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Ensemble Learning for Fraud Detection in Financial Transactions

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Abstract: *Securing financial transactions is essential in the current digital payment environment. This project uses ensemble learning to create a fraud detection framework for net banking and UPI. Our method improves accuracy by combining Random Forests, Decision Trees, and Support Vector Machines, which are ineffective against changing fraud tactics. Data Ingestion, Prepossessing, Exploratory Data Analysis, Model Training, Fraud Detection, and Performance Evaluation are the six modules that make up the system. We decrease false positives and increase the accuracy of fraud detection by utilizing ensemble learning. Our model successfully detects fraudulent transactions, providing insightful information and a scalable financial security solution.*

Keywords: Fraud Detection, Ensemble Learning, UPI & Net Banking Security, Machine Learning Models, Financial Transaction Security

I. INTRODUCTION

Financial transactions are now quicker and easier thanks to the growing use of digital payment methods like UPI and net banking. But this ease of use has also resulted in an increase in fraudulent activity, which puts financial institutions and consumers at serious risk. Preventing financial losses and preserving trust depend on digital transactions being secure. Conventional fraud detection techniques, which are frequently predicated on single machine learning models or rule-based systems, find it difficult to keep up with changing fraud strategies. Advanced detection techniques that can accurately identify fraudulent activities in real time are becoming more and more necessary as cyber criminals use more complex tactics.

A promising method for detecting fraud is ensemble learning, which combines several machine learning models to improve predictive accuracy. Ensemble learning can increase detection rates while reducing false positives by utilizing the advantages of models like Random Forests, Decision Trees, and Support Vector Machines (SVM). The goal of this project is to create a strong framework for detecting fraud by analyzing financial transactions in UPI and net banking systems using ensemble learning techniques. Data Ingestion and Prepossessing, Exploratory Data Analysis (EDA), Model Training and Development, Fraud Detection, Fraud Case Analysis and Reporting, and Model Performance Evaluation comprise the six main modules that make up the framework. Every module is essential to maintaining the effectiveness and precision of the fraud detection system.

Our method improves the capacity to identify fraudulent transactions more precisely by combining several algorithms. In addition to enhancing the security of digital payments, this gives financial institutions important information about fraud trends and transaction patterns. In order to protect financial transactions and preserve user confidence in digital banking platforms, the results of this study aid in the continuous development of scalable and flexible fraud detection systems.

II. OBJECTIVES

The primary objective of this project is to develop a robust, accurate, and scalable fraud detection system that effectively identifies fraudulent activities in financial transactions. For this purpose, we use multiple machine learning

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models such as CNN, Random Forest, SVM, and XGBoost, which are integrated into an ensemble framework. By using stacking, we combine the strengths of individual models to improve detection accuracy and minimize false positives. Data preprocessing steps include Min–Max normalization, noise injection, and stratified sampling, which enhance the generalization capability of the model. The final model is aimed to be suitable for real-time deployment to enable financial institutions to perform timely and accurate fraud detection.

III. LITERATURE REVIEW

Fraud detection in banking and financial transactions has become an increasingly critical area of study, especially with the rise in online banking and digital transactions. Recent literature has explored a variety of machine learning (ML) techniques, with a particular focus on ensemble methods, which have demonstrated promising results in improving detection accuracy and reducing false positives.

Kumar and Singh (2020) conducted a comprehensive survey on fraud detection in banking transactions using machine learning techniques. Their study provided a critical evaluation of widely used algorithms such as decision trees, random forests, and neural networks. The authors highlighted the growing importance of ensemble methods, which combine the strengths of multiple models to enhance overall predictive performance. While the survey offered a valuable synthesis of existing approaches and theoretical insights, it lacked experimental validation, limiting its practical applicability.

Building on empirical analysis, Nihar Ranjan et al. (2024) presented a study on credit card fraud detection using ensemble methods, applying their approach to a large dataset of 2,844,808 European credit card transactions. They addressed the challenge of dataset imbalance through a hybrid resampling technique and implemented the Random Forest algorithm to detect fraudulent behavior. Their model achieved an impressive accuracy of 97.66%, alongside strong precision, recall, and F1-scores. The use of real-world data and effective handling of class imbalance are notable strengths of this study. However, the computational demands of ensemble models, especially those relying on multiple decision trees like Random Forests, remain a concern.

