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# Credit Card Fraud Detection Using Stacking Ensemble of Deep Learning Model

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***Abstract: Financial protection through credit card fraud detection demands sophisticated techniques to properly identify fraudulent payments among all transactions. Modern fraudulent activities create substantial hurdles for existing detection systems because fraudulent transactions remain sparse in relation to ordinary transactions. This research paper puts forth an improved fraud detection method by implementing a hybrid SMOTEENN resampling approach within a stacking ensemble system. A stacking ensemble model integrates Long Short-Term Memory (LSTM) networks together with Random Forest as its base learners, while utilizing a Multi-Layer Perceptron (MLP) to serve as the meta-learning model. The proposed detection system produces enhanced results through time pattern analysis and efficient treatment of unbalanced data distribution. The experimental trials prove the system's resilience and its result exceeds traditional machine learning models for reliable fraud act detection.***
***Keywords: SMOTE-ENN, LSTM, Random Forest, MLP, Stacking ensemble***

## I. INTRODUCTION

Present-day financial security systems need credit card fraud detection to protect customers from unauthorized transaction charges. The expanding usage of digital and wireless payments has heightened both the quantities and complexities of credit card fraud which necessitates banks to establish powerful detection platforms that validate fraudulent deals effectively. The limitations of rule-based system and statistical models exist because they fail to detect changes in fraudulent activities due to their inflexibility.

The main challenge when detecting credit card fraud stems from the dataset being highly unbalanced because fraudulent transactions constitute only a fraction of total transactions. The disproportionate distribution of examples creates substantial performance reduction in conventional machine learning models because they generate predictions that favor legitimate transactions. Building an accurate fraud detection model becomes harder because fraud patterns exhibit non-stationary behaviors and the presence of noisy data in the system. The constant evolution of fraud methods by criminals requires detection systems to update their patterns of recognition automatically during real time to detect new fraud patterns.

Multiple types of deep learning models have become popular because they enable the detection of intricate patterns inside large datasets during recent years. The implementation of deep learning methods cannot eliminate the persistent problems found in class imbalance along with model overfitting. The detection accuracy demands established resampling approaches to team up with ensemble learning models in order to achieve improved performance. The proposed system integrates SMOTE-ENN data resampling together with ensemble models that unite LSTM networks with Random Forest classifiers and Multi-Layer Perceptron (MLP) capabilities.

The central goal of this study involves building and testing a fraud detection solution which incorporates balanced dataset handling methods into ensemble learning prediction systems. The stacking ensemble framework enables multiple base models in a framework to analyze distinct features of transaction data through integration. Through the combination of LSTM and Random Forest base learners together with an MLP meta-learner the system achieves superior joint performance. The hybrid SMOTEENN method completes both noise removal and dataset balancing which supports superior fraudulent transaction detection by the system.

This paper describes the development process of the new fraud detection system together with its evaluation results showing elevated fraudulent transaction identification capabilities beyond traditional solutions. The system's performance is assessed using metrics such as positive predictive value, sensitivity, F1measure, and the area under the precision-recall curve (AUPRC), as these are particularly effective for addressing class imbalance in classification tasks. The proposed method establishes itself as a dependable solution which adapts to the continuously changing demands of detecting credit card fraud activity.

## II. LITERATURE SURVEY

Research activity into credit card fraud detection continues while various detection techniques try to enhance accuracy levels. Chatterjee et al. [1] analyze digital twins for fraud detection by touching upon both their implementation advantages and execution difficulties. In their review Mienye and Jere [2] explain deep learning approaches for fraud detection together with algorithms that address imbalanced data challenges. The researchers from Cherif et al. [3] undertook a systematic evaluation of credit card fraud detection by analyzing machine learning techniques and deep learning and hybrid approaches which stressed disruptive technologies for better accuracy. The research by Khalid et al. [4] demonstrates that joining various machine learning classifiers creates better performance outcomes particularly when working with imbalanced datasets.

