation (loan amount).

Fig. 8. Log Transformation.

the highest precision value of 0.87 for the “Yes” loan status for the KNN model. In contrast, the highest recall achieved for “No” loan status is 0.90, and the highest f1-score value is 0.81 achieved for both “Yes” and “No”. GNB’s highest precision value of 0.87 is achieved for “No” and the highest f1-score for “Yes” is 0.75. On the other hand, the highest recall value of 0.94 is achieved for “Yes”. In the AdaBoost algorithm, the highest precision value of 0.76 is obtained for “No” and the highest f1-score for “Yes” is 0.74. On the other hand, the highest recall value of 0.81 is achieved for “Yes”. We achieved the highest precision value of 0.86 for the “No” loan status for the Gradient Boosting model, whereas the highest recall achieved for the “Yes” loan status is 0.89, and the highest f1-score value was 0.81 achieved for both “Yes”. Overall, DT, RF, ET, and GB yielded strong results across multiple evaluation metrics.

LSTM and RNN performed adequately but with slightly lower precision and recall for the “No” class. DNN exhibited a precision of 0.65 for the “Yes” class and 0.9 for the “No” class. The recall was 0.94 for the “Yes” class and 0.51 for the “No” class, leading to an F1-score of 0.78 for the “Yes” class and 0.65 for the “No” class. LSTM achieved a precision of 0.64 for the “Yes” class and 0.88 for the “No” class. The recall was 0.93 for the “Yes” class and 0.48 for the “No” class, resulting in an F1-score of 0.76 for the “Yes” class and 0.62 for the “No” class. RNN demonstrated a precision of 0.69 for the “Yes” class and 0.79 for the “No” class. The recall was 0.83 for the “Yes” class and 0.62 for the



(a) Before Log Transformation (loanamountterm).

(b) After Log Transformation (loanamountterm).

(c) Before Log Transformation (totalincome).

(d) After Log Transformation (totalincome).

Fig. 9. Log Transformation.

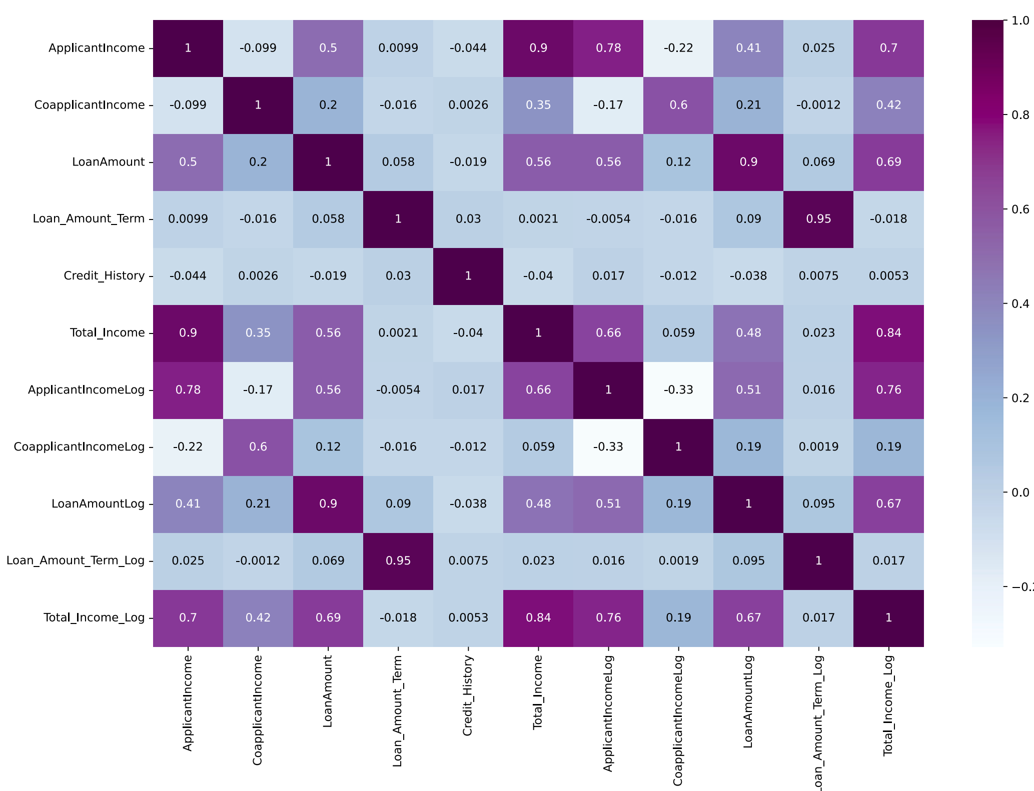


Fig. 10. Correlation Matrix.