Pang and Xu (2021) introduced an innovative ensemble learning approach that integrates clustering with traditional classification models. By grouping similar transactions before classification, their model was better able to detect anomalous and potentially fraudulent activities. The authors reported that this method outperformed individual classifiers in identifying complex fraud patterns. Their contribution lies in the creative fusion of clustering and classification, though its effectiveness is contingent upon the quality of the clustering process. Furthermore, the increased computational overhead associated with this approach may pose implementation challenges in large-scale systems.

Yadav and Singh (2022) proposed a hybrid ensemble learning framework aimed at detecting fraud in online banking transactions. Their research emphasized the role of data preprocessing and feature engineering in boosting model performance. By combining multiple ML algorithms, the study succeeded in enhancing detection accuracy and minimizing false positives—a key concern in fraud detection. Although the hybrid approach offers robustness and improved reliability, it also introduces complexity in model design, development, and maintenance. Balancing the trade-off between accuracy and the rate of false positives remains a notable challenge.

In summary, the reviewed literature underscores the effectiveness of ensemble methods in financial fraud detection. Each study contributes uniquely, from theoretical reviews to real-world implementations and innovative model combinations. Despite their advantages, ensemble methods also bring challenges such as increased complexity and computational costs, which need to be addressed in future research for broader applicability.

IV. METHOD

1. Data Collection & Preprocessing: Our approach first focuses on collecting and preprocessing financial transaction data, which includes both authentic and fraudulent transactions. In real-world datasets, the proportion of fraud cases is usually very low, so we use advanced balancing techniques such as oversampling methodologies and Synthetic Minority Over-sampling Technique (SMOTE). This ensures a better balance of transaction classes. The preprocessing pipeline includes data cleaning, feature normalization using standardization techniques, removal of duplicate

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transaction records, and systematic handling of missing values using imputation methods. All this is done to optimize the performance of the model and maintain consistent scaling of all variables.

2. Model Development Using Ensemble Learning : For fraud detection, we use ensemble learning, which combines multiple advanced machine learning models to achieve better accuracy than single-model approaches. The following models are strategically integrated in this ensemble framework.

I. Support Vector Machine (SVM): A powerful supervised learning algorithm for binary classification tasks. Identifies the best boundary hyperplane between fraudulent and non-fraudulent transactions in a multi-dimensional feature space. Best suited for high-dimensional financial data as it efficiently handles complex feature relationships. It is adaptable for both linear and non-linear classification scenarios.

II. Random Forest: Advanced implementation of multiple decision trees that detects fraud patterns using parallel processing. It is effective in handling noisy datasets and has high generalisation ability.

III. XGBoost: Gradient boosting framework that improves accuracy by iteratively improving weak learners. Efficiently processes structured financial data and can adapt to new fraud trends.

IV. Convolutional Neural Networks (CNNs): Normally used for image processing, but we have modified it to detect sequential patterns in financial transaction data. It is very effective in detecting minute irregularities and hidden temporal patterns that may be missed by traditional detection techniques.

In the Ensemble methodology, each model component is trained separately on the pre-processed dataset. Then the predictions are combined using a weighted voting mechanism. This multi-model approach reduces both false positives and false negatives.

This approach improves the capability to accurately process fraudulent and genuine transactions, and the framework can also adapt to new fraud patterns.