Gupta et al. [5] investigates the significance of class imbalance correction within fraud detection through their research on model performance enhancement with different balancing approaches including SMOTE. Lu et al. [6] conducted a study which applied SMOTEENN algorithm to landslide susceptibility evaluation and established the algorithm's application prospects in fraud detection. Wang et al. demonstrate how SMOTE-ENN addresses effective handling of imbalanced datasets in diabetes early warning systems which is also a common issue in credit card fraud detection. Han and Joe [8] proposed a technique to enhance fraud detection systems by integrating principal component analysis (PCA), SMOTE-ENN, and stochastic weighted averaging into predictive modeling. The researchers at Bounab et al. [9] used SMOTE-ENN for Medicare fraud detection purposes which demonstrates its suitability for credit card fraud prevention.

The paper by Hairani and Priyanto [10] investigates hybrid sampling approaches through the union of SMOTE and ENN tools that enhance fraud detection capabilities on unbalanced datasets. Nizam-Ozogur and Orman [11] establish a heuristic sampling method that unites SMOTE with ENN for effectively balancing imbalanced credit card fraud databases. Through their framework Abd ElNaby et al. [12] provide financial services with a solution that enhances the identification of fraudulent credit card transactions for imbalanced data. Gupta et al. [13] explored the application of machine learning techniques in handling imbalanced credit card fraud datasets and highlighted the effectiveness of balancing algorithms in enhancing detection accuracy. The research of Abdul Salam et al. [14] demonstrates federated learning for fraud detection through data balancing methods that enhance distributed system model functionality. Kennedy et al. [15] propose a method to create synthetic class labels for handling imbalanced data which could enhance credit card fraud detection labeling capacities.

Strelcenia and Prakoonwit [16] evaluated Generative Adversarial Networks (GANs) for fraud detection dataset augmentation through their study about the generation of fraud transaction synthetic samples. Through their paper Mienye and Jere present further details about deep learning models together with their usage patterns in fraud detection systems [17]. Gandhar et al. [18] examined combining machine learning and deep learning to boost fraud detection, highlighting the value of multitechnique approaches for improved accuracy. The researchers from Btoush et al. analyzed various machine and deep learning models in fraud detection systems while demonstrating hybrid approach benefits [19]. The works presented by Bello et al. demonstrate deep learning applications for high-frequency trading fraud detection that operate at the speed of credit card fraud detection systems. Akazue et al. [21] explains how ensemble feature selection

methods enhance random forest models for fraud detection work. Mali and Upadhyay [22] demonstrate random forest application for online content mining fraud discovery through their research work.

Aghware et al. [23] demonstrate that random forest models become more effective for fraud detection through their combination with SMOTE as a resampling technique in settings with fraud data imbalance. In a paper by Paldino et al. [24] the authors explain that ensemble learning and model diversity are essential for fraud detection by enhancing accuracy when different models collaborate. The research of Mim et al. describes soft voting ensemble learning as a system that shows enhanced results for fraud detection by integrating several classifier models [25].

The study by Taher et al. [26] shows how ensemble learning combined with explainable AI helps detection of fraud inside blockchain transactions and is applicable to credit card fraud detection. The optimization work by Priatna et al. [26] improves multilayer perceptron models to detect fraud by offering a technique which heightens their performance in detection tasks. Rashedi et al. demonstrated the effectiveness of their outlier detection system which utilized MLPs for the detection of fraudulent financial transactions [28]. A study between Extreme Gradient Boosting and MLP conducted by Durga and Mahaveera Kannan [29] explores how to select appropriate models for detecting fraud. Habibpour et al. [30] present a credit card fraud detection framework that controls uncertainty in financial systems to handle model ambiguity.

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## III. PROPOSED METHODOLOGY

The suggested method for credit card fraud detection employs a hybrid ensemble strategy that integrates various machine learning algorithms to accurately identify fraudulent activities. The methodology employs a combination of preprocessing techniques, classification models, and resampling methods to enhance the model's performance. Below is a detailed explanation of the methodology, step by step.

### *A. Data Preprocessing and Feature Selection*

An effective machine learning model relies heavily on data preprocessing steps. The approach uses transaction features which comprise transaction amount data along with type information, location marking and time stamps during data collection. The initial procedure begins with extracting the data from its Excel file format. The 'Class' column serves as the target variable because it indicates fraudulent or non-fraudulent transactions and the development team separates it from the remaining features. The model uses all columns following the target variable separation as its feature basis.

