Comparative Evaluation of Fraud Detection Algorithms in Credit Card Transactions and Online Banking

Moinul Islam[1]

[1]Algonquin College of Applied Arts and Technology Ottawa, Ontario, Canada

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Abstract: Credit card and online banking fraud have become a threat to financial security in the digital economy today and therefore require smart and automated detectors. The current study presents an AI-driven model of Credit Card Transaction Fraud Detection based on publicly available data on Credit Card Fraud Detection. The systematic workflow is the methodology, which is viewed as data preprocessing, feature selection, min-max scaling, and class balancing with the help of SMOTE. Machine learning and deep learning models included Extra Trees, ANN, and CatBoost that differentiated fraud and legitimate transactions. The measures of performance used in the evaluation were the accuracy, precision, recall, and the F1-score. The Extra Trees model which had an outstanding accuracy of 99.97 was above Cat Boost (99.74) and ANN (98.12) in the experiment. Moreover, among various Explainable AI methods, LIME and SHAP were utilized to enhance the interpretability of the model and identify the most significant factors that influence the fraud prediction. The proposed system as an appropriate solution to the real-life financial conditions enhances and increases the validity of fraud detection.

Keywords: *Credit Card, Fraud Detection, Transaction, Machine Learning, Deep Learning, Banking.*

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I. INTRODUCTION

The credit cards are the most efficient means of safe and convenient transactions in the constantly expanding global network of online payment systems, online banking, and online shopping [1]. However, this internet expansion has given rise to a new frontier of fraud, and cyber criminals are devising new ways to use the system, including Synthetic Identity Fraud, Phishing and illegal data breaches [2]. Fraud detection has become one of the most significant aspects of contemporary banking security systems due to the use of such malicious activities which undermine the security of cardholders and financial institutions [3]. Fraud detection systems, largely made of primarily static rule-based and manual examine methods, can longer meet the sheer volume, complexity, and dynamism of fraudulent transactions.

The use of electronic transactions has contributed to increase in different categories of financial scams, which include, but not restricted to identity theft, insurance fraud and money laundering [4]. The dynamism of these threats constantly makes it a requirement of intelligent systems that can immediately detect an unusual transaction and distinguish the genuine users with the frauds [5]. Fraud is a problem in the banking industry and in other areas such as energy distribution where fraudulent alterations of data frustrate the process that results in enormous losses of operations.

Over the last few years, AI, ML, and DL have been identified as the key factors in the evolution of fraud detection. This ability of AI to provide the power of human-like choice to the systems, in its turn, increases the flexibility and responsiveness of the detection mechanisms [6]. Machine Learning algorithms can be used to process past data to identify patterns of fraud that are recurrent and predict future risks with high accuracy. This process is also becoming more efficient with the Deep Learning (DL) technology that introduces non-linear dependencies in large datasets that are hardly noticeable even with the most effective detecting accuracy in very fine or new fraud patterns [7]. Collectively, these smart technologies allow financial institutions to detect transactions beforehand, minimize false alerts and ensure fraudulent activities are detected in real-time. The Key contributions are as follows:

- Presented an ML and DL model-based fraud detection system that uses AI to detect and weed out fraudulent credit card and online banking activity.
- Applied effective data pre-processing such as noise removal, feature selection, data normalization with

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Minimum-max scaling and data balancing with SMOTE in order to enhance model performance and generalization.

- Created and tested several classification models, Extra Trees, ANN, and CatBoost, with the best accuracy being the Extra Trees model.
- Using LIME and SHAP as XAI tools to help in interpreting the model's structure and identifying sets or essential elements for predicting fraud.

The emerging trend of online banking and computerized transactions has amplified the risk of economic fraud and has necessitated the deployment of more advanced detection systems. Traditional rule-based systems are unable to pick up the transformation of fraud trends, which may result in the delayed or incorrect detection. The reason for conducting the research is the requirement of a smart and data-oriented framework that can identify the fraudulent credit card transactions in real time. The proposed technique will be based on AI, ML, and DL to reach greater detection accuracy, reduce false positives and gain confidence in financial systems based on automated, flexible and explainable fraud detection.

