Research Article

A Deep Learning Ensemble With Data Resampling For Credit Card Fraud Detection

Siddireddy Narendra Reddy[1], Dr. S. Vijaya Krishna[2]

[1]Department of Computer Science and Engineering KL University, India, Email: siddireddynarendrareddy@gmail.com
[2]Department of Computer Science and Engineering KL University, India Email: svijayakrishna@kluniversity.in

Abstract

Credit cards play an essential role in today's digital economy, and their usage has recently grown tremendously, accompanied by a corresponding increase in credit card fraud. Machine learning (ML) algorithms have been utilized for credit card fraud detection. However, the dynamic shopping patterns of credit card holders and the class imbalance problem have made it difficult for ML classifiers to achieve optimal performance. In order to solve this problem, this paper proposes a robust deep-learning approach that consists of long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks as base learners in a stacking ensemble framework, with a multilayer perceptron (MLP) as the meta-learner. Meanwhile, the hybrid synthetic minority oversampling technique and edited nearest neighbor (SMOTE-ENN) method is employed to balance the class distribution in the dataset. The experimental results showed that combining the proposed deep learning ensemble with the SMOTE-ENN method achieved a sensitivity and specificity of 1.000 and 0.997, respectively, which is superior to other widely used ML classifiers and methods in the literature. Next we introduce advanced ensemble models, including Stacking and Voting Classifiers, evaluating them on both original and SMOTE-ENN datasets. Additionally, a Flask framework with SQLite integration enables user signup, signin, and testing for enhanced project functionality and user interaction.

Keywords: Credit card, deep learning, ensemble learning, fraud detection, machine learning, neural network".

1. Introduction

Information technology advancements have significantly impacted the financial sector, leading to the broad adoption of electronic commerce (e-commerce) platforms. Also, the recent outbreak of the novel coronavirus (COVID-19) pandemic has further shown the need for a more digital world and further expanded the e-commerce industry [1], [2]. One of the major issues associated with modern e-commerce is the high cases of credit card fraud [3]. Also, in the last decade, there has been an increase in credit card fraud, which is a huge burden on financial institutions [4]. The increased credit card fraud rate is associated with the expansion of e-commerce and increased online transactions. Therefore, credit card fraud detection (CCFD) is crucial for financial companies to avoid losses.

Artificial intelligence (AI) and machine learning applications in the financial sector can produce excellent results for companies, such as improved efficiency, reduced operational cost, and enhanced customer satisfaction [5]. Several ML-based systems have been developed to detect credit card fraud. For example, Malik et al. [6] studied the use of hybrid models in CCFD. The hybrid models were achieved by combining a variety of ML algorithms, including extreme gradient boosting (XGBoost), random forest, adaptive boosting (AdaBoost), and light gradient boosting machine (LGBM). The experimental results indicated that the hybrid model based on AdaBoost and LGBM obtained the best classification performance. In a similar research work, Alfaiz and Fati [7] conducted a performance evaluation of ML classifiers and data resampling techniques for detecting credit card fraud. The classifiers used in the study include LGBM, XGBoost, random forest, categorical boosting (CatBoost), logistic regression, and naïve Bayes. The results indicated that the CatBoost classifier integrated with a k-nearest neighbor-based undersampling technique performed better than the other methods.

Meanwhile, building robust machine learning-based CCFD models has remained a challenge for some reasons. Firstly, conventional classifiers make predictions based on the transaction details only, such as amount, transaction country, and transaction type, ignoring the sequence of transactions that defines the clients' shopping behaviour, which is useful in identifying appropriate fraud patterns [8], [9]. Secondly, credit card fraud datasets are highly imbalanced since genuine transactions significantly outnumber fraudulent transactions [10]. Imbalance classification is a predictive modelling problem where there is an uneven distribution of samples across the classes [11]. The class that makes up a

large proportion of the dataset is called the majority class, while the class with a smaller proportion is called the minority class. Imbalance classification is a challenge because most ML algorithms were designed with the assumption of an even class distribution. Therefore, using imbalanced data such as the credit card dataset results in models with poor classification performance, especially for the minority class, i.e., fraudulent transactions. Furthermore, correctly identifying the minority class samples is of utmost importance in imbalance classification problems [12].