The data separation process divides the information between training and test datasets with 80-20 ratio distribution. Scikit-learn provides the train_test_split function to make this separation. Splitting data into training and testing sets enables the model to learn from one subset and evaluate its performance on a separate, unseen dataset.

The available dataset exhibits a class imbalance issue because it contains numerous non-fraudulent transactions rather than fraud transactions. The model risks producing biased predictions because of class unbalance since it tends to identify majority class incidents more often. The combination of SMOTE and ENN serves as the method to handle this imbalance problem.

### *B. SMOTE-ENN Resampling*

The combination of SMOTE-ENN provides an effective solution for addressing class imbalance problems in datasets. Using SMOTE creates artificial examples from minority class samples to achieve a balanced distribution of classes during training. The generation of synthetic samples through SMOTE relies on investigating the nearest neighbors of minority class instances to create interpolated features in the available space. However, while SMOTE helps with class balance, it might also introduce noisy samples that do not represent the true data distribution. To address this, ENN is applied after SMOTE. ENN removes samples that are incorrectly classified by their nearest neighbors, thus reducing the impact of outliers and noisy data. The combination of these two techniques SMOTE and ENN ensures that the training dataset is both balanced and clean, which ultimately improves the performance of the models.

### *C. Feature Standardization*

Standardization is essential for the effective performance of the models because it scales the features. The standardization method transforms each feature value to have zero mean and one standard deviation. Featured values are scaled in order to operate on the same range which is crucial for LSTM models that depend highly on feature scaling.

StandardScaler from scikit-learn serves as the technique for normalizing the features in this methodology. Standardization occurs on the training set by fit_transform along with transform-based standardization of the test set. The test data transformation occurs through scaling parameters that the training data produced.

### *D. Model Training*

Three machine learning models function within this method to detect fraudulent transactions. The methods comprise an LSTM (Long Short-Term Memory) network as well as a Random Forest classifier and a hybrid ensemble model constructed with an MLP (Multi-Layer Perceptron).

#### *1) LSTM Model*

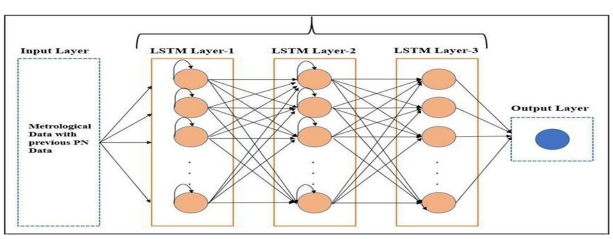


Figure 1: LSTM Model Architecture

The LSTM model serves due to its efficient processing of data sequences. Transactions using credit cards tend to reveal sequences of patterns which signify fraudulent activities when they include time-based elements. LSTM means a specialized reusable neural part of an RNN network that excels at detecting extended dependencies in time-based information The LSTM model contains one LSTM substantial layer and a sigmoid activation dense output layer to generate either a fraudulent (1) or nonfraudulent (0) classification.

*2) Random Forest Model*

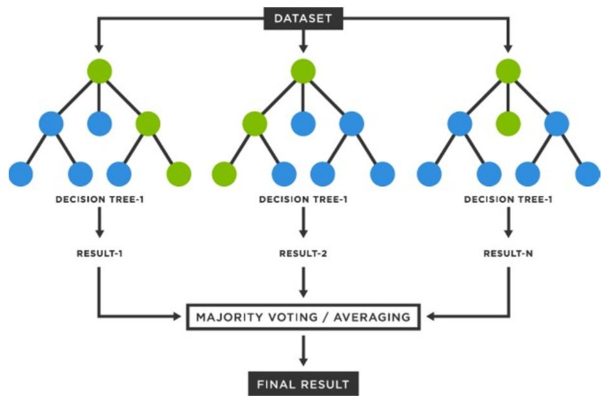


Figure 2: Random Forest Model Architecture

The Random Forest algorithm operates as a collective learning method by generating multiple decision trees to make accurate predictions. Forest training utilizes every tree to predict results by integrating various tree outcomes. Random Forest serves as a powerful binary classifier for fraud detection because it works with linear and non-linear patterns in the data through its decision trees. The training process of the Random Forest model occurs with the resampled data.