The primary cause of the research is the current inefficiency of conventional methods of detection of fraud that often depend on rigid rules and human verification that cannot keep abreast with the dynamic and sophisticated methods of online banking and credit card fraud. The created framework therefore goes an extra mile and introduces a novel hybridization of ensemble learning (Extra Trees, CatBoost) and DL models to thereby improve the accuracy and strength of detection. The novel research is novel in that it combines the newest methods of data pre-processing such as SMOTE to balance the number of classes and Min-Max normalization to make the decision processes more transparent with the help of Explainable AI (LIME and SHAP). The two-fold emphasis on high predictive accuracy and interpretability ensures the suggested framework is effective and reliable in real-world activities of financial fraud detection.

- *Structure of the Paper*

The research is set up as follows: Section II covers Internet banking and credit card transaction review papers. Section III discusses the approach, whereas Section IV gives the proposed system's findings and analysis. Section V ends the research and outlines future efforts.

II. LITERATURE REVIEW

This section discusses some review articles on Credit Card transactions and online banking using ML and DL approaches.

Dharma and Latha (2025) the dataset used in this analysis consists collected 284,807 transactions in September 2013 from European cardholders. Results state that, described model achieves high performance parameters Acc, Prec, Rec and F1score of 97%,96%,97%,970/0 respectively, than other models [8].

Mishra, Biswal and Padhy (2025) used several machine learning classifiers to detect fraudulent behaviour in the banking system. Used classifiers like: - LR, RF, SVM, KNN, GB, AdaBoost, and DT. Result: From the experimental observation, they found that RF gives the highest accuracy of 0.985, Recall at 0.985000, and the classifier KNN has the highest score at 0.988937 [9].

Thakkar and Kapadia (2025) utilized a dataset comprising 284,807 European credit card transactions, and SMOTE was used to balance the dataset. The F1score for the hybrid DL model was 97.90%, thanks to its 98.76% acc, 98.01% prec, and 97.81% recall [10].

Kiran et al. (2024) selected the CCFD dataset. In performing feature selection, the dataset is split into two datasets, training data and test data and alerts the User when the model predicts the transaction as fraud. Among all ML models RF outperforms all with the detection accuracy of 94.98% [11].

Kali (2024) proposes the best framework for detecting fraud. Model efficiency may be enhanced by the use of feature selection procedures. The LSTM model achieves an acc of 92.54%, satisfying important assessment criteria such as F1-score, AUC, recall, and accuracy [12].

Singh (2023) The 2,84,807 transactions included in the dataset were sourced from cardholders throughout Europe. The results demonstrate that the best accuracy rates for the following classifiers: NB (98.72%), LR (52.34%), KNN (96.89%), and RF (91.67%) [13].

Verma (2023) presents a deep learning-based framework for CCFD using ANN and advanced convolution neural network (CNN) architectures such as VGG16 and VGG19. ANN is used as a baseline model due to its simplicity and speed, while VGG16 and VGG19 are finetuned to learn complex features and detect subtle anomalies in transaction patterns [14].

Gupta et al. (2022) the problem is that they can't find any fraudulent transactions when they look at past credit card transactions that used both valid and fraudulent purchases. The DTC achieved a higher training accuracy of 95% while the RFC showed a higher testing accuracy of 94.11% [15].

III. METHODOLOGY

The suggested approach to credit card transactions and online banking fraud detection, as depicted in Figure 1, applies to the Credit Card Fraud Detection dataset and has a systematic workflow. This involves data gathering, pre-processing to eliminate noise and other irregularities, feature selection, Minmax normalization, and data balancing using SMOTE. Separate training and testing sets of processed data are prepared for testing using ML and DL models, namely Extra Trees, ANN, and Cat Boost. The model's performance is evaluated by its acc, prec, recall, and F1score. Additionally, in order to provide transparency and enhance interpretability in fraud prediction, Explainable AI approaches like SHAP and LIME are used.