Deep learning (DL) and ensemble learning have recently dominated the ML field [13], [14], [15], [16], achieving excellent prediction performances in complex problems, and they could be applied to solve the challenges in credit card fraud detection. Deep learning, a subset of machine learning, is mainly a neural network with multiple layers [17]. Deep learning models using recurrent neural networks (RNN) have been employed for different sequential modelling-based ML tasks [18], [19], [20]. For example, Shen et al. [21] noted that algorithms that utilize sequential modelling, such as RNNs, usually perform better than conventional ML models. Meanwhile, simple RNN-based models are prone to the vanishing gradient problem, a situation where the RNN is unable to propagate relevant gradient information from the model's output end back to the layers near the input end [22]. However, LSTM and GRU-based RNNs were proposed to solve the vanishing gradient problem and have shown good performances in different sequence classification tasks [8], [23], [24].

2. Literature Survey

The Countless research works of deep neural networks (DNNs) in the task of credit card fraud detection have focused on improving the accuracy of point predictions and mitigating unwanted biases by building different network architectures or learning models [1]. Quantifying uncertainty accompanied by point estimation is essential because it mitigates model unfairness and permits practitioners to develop trustworthy systems which abstain from suboptimal decisions due to low confidence. Explicitly, assessing uncertainties associated with DNNs predictions is critical in real-world card fraud detection settings for characteristic reasons, including (a) fraudsters constantly change their strategies, and accordingly, DNNs encounter observations that are not generated by the same process as the training distribution, (b) owing to the time-consuming process, very few transactions are timely checked by professional experts to update DNNs [8,23,24]. Therefore, this study proposes three uncertainty quantification (UQ) techniques named Monte Carlo dropout, ensemble, and ensemble Monte Carlo dropout for card fraud detection applied on transaction data. Moreover, to evaluate the predictive uncertainty estimates, UQ confusion matrix and several performance metrics are utilized. Through experimental results, we show that the ensemble is more effective in capturing uncertainty corresponding to generated predictions. Additionally, we demonstrate that the proposed UQ methods provide extra insight to the point predictions, leading to elevate the fraud prevention process.

Credit card fraud is becoming a serious and growing problem as a result of the emergence of innovative technologies and communication methods, such as contactless payment. In this article, [2] we present an in-depth review of cutting-edge research on detecting and predicting fraudulent credit card transactions conducted from 2015 to 2021 inclusive. The selection of 40 relevant articles is reviewed and categorized according to the topics covered (class imbalance problem, feature engineering, etc.) and the machine learning technology used (modelling traditional and deep learning). Our study shows a limited investigation to date into deep learning, revealing that more research is required to address the challenges associated with detecting credit card fraud through the use of new technologies such as big data analytics, large-scale machine learning [13], [14], [15], [16], and cloud computing. Raising current research issues and highlighting future research directions, our study provides a useful source to guide academic and industrial researchers in evaluating financial fraud detection systems and designing robust solutions.

With the development of e-commerce, fraud behaviors have been becoming one of the biggest threats to the e-commerce business. [3] Fraud behaviors seriously damage the ranking system of e-commerce platforms and adversely influence the shopping experience of users. It is of great practical value to detect fraud behaviors on e-commerce platforms. However, the task is non-trivial, since the adversarial action taken by fraudsters. Existing fraud detection systems used in the e-commerce industry easily suffer from performance decay and cannot adapt to the upgrade of fraud patterns, as they take already known fraud behaviors as supervision information to detect other suspicious behaviors. In this article, we propose a competitive graph neural networks (CGNN)-based fraud detection system (eFraudCom) to detect fraud behaviors at one of the largest e-commerce platforms, "Taobao"1. In the eFraudCom system, (1) the competitive graph neural networks (CGNN) as the core part of eFraudCom can classify behaviors of users directly by modeling the distributions of normal and fraud behaviors separately; (2) some normal behaviors will be utilized as weak supervision information to guide the CGNN to build the profile for normal behaviors that are more

stable than fraud behaviors [31,32]. The algorithm dependency on fraud behaviors will be eliminated, which enables eFraudCom to detect fraud behaviors in presence of the new fraud patterns; (3) the mutual information regularization term can maximize the separability between normal and fraud behaviors to further improve CGNN. eFraudCom is implemented into a prototype system and the performance of the system is evaluated by extensive experiments. The experiments on two Taobao and two public datasets demonstrate that the proposed deep framework CGNN is superior to other baselines in detecting fraud behaviors. A case study on Taobao datasets verifies that CGNN is still robust when the fraud patterns have been upgraded.