Table 3
Precision, recall f1-score performance for all model.

Parameter	Precision		Recall		F1-Score	
	Yes	No	Yes	No	Yes	No
Logistic Regression	0.63	0.94	0.97	0.42	0.77	0.58
Decision Tree	0.81	0.77	0.76	0.82	0.78	0.8
Random Forest	0.83	0.85	0.86	0.82	0.84	0.84
Extra Trees	0.83	0.88	0.89	0.82	0.86	0.85
SVM	0.62	0.94	0.97	0.38	0.75	0.55
KNeighbors	0.87	0.74	0.7	0.9	0.77	0.81
GaussianNB	0.62	0.87	0.94	0.42	0.75	0.57
AdaBoost	0.68	0.76	0.81	0.62	0.74	0.68
Gradient Boosting	0.75	0.86	0.89	0.71	0.81	0.77
Dense Neural Network	0.65	0.90	0.94	0.51	0.78	0.65
Long Short-Term Memory	0.64	0.88	0.93	0.48	0.76	0.62
Recurrent Neural Network	0.69	0.79	0.83	0.62	0.75	0.70

Table 4
Model Wise Accuracy Performance.

Model Name	Accuracy (%)
Logistic Regression (LR)	70.06
Decision Tree (DT)	78.98
Random Forest (RF)	84.71
Extra Trees (ET)	**86.64**
Support Vector Machine (SVM)	68.15
K-Nearest Neighbors (KNN)	79.61
Gaussian Naive Bayes (GNB)	68.15
AdaBoost (AdB)	71.33
Gradient Boosting Classifier (GBC)	79.61
Dense Neural Network (DNN)	73.24
Long Short-Term Memory (LSTM)	71.33
Recurrent Neural Network (RNN)	73.24

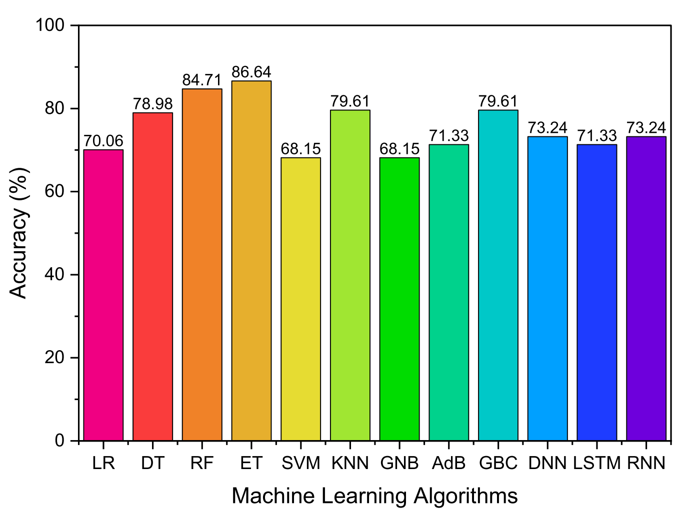


Fig. 11. Model Accuracy Comparison.

"No" class, leading to an F1-score of 0.75 for the "Yes" class and 0.7 for the "No" class.

Table 4 presents the accuracy performance of different models. We can observe that the three deep learning models, namely DNN (73.24%), LSTM (71.33%), and RNN (73.24%), did not perform better than the other machine learning models for the loan dataset. This indicates that for the given dataset, the deep learning models did not yield higher accuracy compared to traditional machine learning algorithms.

The best-performing model, as depicted in Table 4, was determined based on overall accuracy. The ET demonstrated the highest accuracy of 86.64%, surpassing other models by more than 6%. This superiority of the ET classifier can be visually observed in Fig. 11, which presents the accuracy performance of each model.

Table 5
Voting Ensemble Learning Performance for all Model.