V. FIGURES

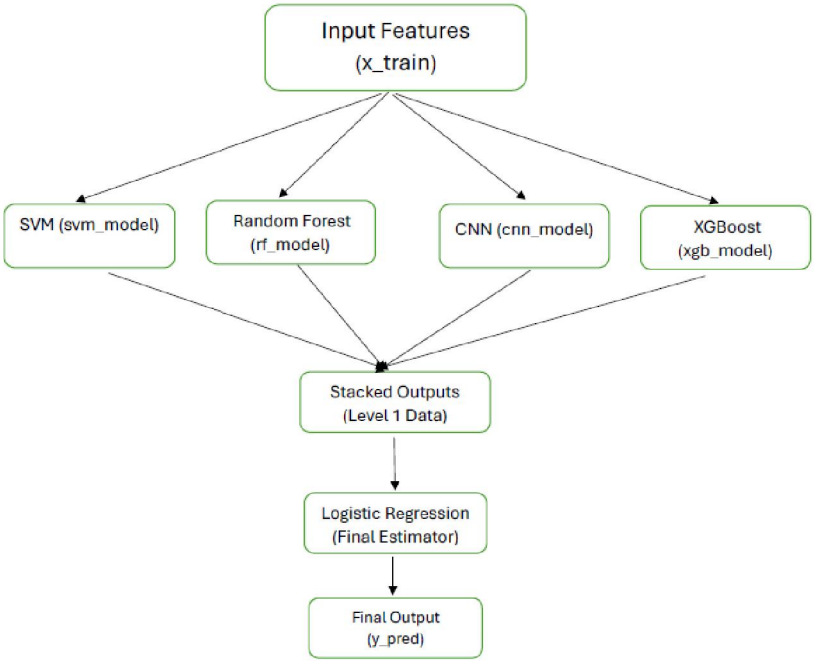

Fig.1 : Ensemble Model

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CONFUSION MATRIX:

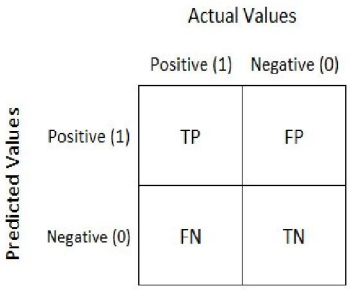

Fig.2 :Confusion matrix

Components of a Confusion Matrix

- True Positives (TP): Correctly predicted positive cases.
- True Negatives (TN): Correctly predicted negative cases.
- False Positives (FP): Incorrectly predicted positive cases .
- False Negatives (FN): Incorrectly predicted negative cases.
- The formulas for metrics derived from a confusion matrix:

i. Precision :

The proportion of correctly predicted positive cases out of all predicted positives.

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

Measures how many predicted fraud cases are actually fraud (focuses on false positives).

ii. Recall :

The proportion of correctly predicted positive cases out of all actual positives.

Recall = $\frac{TP}{TP+FN}$

Measures how many actual fraud cases are caught (focuses on false negatives).

iii. F1-Score:

The harmonic mean of precision and recall, balancing both metrics.

$$F1 = 2\frac{Precision \cdot Recall}{Precision + Recall}$$

A balanced score combining precision and recall, useful for imbalanced datasets.

iv. Accuracy

The proportion of correctly predicted instances (both positive and negative) out of the total predictions.

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

Measures overall correctness but can be misleading with imbalanced data.

VI. RESULTS

For this project, a simple and user-friendly GUI has been developed which works for Financial Transaction Fraud Detection. Below is a description of the main screens of this GUI:

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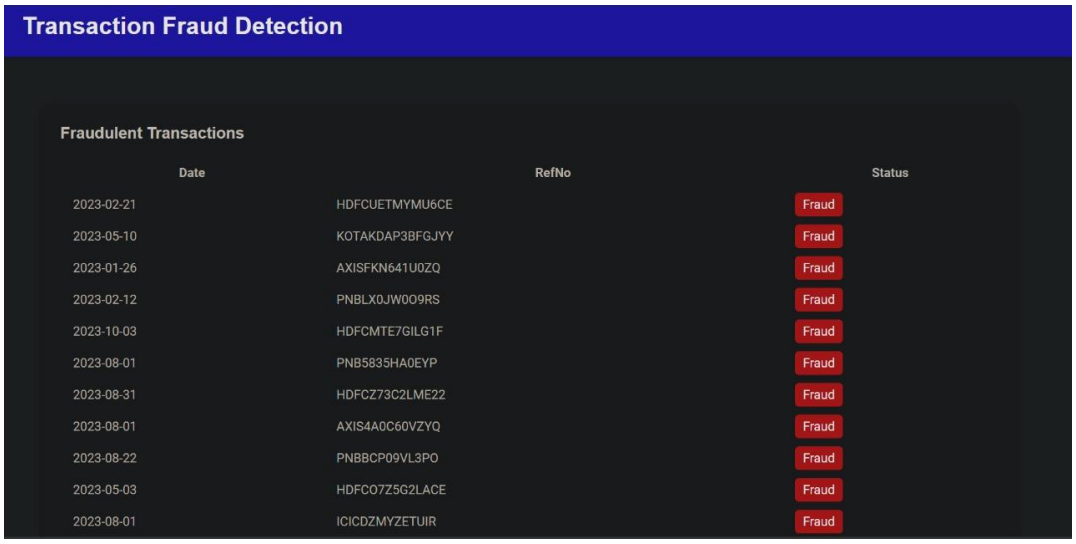