The problem of imbalanced datasets is a significant concern when creating reliable credit card fraud (CCF) detection systems. In this work, we study and evaluate recent advances in machine learning (ML) algorithms and deep reinforcement learning (DRL) used for CCF detection systems, including fraud and non-fraud labels. Based on two resampling approaches, SMOTE and ADASYN are used to resample the imbalanced CCF dataset. [4] ML algorithms are, then, applied to this balanced dataset to establish CCF detection systems. Next, DRL is employed to create detection systems based on the imbalanced CCF dataset. The diverse classification metrics are indicated to thoroughly evaluate the performance of these ML and DRL models. Through empirical experiments, we identify the reliable degree of ML models based on two resampling approaches and DRL models for CCF detection. When SMOTE and ADASYN are used to resampling original CCF datasets before training/test split, the ML models show very high outcomes of above 99% accuracy. However, when these techniques are employed to resample for only the training CCF datasets, these ML models [4] show lower results, particularly in terms of logistic regression with 1.81% precision and 3.55% F1 score for using ADASYN. Our work reveals the DRL model is ineffective and achieves low performance, with only 34.8% accuracy.

The negative effect of financial crimes on financial institutions has grown dramatically over the years. To detect crimes such as credit card fraud, several single and hybrid machine learning approaches have been used. However, these approaches have significant limitations as no further investigation on different hybrid algorithms for a given dataset were studied. This research [6] proposes and investigates seven hybrid machine learning models to detect fraudulent activities with a real word dataset. The developed hybrid models consisted of two phases, state-of-the-art machine learning algorithms were used first to detect credit card fraud, then, and hybrid methods were constructed based on the best single algorithm from the first phase. Our findings indicated that the hybrid model Adaboost + LGBM is the champion model as it displayed the highest performance. Future studies should focus on studying different types of hybridization and algorithms in the credit card domain.

3. Methodology

i) Proposed Work:

The proposed system introduces a powerful solution for credit card fraud detection, harnessing the capabilities of deep learning ensembles. It combines long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks as base learners in a stacking ensemble, with a multilayer perceptron (MLP) serving as the meta-learner. This approach effectively tackles the challenges of dynamic shopping patterns and class imbalance in credit card fraud detection. To mitigate class imbalance, the system employs the hybrid Synthetic Minority Oversampling Technique and Edited Nearest Neighbor (SMOTE-ENN) method. Experimental results demonstrate its superior sensitivity and specificity compared to conventional machine learning methods, making it a compelling choice for real-time fraud detection. The proposed system is compared with AdaBoost, Random Forest, MLP, LSTM, GRU models [8], [23], [24]. And then we incorporate advanced ensemble techniques such as Stacking Classifier, comprising Random Forest and MLP, and a Voting Classifier combining AdaBoost and RandomForest. These models are evaluated on both the original and SMOTE-ENN enhanced datasets. Furthermore, a Flask framework with SQLite integration has been developed, facilitating user signup, signin, and testing functionalities. This extension enhances the project's robustness, providing a comprehensive evaluation of diverse classifiers and incorporating a user-friendly interface for seamless interaction and testing.

ii) System Architecture:

The system begins by collecting credit card transaction data, which includes information on both normal and potentially fraudulent transactions. The collected data undergoes preprocessing, which involves tasks like data cleaning, handling missing values, and data transformation to ensure data quality. To address class imbalance, data sampling techniques are applied. This includes oversampling the minority class (fraudulent transactions) using methods like SMOTE-ENN [27], [28], [29], which generates synthetic samples, and possibly undersampling the majority class to balance the dataset. Feature selection methods are employed to identify the most relevant attributes or features for fraud detection. This reduces dimensionality and focuses on the data attributes that contribute the most to the classification. The selected

features are used as input for ML and DL classifiers. These classifiers are trained on the preprocessed and sampled data to learn patterns that distinguish between normal and fraudulent transactions. The system incorporates a validation phase to assess the performance of the trained classifiers. This typically involves using a separate validation dataset to evaluate the model's ability to generalize. The performance of the classifiers is evaluated using metrics such as accuracy, precision, recall, F1 score, ROC curve, AUC, sensitivity, and specificity. This evaluation is conducted for both normal and fraudulent transactions to measure the system's effectiveness. Based on the evaluation, the system generates results indicating the classification of new credit card transactions as either normal or potentially fraudulent.