Parameter	Precision		Recall		F1-Score	
	Yes	No	Yes	No	Yes	No
Voting Ensemble 1	0.78	0.95	0.96	0.72	0.86	0.82

Table 6
Voting Ensemble Learning Performance for the Best Three Models.

Parameter	Precision		Recall		F1-Score	
	Yes	No	Yes	No	Yes	No
Voting Ensemble 2	0.84	0.89	0.90	0.82	0.87	0.85

Table 7
All model (nine) and best three model accuracy performance for voting ensemble learning.

Model Name	Accuracy(%)
Voting Ensemble 1	84.07
Voting Ensemble 2	**87.26**

5.4. Performance for voting ensemble

We applied the voting ensemble learning approach to get the best accuracy. Here, we applied ensemble learning in two ways. First, we pick all nine models and apply the ensemble learning. Secondly, we pick the best three models (Table 4 or Fig. 11) considering their performances.

From the classification report, we can observe that the highest precision value of 0.95 for "No" loan status considering all the models (LR, DT, RF, ET, SVM, KNN, GBN, AdB, and GB). In contrast, the highest recall for "Yes" loan status is 0.96; the highest f1-score value is 0.86, achieved for "Yes". The result is illustrated in Table 5.

From Table 6, we see that the highest precision value of 0.89 for "No" loan status by considering the best three (from Fig. 11) model (RF, ET, and KNN), whereas the highest recall is achieved for "Yes" loan status, is 0.90 the highest f1-score value 0.87 achieved for "Yes".

We achieved the best accuracy of 87.26% (Table 7) from the best three models after applying the voting ensemble learning. The result was greater than all the other existing work performances and around a 2% increase when we applied the voting ensemble for all models.

5.5. Discussions

Table 8 shows the overall performance comparison of this project work. Here, we achieved precision, recall, and f1-score best performance in the Extra Trees Classifier before applying voting ensemble learning. The comparison of our proposed model with existing works is shown in Table 10. Some existing work (Anand et al., 2022, Kumar et al., 2022, Dosalwar et al., 2021, Alsaleem & Hasoon, 2020, Blessie & Rekha, 2019) did not use the classification report for result analysis. A little decrease in performance occurs after applying an ensemble in all models. However, we have achieved much better performance when we apply ensemble learning based on our proposed model.

Fig. 12 shows the binary classification confusion matrix. Here 0 means 'No' and 1 means 'Yes' for loan status.

From the overall accuracy performance, we achieved the best accuracy of 87.26% for our proposed model (apply ensemble in best three models). Our result is greater than compared to the existing work (Table 1), which is illustrated in Table 9.

Table 9 represents the model-wise accuracy performance with existing work. In this section, we can see that Paper1 (ET), Paper2 (DT with

Table 8
Overall Performance Comparison.

Parameter		Precision		Recall		F1-Score	
		Yes	No	Yes	No	Yes	No
Before apply voting ensemble learning	Logistic Regression	0.63	0.94	0.97	0.42	0.77	0.58
	Decision Tree	0.81	0.77	0.76	0.82	0.78	0.8
	Random Forest	0.83	0.85	0.86	0.82	0.84	0.84
	Extra Trees	0.83	0.88	0.89	0.82	0.86	0.85
	SVM	0.62	0.94	0.97	0.38	0.75	0.55
	KNeighbors	0.87	0.74	0.7	0.9	0.77	0.81
	GaussianNB	0.62	0.87	0.94	0.42	0.75	0.57
	AdaBoost	0.68	0.76	0.81	0.62	0.74	0.68
	Gradient Boosting	0.75	0.86	0.89	0.71	0.81	0.77
	Dense Neural Network	0.65	0.90	0.94	0.51	0.78	0.65
	Long Short-Term Memory	0.64	0.88	0.93	0.48	0.76	0.62
	Recurrent Neural Network	0.69	0.79	0.83	0.62	0.75	0.70
After apply voting ensemble learning for all model	Voting Ensemble 1	0.78	0.95	0.96	0.72	0.86	0.82
After apply voting ensemble learning for best three model	**Voting Ensemble 2**	0.84	0.89	0.9	0.82	0.87	0.85