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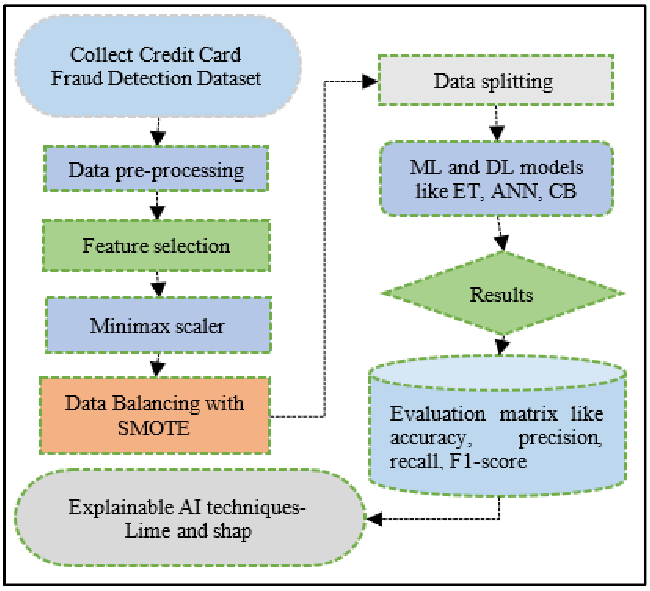

Fig 1 Flowchart for Methodology

The following is a quick discussion of the stages in the suggested methodology:

➢ *Data Collection*

This dataset represents a complete enumeration of credit card transactions for European cardholders in September 2013. The data spans 2 days and includes both legitimate and fraudulent transactions to demonstrate real-life financial activity. There were 492 fraudulent transactions out of 284,807 total transactions for the two days covered by this data. Some EDA graphs are shown below:

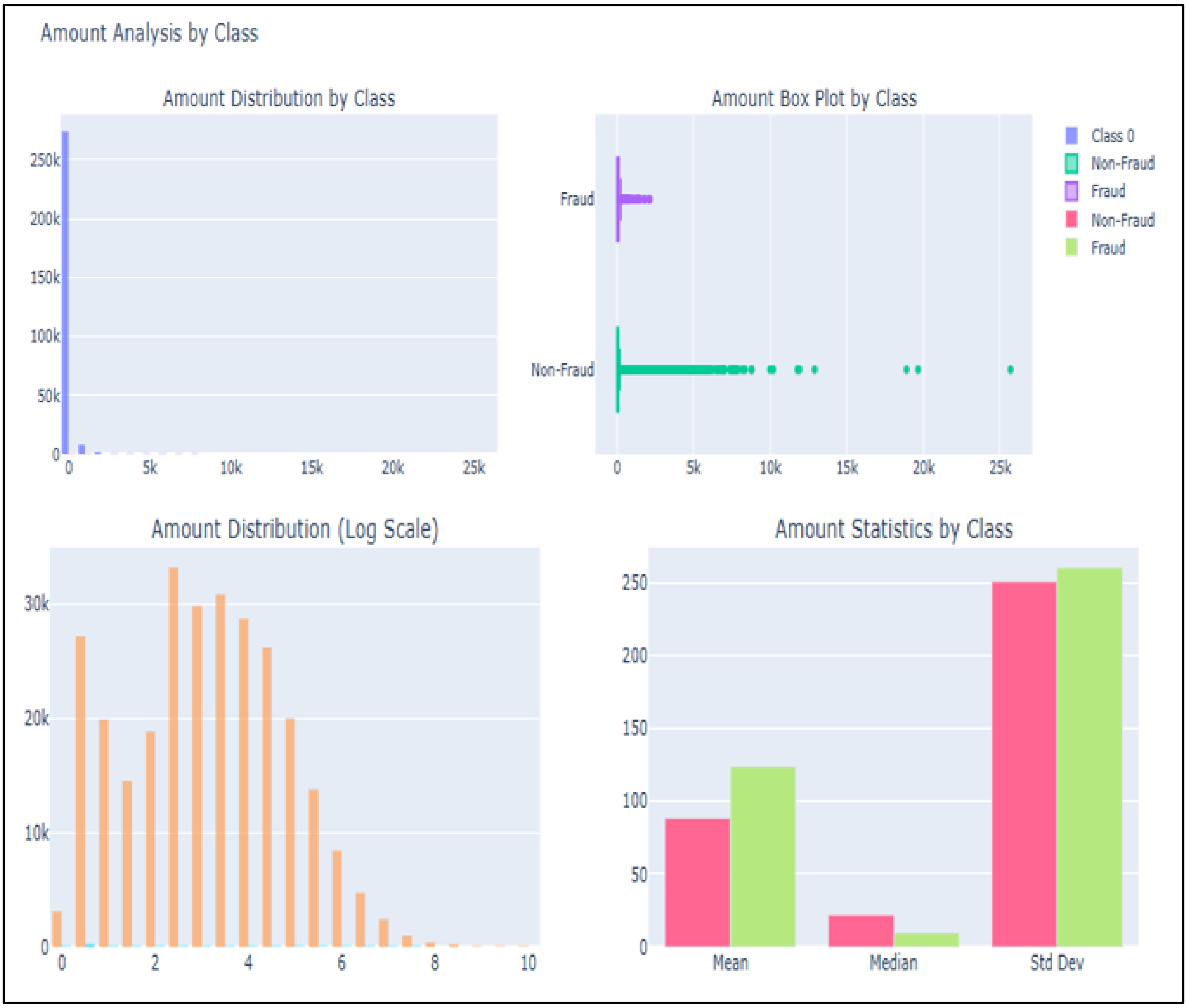

Fig 2 Amount Analysis by Class Using Distribution, Box Plot, Log Transformation, and Statistical Summary.

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The analysis of the number of transactions by class is shown in Figure 2. Fraud and non-fraud transactions are mostly small, with a skewed distribution to the right and only a few transactions above 10,000. Fraud transactions are focused on smaller values with a narrow range of dispersion, but non-fraud transactions are more variable with extreme values exceeding 20,000. The log transformation equalizes the distribution, and the statistics show high mean and variability of non-fraud cases, both classes have low median.