Fig.3 Fraudulent Transactions

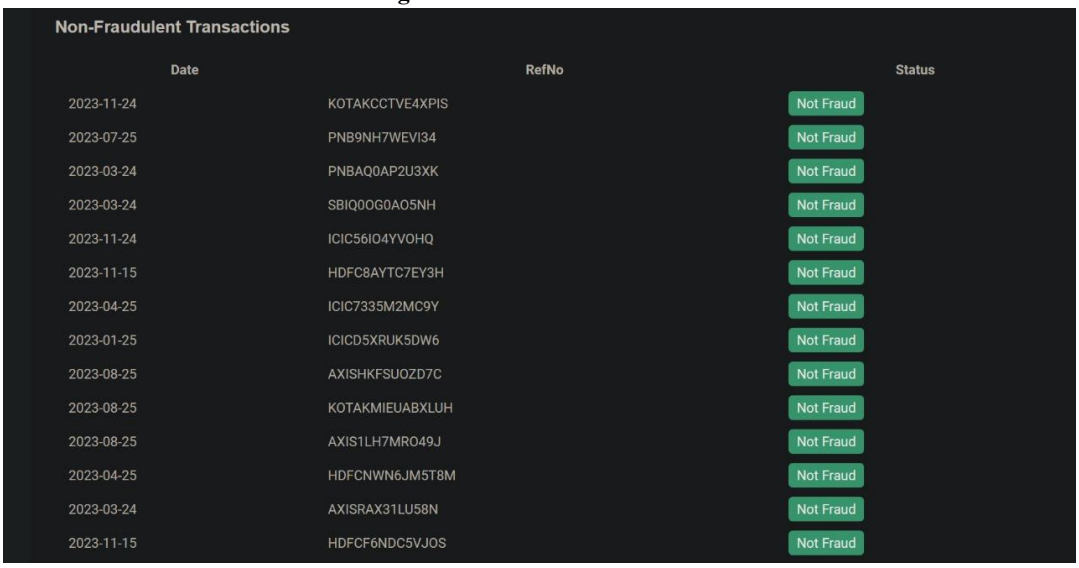

Fig.4 Non-Fraudulent Transactions

Display of Fraudulent and Non-Fraudulent Transactions. It show the output of our GUI where the fraud status of different transactions is shown.

Fraudulent Transactions Screen: This screen shows the list of transactions that the model has detected as fraudulent. Each transaction is accompanied by its date, reference number, and status. If the transaction is fraudulent, there is a red button next to the status that says 'Fraud'.

Non-Fraudulent Transactions Screen: This screen lists transactions that are safe as per the model. That is, no fraudulent activity has been detected in them. Here also the date, reference number, and status are given. There is a green button next to the status of safe transactions that says 'Not Fraud'.

Comparison of Different Machine Learning Models. These images show the model comparison section of our GUI.