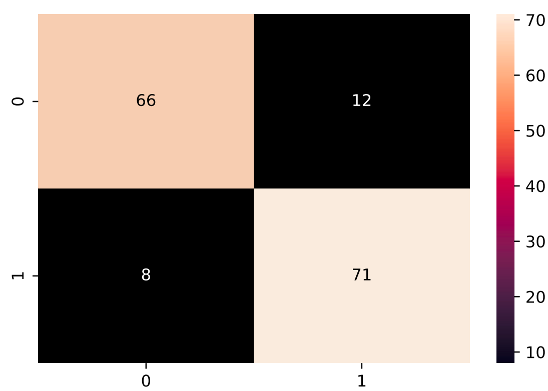


Fig. 12. Confusion matrix for binary classification.

Table 10
Model wise highest accuracy comparison with existing work.

	Model	Accuracy (%)	Paper
Existing Work	Extra Tree	86.2	(Anand et al., 2022)
	Decision Tree with AdaBoost	84	(Kumar et al., 2022)
	Logistic Regression	78.5	(Dosalwar et al., 2021)
	Multilayer Perceptron	80	(Alsaleem & Hasoon, 2020)
	Naïve Bayesian	80.4	(Blessie & Rekha, 2019)
Proposed work	Model Wise(ExTree)	86.64	Table 9
	Ensemble with All	84.07	
	Ensemble with best Three	87.26	

Table 9
Overall Accuracy Performance.

Model Name	Accuracy (%)
Best model before ensemble (Table 4)	86.64
Ensemble all model (Table 7)	84.07
Ensemble best three model (Table 7)	**87.26**

AdaBoost), Paper3 (LR), Paper4 (MLP), and Paper5 (NB) have achieved an accuracy of 86.2%, 84%, 78.5%, 80%, and 80.42% respectfully for existing work. Our work has achieved Extra Trees Classifier accuracy of 86.64% greater than the existing work.

Finally, we achieved the best accuracy of 87.26% (Table 9) based on our proposed model (ensemble for best three models) compared to the model-wise highest accuracy with existing work (Table 10).

5.5.1. User interface performance

Fig. 13 shows the mandatory data input validation check. All the data must be input before the loan status check for the specific customer.

No negative data is allowed in any input shown in Fig. 13. Any negative input in the user interface form can not be performed with the specific customer for loan availability check. When all the input data fulfills loan availability for the specific customer, the developed user interface (UI) shows the message ‘Customer is eligible for the loan’. If not fulfilled, show the message ‘Customer is not eligible for the loan’ in Fig. 13.

The performance of machine learning techniques depends on the nature of the dataset used to train and evaluate the model. This study is conducted utilizing publically available secondary loan data from the Kaggle repository. In this work, we’ve used different built-in Machine Learning models. We target to train the machine learning models with real-time data in the future. We used only one ensemble learning approach. We can also use ensemble learning approaches like Stacking, Blending, and Bagging to compare the model’s performance.

Deep learning models such as Convolutional Neural Networks (CNNs) and their variations like VGG16, MobileNet, and DenseNet are widely recognized as effective models for image-based object identification and prediction. However, these deep learning models are not considered the most suitable choice when it comes to tabular data, such as the loan dataset. Instead, models like DNNs, LSTM, and RNNs are commonly used for tabular data analysis. These models excel in handling temporal and sequential data, where the order and timing of the data points matter. However, in the case of the loan dataset, this does not possess a purely sequential or temporal nature, and as a result, deep learning algorithms do not achieve significantly higher accuracy compared to machine learning algorithms. Our experimental results support this observation, indicating that machine learning algorithms are more effective for the loan dataset than deep learning algorithms.