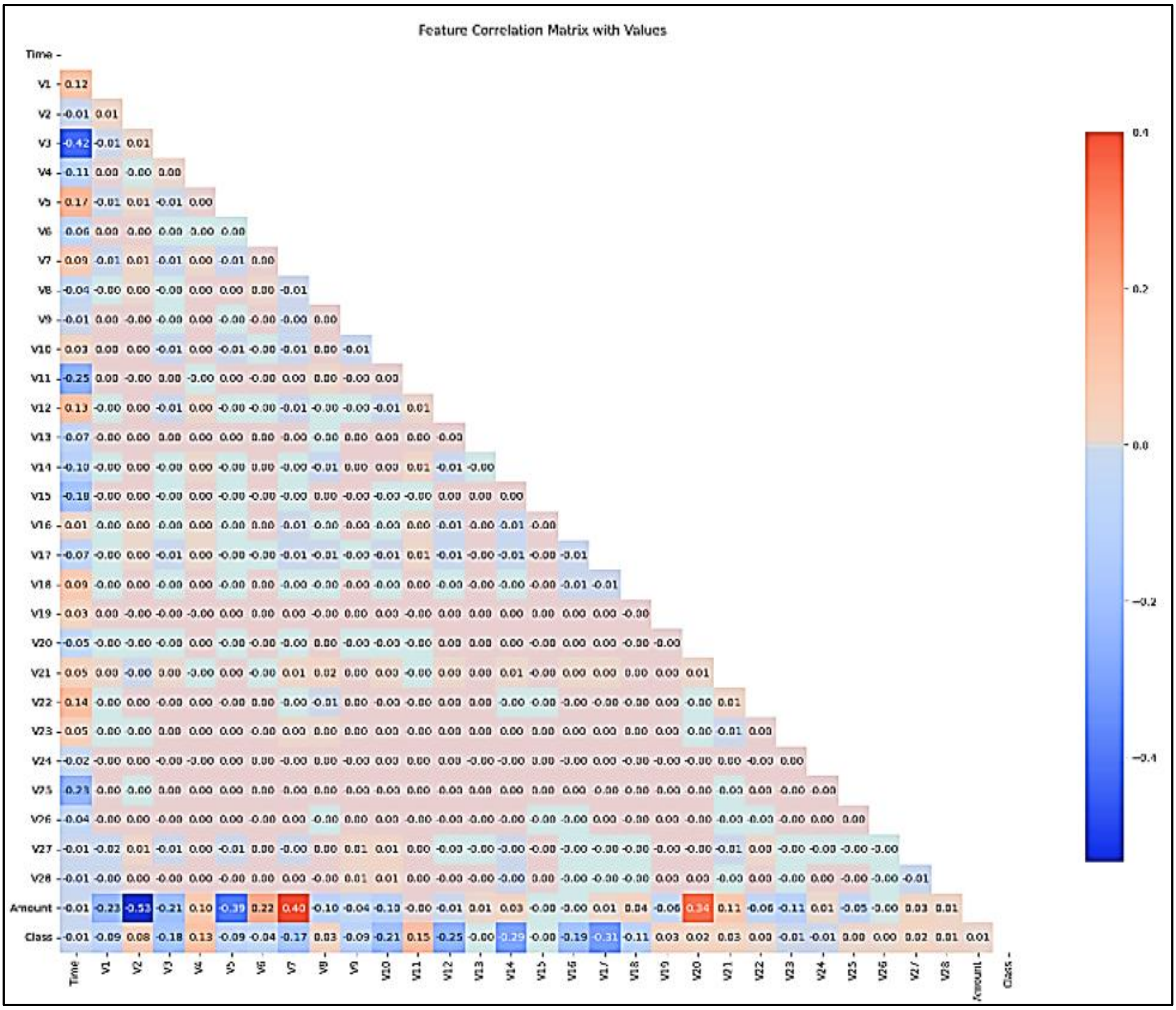

Fig 3 Feature Correlation Matrix with Values

The features' correlation table with the dataset's values is displayed in Figure 3. The correlation of most of the features with one another is very weak, implying that there is minimal multicollinearity, whereas several variables like V3, V10, V12 and V25 all have moderate correlations with the target class.

➢ *Data Preprocessing*

Pre-processing of the CCFD dataset was an essential process to handle the innate noise and irregularities. It started with an initial data exploration by calling functions like .head, .tail, .info and .describe to learn the form of the dataset, the type of data and the statistical distribution. Also, the .is null().sum () function was utilized to identify the missing values that can be handled and imputed where necessary. Such pre-processing operations are standard in the literature to give optimum data quality in order to have good model training.

➢ *Feature Selection*

The feature selection process is an essential part of fraud detection, which helps to identify and keep the most suitable variables of the dataset and remove redundant or irrelevant features. Correlation analysis, mutual information, and recursive feature elimination are some of the techniques applied to make sure that only relevant features used to aid fraud identification are being used during model training thus giving more accurate and interpretable findings.