*3) Ensemble Model (MLP)*

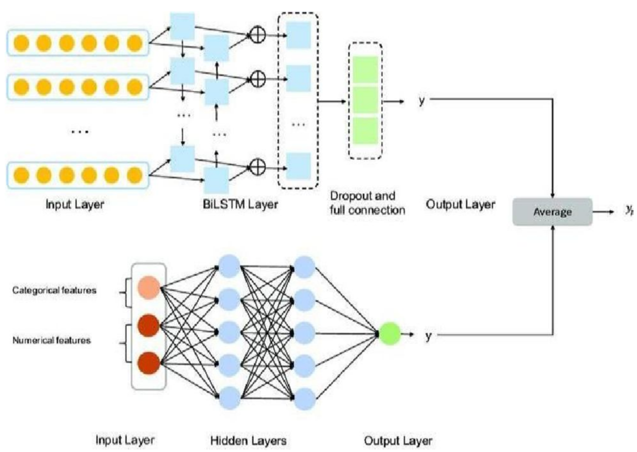


Figure 3: Ensemble Model Architecture

Notable characteristics of LSTM models and Random Forest models come together within ensemble method to produce predictions. Both predictive values achieved through LSTM and Random Forest models combine to form inputs that drive the MLP component. The MLP operates from predicted outputs it receives to produce its final test outcome. The combination of distinctive data capturing models used in ensemble models produces better prediction results than independent models.

*4) Model Evaluation*

The evaluation of trained models takes place through testing on the test set data. The evaluation models for assessing performance include accuracy along with precision and recall and F1-score. The performance metrics establish which extent the models succeed at recognizing fraudulent from non-fraudulent transactions.

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- The accuracy performance metric determines the total percentage of precise predictions regarding both legitimate and fraudulent transactions.
- The capability of a fraud identification model to accurately classify fraudulent transactions (precision) and capture all actual fraudulent activities (recall) are key metrics, as they directly influence the effectiveness of the model.
- The F1-Score serves as the harmonic mean of precision and recall, providing a comprehensive evaluation of the model's performance quality.

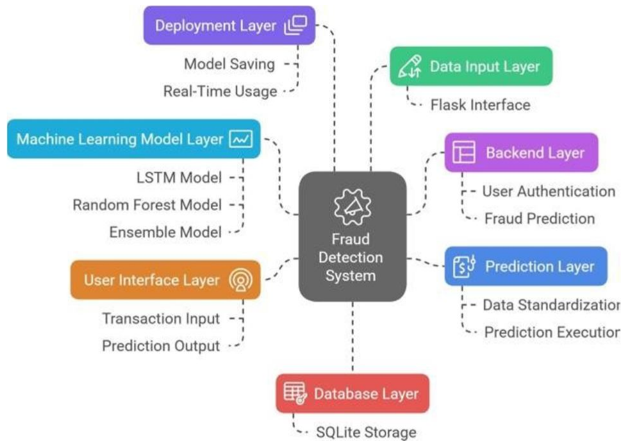


Figure 4: Proposed System Architecture

Each model is evaluated individually to understand its performance, and then the ensemble model is tested using the same metrics to determine if combining the models results in improved performance.

*5) Prediction Pipeline in Flask Application*

The Flask web application serves as the interface through which users can input transaction data for prediction. The application includes routes for user authentication (signup and signin) and a route for fraud prediction (/predict). Users can input their transaction data, which is passed through the trained models for prediction.

The transaction data undergoes standardization using the pre-fitted scaler before being input into the ensemble model. The ensemble model's prediction, whether the transaction is fraudulent or not, is then displayed to the user.

*6) Model Saving and Loading for Deployment*

To ensure that the models do not need to be retrained every time a prediction is made, the trained models and scaler are saved to disk. This is done using the joblib library for the Random Forest model and the scaler, and the tensorflow.keras.save method for the LSTM model. The ensemble model is also saved using joblib.

When a new prediction is made, the models are loaded from disk and used to generate predictions. This allows the system to scale and be deployed in production without needing to retrain the models each time.