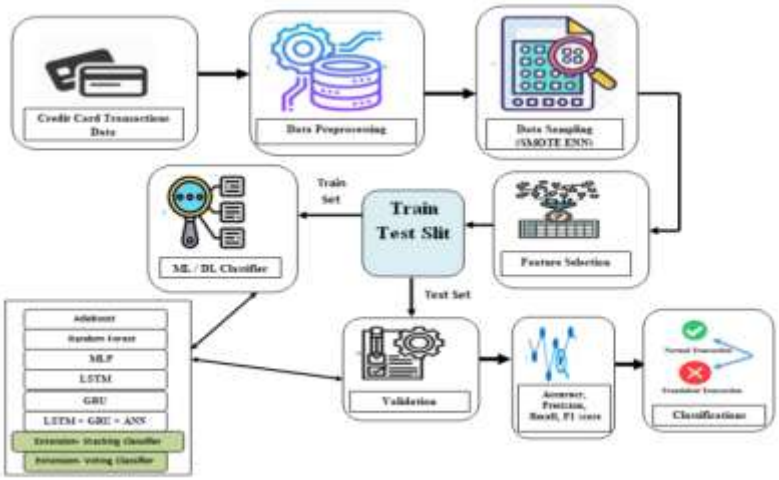


Fig 1 System Architecture

iii) Dataset collection:

The study utilizes a dataset available on Kaggle and employs data augmentation techniques to address the Problem using card fraud data, employ exploratory data analysis, and feature correlation analysis to better understand the dataset. These techniques help reveal data distributions, outliers, and relationships between variables, aiding in subsequent data processing and model building. We have used Credit Card Fraud Detection dataset taken from Kaggle to train machine learning algorithms [17]. The dataset originally had various transaction-related features, like "Amount," "Time," and "V1" to "V28." Details about the original features were kept confidential to safeguard sensitive information.

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V23	V
-0.611712	-0.769705	-0.149759	-0.224877	2.028577	-2.019887	0.292491	-0.523020	0.358468	0.070050	...	0.380739	0.0234
-0.814682	1.319219	1.329415	0.027273	-0.284871	-0.653985	0.321552	0.435975	-0.704298	-0.600684	...	0.090660	0.4011
-0.318193	1.118618	0.969864	-0.127052	0.569563	-0.532484	0.706252	-0.064966	-0.463271	-0.528357	...	-0.123884	-0.4956
-1.328271	1.018378	1.775426	-1.574193	-0.117696	-0.457733	0.681867	-0.031641	0.383872	0.334853	...	-0.239197	0.0099
1.276712	0.617120	-0.578014	0.879173	0.061706	-1.472002	0.373692	-0.287204	-0.084482	-0.696578	...	-0.076738	0.2587

32 columns

Fig 2 Dataset

iv) Data Processing:

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software

programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

v) Feature selection:

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

vi) Algorithms:

AdaBoost, or Adaptive Boosting, is a machine learning algorithm that enhances classification accuracy by combining multiple simple models. It starts with a basic model, like a one-level decision tree, and iteratively trains new models while giving more importance to the data points that the previous models misclassified. By combining these models, AdaBoost creates a powerful ensemble that can make accurate predictions, making it valuable in your project for improving credit card fraud detection by learning from the mistakes of previous models and boosting overall performance.

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It works by training a collection of decision trees on random subsets of the data and then averaging their predictions. This ensemble approach enhances accuracy, reduces overfitting, and provides robust performance for both classification and regression tasks.

The Multilayer Perceptron (MLP) is a type of artificial neural network used in this project for credit card fraud detection. It comprises multiple layers of interconnected neurons that process data and learn complex patterns. During training, the MLP adjusts its internal parameters to minimize prediction errors. This adaptability and its ability to capture non-linear relationships in data make the MLP an effective tool for identifying fraudulent credit card transactions.

$$\hat{y} = f\left(W^L f\left(W^{L-1} \cdots f(W^1 X + b^1) + b^{(L-1)}\right) + b^L\right)$$

LSTMs are designed to overcome the limitations of traditional RNNs when working with sequential data. They are capable of learning and remembering over long sequences, making them well-suited for various tasks like natural language processing, speech recognition, time series analysis, and more. [9] LSTMs utilize a system of cells, gates, and states to capture and propagate information over time, allowing them to model complex dependencies and patterns in sequential data effectively.