Financial Fraud Detection - ML Model Dashboard: This screen has different buttons to view the outputs of different machine learning algorithms such as:

- CNN Output

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- Random Forest Output
- XGBoost Output
- SVM Output
- Ensemble Output

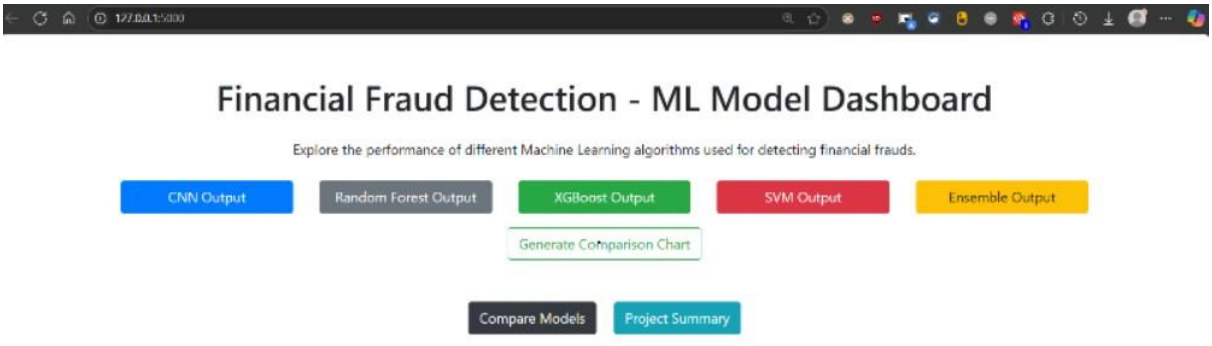

Fig.5: Comparison gui main page

Along with this, a button is given 'Generate Comparison Chart' through which you can view the comparative analysis of all the models.

Compare Machine Learning Models Screen: This screen shows the performance of two or more models by selecting them. On comparing, a table is shown in which the Accuracy, Precision, Recall and F1 Score of each model is given.

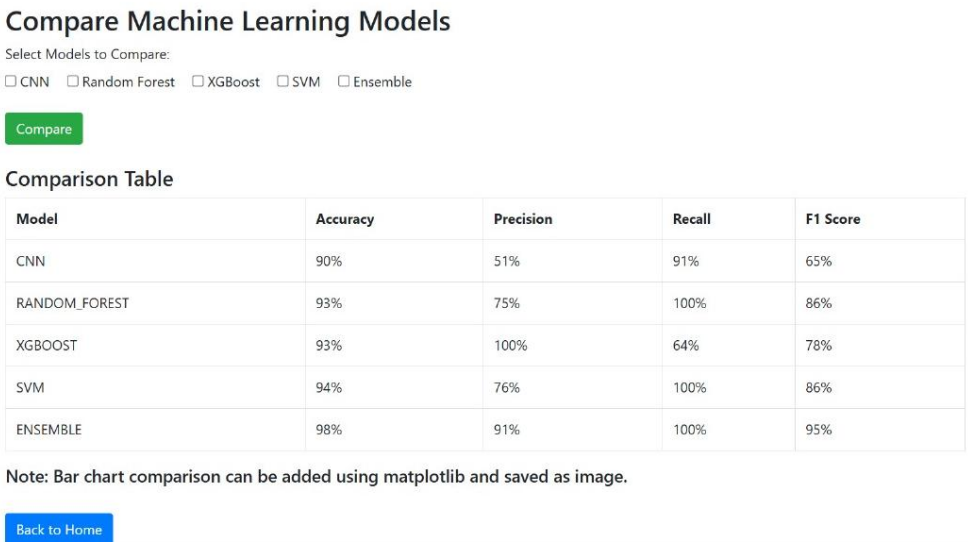

Fig.6: Comparison of Machine Learning Models

For example:
The accuracy of CNN is 90%.
The accuracy of both Random Forest and XGBoost is 93%.
The accuracy of SVM is 94%.
And the best accuracy of Ensemble model is 98%.

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VII. CONCLUSION

In this project, financial transaction fraud detection was done using different machine learning algorithms. The performance of models like SVM, CNN, Random Forest, XGBoost was compared, but the Ensemble Learning model gave the best result.The Ensemble model showed the best performance with its high accuracy, precision, recall, and F1-score. Its accuracy was recorded up to 98%, which was better than all the other models. This proves that the Ensemble model created by combining multiple models is more reliable and efficient, especially when it comes to sensitive and critical applications like fraud detection.The GUI developed for this project is also user-friendly and interactive, allowing users to easily view fraudulent and non-fraudulent transactions and compare different models.

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