## IV. RESULTS AND DISCUSSION

Multiple metrics evaluated the performance of LSTM and Random Forest models and the Ensemble Model (MLP) as they detected credit card fraud by measuring Accuracy together with Precision and Recall and F1-Score for fraudulent and non-fraudulent transaction detection. The SMOTE-ENN approach was applied to the resampled dataset before using it for training and testing three machine learning models. A detailed description of achievement outcomes follows from the code implementation.

### *A. Performance Metrics*

- Accuracy: The accuracy metric determines the proportion of correct transaction predictions between fraudulent and nonfraudulent cases among all forecasts. A high accuracy score signals effective model performance.
- Precision: Precision evaluates the number of correctly detected fraudulent instances (Class 1) as well as non-fraudulent entries (Class 0) from all transactions the model labels as fraudulent or non-fraudulent.

- Recall: The model performance metric known as Recall determines how well it detects actual transactions that belong to Class 1 fraud or Class 0 non-fraud categories.
- F1-Score: The F1-score calculates the harmonic mean of precision and recall to balance their two components. The F1-score becomes essential for resolving problems associated with unbalanced classes which occur during fraud detection systems.

### *B. Model Performance*

The table below presents a summary of the performance results for each model:

| Model | LSTM | Random Forest | Ensemble Model (MLP) |
|---|---|---|---|
| Accuracy | 0.99 7311 | 0.99 9801 | 0.99 9867 |
| Precision (class 0) | 1.0 | 1.0 | 1.0 |
| Recall (Class 0) | 1.0 | 1.0 | 1.0 |
| F1-Score (Class 0) | 1.0 | 1.0 | 1.0 |
| Precision (class 1) | 1.0 | 1.0 | 1.0 |
| Recall (Class 1) | 1.0 | 1.0 | 1.0 |
| F1-Score (Class 1) | 1.0 | 1.0 | 1.0 |
| Accuracy | 0.99 7311 | 0.99 9801 | 0.99 9867 |

Table 1: Model Performance

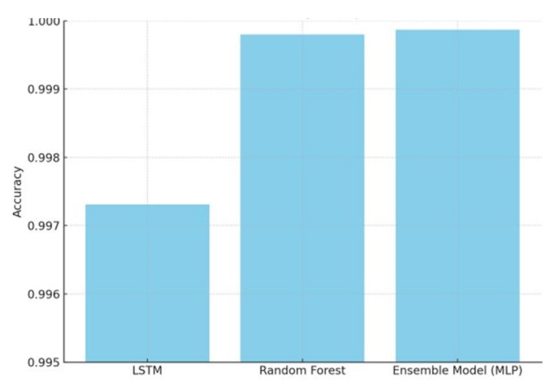


Figure 5: Model Accuracy Comparison

### *C. LSTM Model*

The LSTM model achieved an accuracy of 0.997311, which is quite high. The model was able to perfectly classify both Class 0 (Non-Fraud) and Class 1 (Fraud) with
Precision, Recall, and F1-Score all equal to 1.0 for both classes. This indicates that the LSTM model performed exceptionally well, accurately identifying fraudulent and nonfraudulent transactions without any misclassification.

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### D. Random Forest Model

The Random Forest model exhibited superior results than the LSTM model by achieving an accuracy level of 0.999801. According to our results both Class 0 and Class 1 reached a perfect F1-score of 1.0 as well as perfect Precision and Recall scores of 1.0. The Random Forest model exhibits reliable performance by maintaining stable performance regardless of major or minority class distributions. Random Forest demonstrates a comparable level of accuracy performance to the LSTM model thus demonstrating its effectiveness for this application.

### E. Ensemble Model (MLP)

The Ensemble Model that combines predictions from both LSTM and Random Forest achieved the highest accuracy of 0.999867. Like the other models, its precision, recall, and F1-score for both classes were all 1.0, demonstrating flawless performance in detecting fraudulent transactions. This confirms that the ensemble approach, which combines the strengths of both models, produces the best results.