The Stacking Classifier is a machine learning technique that combines the predictive abilities of multiple base classifiers to create a more powerful and accurate model. In your provided code, two base classifiers, Random Forest and Multilayer Perceptron (MLP), are used within the Stacking Classifier framework. The final prediction is determined by the Light Gradient Boosting Machine (LGBM) classifier. By leveraging the diverse strengths of these classifiers, the Stacking Classifier aims to improve overall prediction performance. This ensemble approach can be valuable for addressing complex datasets and challenging classification tasks by amalgamating the knowledge from different base classifiers.

$$\hat{y} = g(Y_{base}) = g(f_1(x), f_2(x), \ldots, f_m(x)) \quad (2)$$

The Gated Recurrent Unit (GRU) is a recurrent neural network (RNN) architecture that excels at processing sequential data. In this project, a powerful ensemble model is crafted by combining Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and an Artificial Neural Network (ANN) Multilayer Perceptron (MLP). LSTM and GRU, two types of recurrent neural networks (RNNs), excel at understanding sequences and their dependencies, with LSTM being

proficient at long-range connections and GRU providing computational efficiency [8]. The addition of MLP as the meta-learner enhances the ensemble's capacity to learn intricate patterns in credit card transaction data. This combination, known for its ability to capture both short-term and long-term dependencies, significantly boosts the accuracy and effectiveness of fraud detection in the project.

The Soft Voting Classifier algorithm is a part of ensemble learning in machine learning. In this approach, it combines the predictions from multiple individual classifiers to make a final prediction. Instead of assigning equal weight to each classifier, it takes into account the probability estimates assigned by each classifier for different classes. The algorithm then combines these probability estimates, effectively giving more weight to the classifiers that are more confident in their predictions. This results in a more refined and accurate final prediction. In the context of credit card fraud detection, using a Soft Voting Classifier with diverse base classifiers like AdaBoost and Random Forest can improve the system's performance by leveraging the strengths of different models.

$$\hat{y} = argmax_c(\sum_{i=1}^{n} II\ (\hat{y_i} = c))$$

4. Experimental Results

Accuracy: A test's accuracy is its capacity to distinguish patient from healthy cases. To measure test accuracy, calculate the fraction of true positive and true negative in all evaluated cases. Mathematically, this is:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (4)$$

Precision: Precision measures the percentage of positive cases or samples accurately classified. Precision is calculated using the formula:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (5)$$

Recall: Machine learning recall evaluates a model's capacity to recognise all relevant instances of a class. It shows a model's completeness in capturing instances of a class by comparing accurately predicted positive observations to total positives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (6)$$

F1-Score: Machine learning model accuracy is measured by F1 score. Combining model precision and recall scores. The accuracy statistic measures how often a model predicted correctly throughout the dataset.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100 (7)$$

Table (1 and 2) evaluate the performance metrics—Accuracy, precision, recall and F1-score —for each algorithm. The voting classifier consistently outperforms compared to other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms.