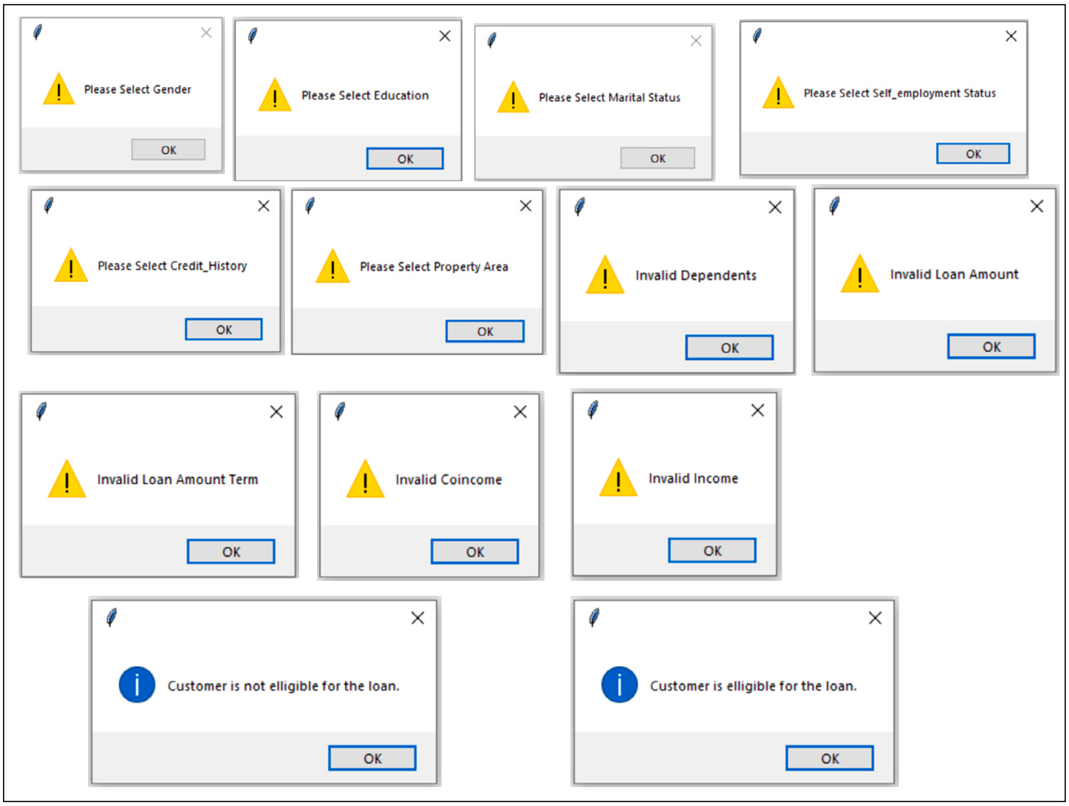


Fig. 13. Data input and validation check for the users.

6. Conclusion

The study focused on the estimation of loan default risks using machine learning and deep learning algorithms in the banking sector. The choice of algorithm plays a crucial role in loan decision management, as this helps determine the likelihood of loan default by clients. Banks can minimize the risk of financial loss when granting loans by accurately predicting the probability of a defaulted loan. Initially, we performed the dataset cleansing, which involved removing variables with a high proportion of missing data. We addressed unbalanced data and outliers issues before feeding the data to machine learning algorithms. We explored multiple machine learning algorithms, including LR, DT, RF, ET, SVM, KNN, GNB, AdaBoost, GB, and a few deep learning models, including DNN, RNN, and LSTM models. We discovered the three top-performing models and proposed an effective ensemble classifier for forecasting bank loan defaults. Our comprehensive evaluation confirmed that our approach effectively enhances the accuracy and reliability of loan default predictions. In addition, a user-friendly desktop-based interface was developed to check the loan eligibility for specific customers. This interface can enable banks to easily assess the eligibility of customers for loans, streamlining the loan approval process and enhancing operational efficiency. The findings of this study might contribute to the advancement of risk management practices in the banking industry and provide valuable insights for future research in this domain.

Although our proposed models have showcased enhanced performance rates, we have certain limitations. We have not explored various data balancing techniques such as Random Oversampling, SMOTE-Tomek, SMOTEENN, and ADASYN, nor have we optimized algorithm parameters through hyperparameter tuning. Additionally, the potential benefits of employing unsupervised machine learning models due to the unlabeled nature of real-world data and ensemble techniques like the Stack ensemble have not been investigated. To address these limitations and enhance the applicability of our bank loan prediction models in real-life scenarios, our future work will encompass the collection of more diverse and extensive real-life data, hyperparameter tuning, a wider range of data balancing approaches, exploration of unsupervised learning methods, and the utilization of ensemble techniques for building more reliable models for banking and financial institutions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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