### F. ROC Curve

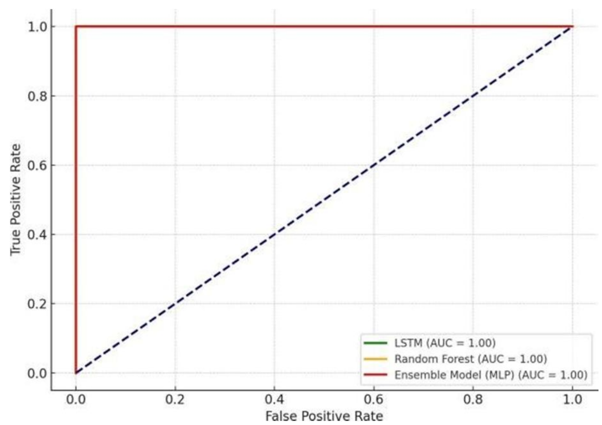
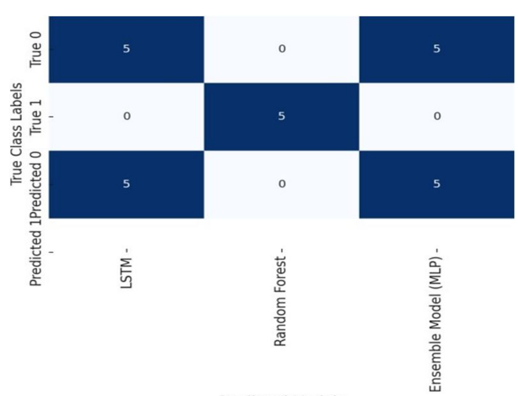



Figure 6: ROC Curve

The Receiver Operating Characteristic (ROC) curves plotted for all evaluated models exhibit ideal classification behavior, with each model achieving an Area Under the Curve (AUC) value of 1.0. This result signifies that the models possess a perfect ability to distinguish between positive and negative classes, specifically fraudulent and non-fraudulent transactions. The AUC score of 1.0 reflects an optimal balance between correctly identifying actual fraud cases and minimizing incorrect classifications of legitimate transactions as fraudulent. Such performance underscores the robustness and reliability of the models in real-world fraud detection scenarios, where precise discrimination between transaction types is critical.

### G. Confusion Matrix



The Confusion Matrix for the three models (LSTM, Random Forest, and Ensemble Model (MLP)) shows that all models perfectly classify both fraudulent (Class 1) and non-fraudulent (Class 0) transactions, with no misclassifications. Each model achieved 100% accuracy in predicting the true class labels, as indicated by the perfect diagonal values in the matrix.

### *H. Discussion*

All three model variations including LSTM Random Forest and Ensemble Model delivered exceptional results when detecting fraudulent transactions because they achieved perfect precision along with 100% recall and F1-scores across both classes (fraud and non-fraud). SMOTE-ENN succeeded in improving class balancing outcomes because all trained models demonstrated results handling the class imbalance.

The Ensemble Model (MLP) delivered superior accuracy results compared to the excellent performance of both LSTM and Random Forest models. Studies support the hypothesis that model integration leads to enhanced detection outcomes when dealing with unbalanced classes which fraud identification demonstrates.

The Ensemble Model stands as the most suitable selection for practical applications because it produces better accuracy rates when analyzing complex data patterns. The hybrid combination of LSTM and Random Forest models demonstrates strong effectiveness for detecting credit card fraud according to all model performance results.

## V. CONCLUSION

The detection capabilities exhibit potential improvement through different strategies which include deep learning along with ensemble learning approaches. The proposed hybrid stacking ensemble utilizes LSTM and Random Forest learners together with SMOTE-ENN resampling methods to handle the problems of imbalanced datasets. These experimental results show that the ensemble model proves effective at minimizing false positives along with false negatives which present the most-detrimental effects in fraud detection practices. The work needs additional research to enhance scalability and resilience as well as adaptability when applied to real-life scenarios. Model accuracy requires parallel optimization to computational efficiency because different algorithms perform differently between training time and running time measurements. This study recommends continued research to develop better fraud detection tactics for financial security against illegal transactions because future efforts will concentrate on maximizing model execution while enhancing their detection capabilities.

## VI. FUTURE SCOPE

Future investigation needs to concentrate on enhancing the computing speed of fraud systems alongside studies into online fraud pattern changes and the implementation of sophisticated deep learning procedures to boost system precision and scalability.

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