Table.1 Performance Evaluation Original Dataset

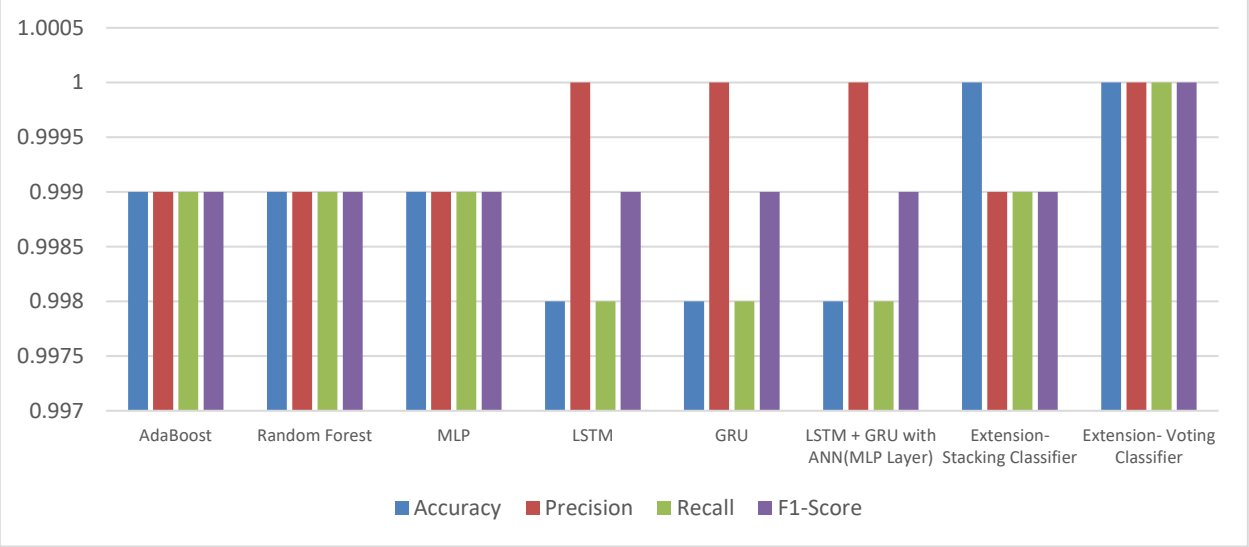
ML Model	Accuracy	Precision	Recall	F1-Score
AdaBoost	0.999	0.999	0.999	0.999
Random Forest	0.999	0.999	0.999	0.999
MLP	0.999	0.999	0.999	0.999
LSTM	0.998	1.000	0.998	0.999
GRU	0.998	1.000	0.998	0.999
LSTM + GRU with ANN(MLP Layer)	0.998	1.000	0.998	0.999
Extension- Stacking Classifier	**1.000**	**0.999**	**0.999**	**0.999**

Extension- Voting Classifier	**1.000**	**1.000**	**1.000**	**1.000**

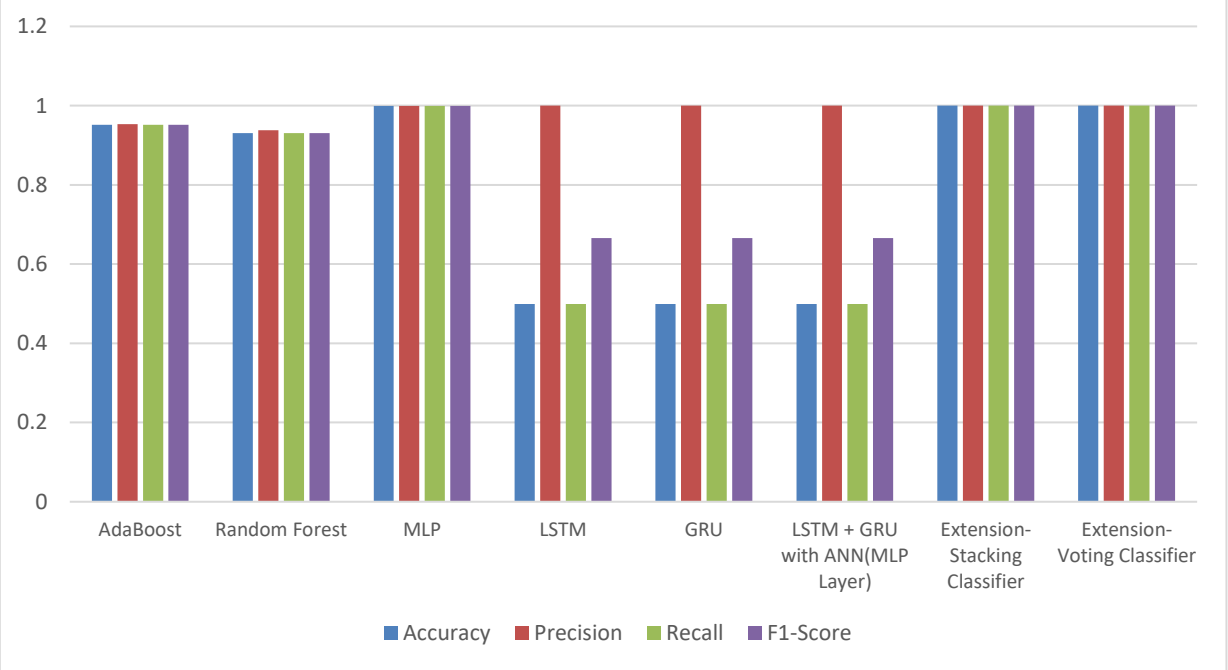
Table.2 Performance Evaluation SMOTE-ENN Dataset

ML Model	Accuracy	Precision	Recall	F1-Score
AdaBoost	0.952	0.953	0.952	0.952
Random Forest	0.931	0.938	0.931	0.931
MLP	0.999	0.999	0.999	0.999
LSTM	0.499	1.000	0.499	0.666
GRU	0.499	1.000	0.499	0.666
LSTM + GRU with ANN(MLP Layer)	0.499	1.000	0.499	0.666
Extension- Stacking Classifier	**1.000**	**1.000**	**1.000**	**1.000**
Extension- Voting Classifier	**1.000**	**1.000**	**1.000**	**1.000**

Graph.1: Comparison graph - Original Dataset



Graph.2: Comparison graph - SMOTE-ENN Dataset



Accuracy in blue, precision is represented in red, recall in green and F1-Score in violet, Graphs (1 & 2). In comparison to the other models, the voting classifier model shows superior performance across all metrics, achieving the highest values. The graphs above visually illustrate these findings.



Fig 3 Home page

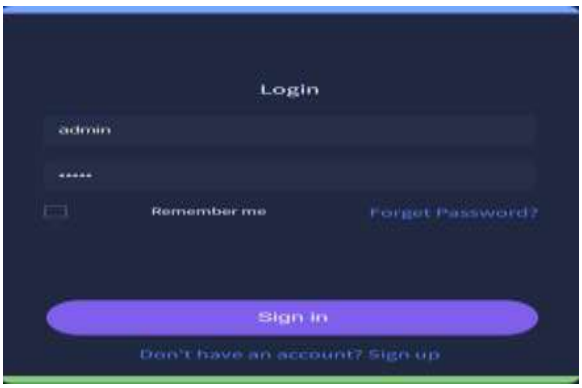


Fig 4 Login page



Fig 5 User input



Fig 6 Predict result for given input

5. Conclusion

The project successfully addresses the growing challenge of credit card fraud detection in the digital era, providing a crucial solution as reliance on digital transactions continues to rise globally. Utilizing various data sampling and scaling techniques, the project ensures the dataset's optimal condition for machine learning models, reflecting the importance of meticulous data organization in enhancing model performance. Building and assessing diverse models, including AdaBoost, Random Forest, MLP, LSTM, GRU, and LSTM + GRU + MLP, revealed their effectiveness [8], [23], [24].. The subsequent introduction of voting and stacking classifiers as an extension to the project, with the Voting Classifier outperforming others, showcased improved accuracy. The incorporation of ensemble methods significantly elevated the accuracy and robustness of the fraud detection system. By emphasizing teamwork among models, the project achieved outstanding results, highlighting the potential for further advancements in the field. The integration of a user-friendly front-end interface using the Flask framework, coupled with user authentication, underscores the project's commitment to accessibility and ease of use. This approach ensures the system's practicality for users, allowing convenient interaction for input and classification of fraudulent transactions [10].

6. Future Scope

Future research can explore enhancing model diversity by combining LSTM with various other classifiers, including random forest, logistic regression, or SVM, to further improve credit card fraud detection accuracy [34]. Conducting feature importance analysis in upcoming studies can help identify the most critical variables in credit card fraud detection, aiding in the development of more effective and efficient detection methods. Future research might delve into risk factor analysis to understand the underlying elements contributing to credit card fraud. This understanding can inform the development of more robust detection methods. Improvements to the proposed deep learning ensemble approach could involve investigating different model architectures, optimization techniques, and hyperparameter tuning methods to refine the system's performance. The proposed approach's applicability can be extended to encompass other fraud detection domains beyond credit card fraud, such as insurance fraud or online transaction fraud, contributing to a broader range of fraud prevention solutions. Additionally, exploring real-time implementation and deployment possibilities can provide immediate fraud detection and prevention in financial transactions.

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