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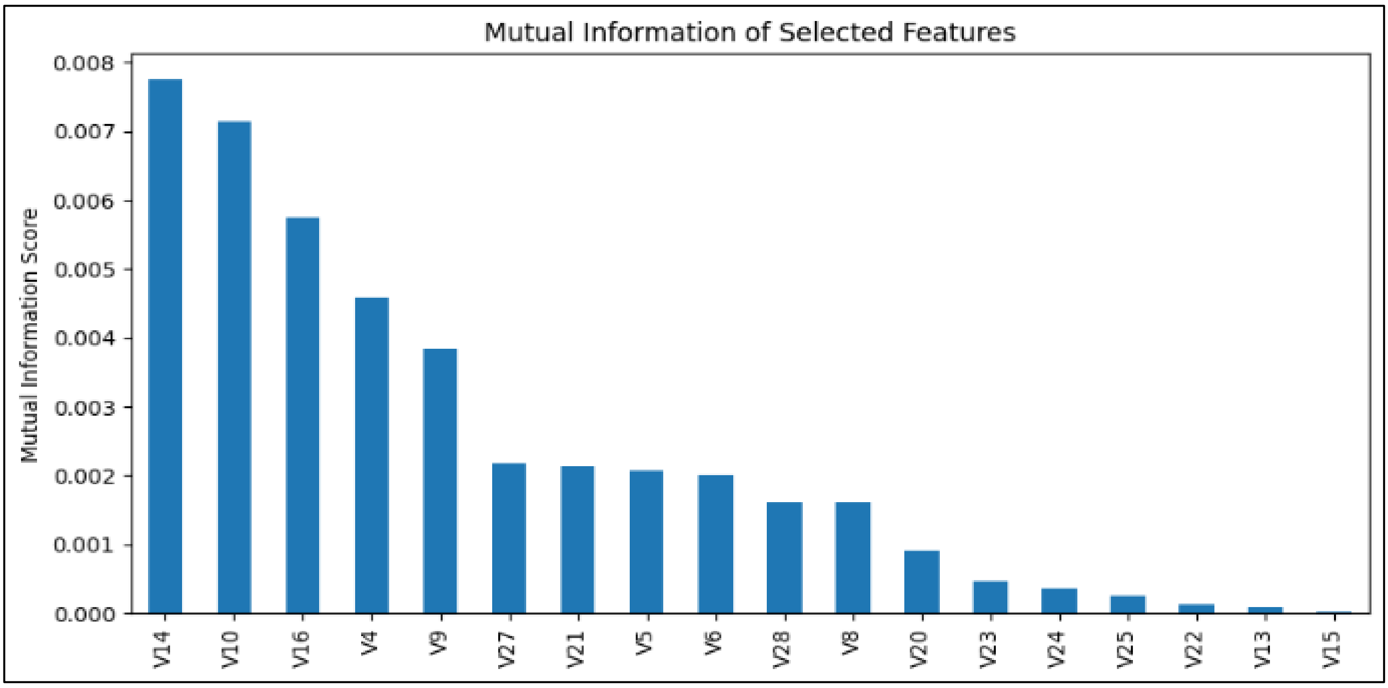

Fig 4 Mutual Information of Selected Features

In Figure 4 this graph indicates the Mutual Information Scores of a sample of features (18) which are denoted by V1, V4, V5, V6 etc. This measures the amount of information that is given by a particular feature in predicting the target variable with higher values indicating its importance.

➢ *Feature Scaling with Minimax Scaler*

The dataset was subjected to normalization using the Min-Max scaling approach, which maintains the relative differences between features while transforming them into a common range [16]. The efficiency of ML models is enhanced, and fair comparisons across variables are guaranteed. The following formula was used to apply the transformation in Equation (1):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

➢ *Balancing with SMOTE*

SMOTE is used to get a balanced dataset. In SMOTE, new synthetic instances are generated by creating combinations of feature values along the line segments that connect the minority class instance with its neighbours, which are then added to the dataset. Figure 5 illustrates how SMOTE addresses class imbalance by generating synthetic samples for the minority class.

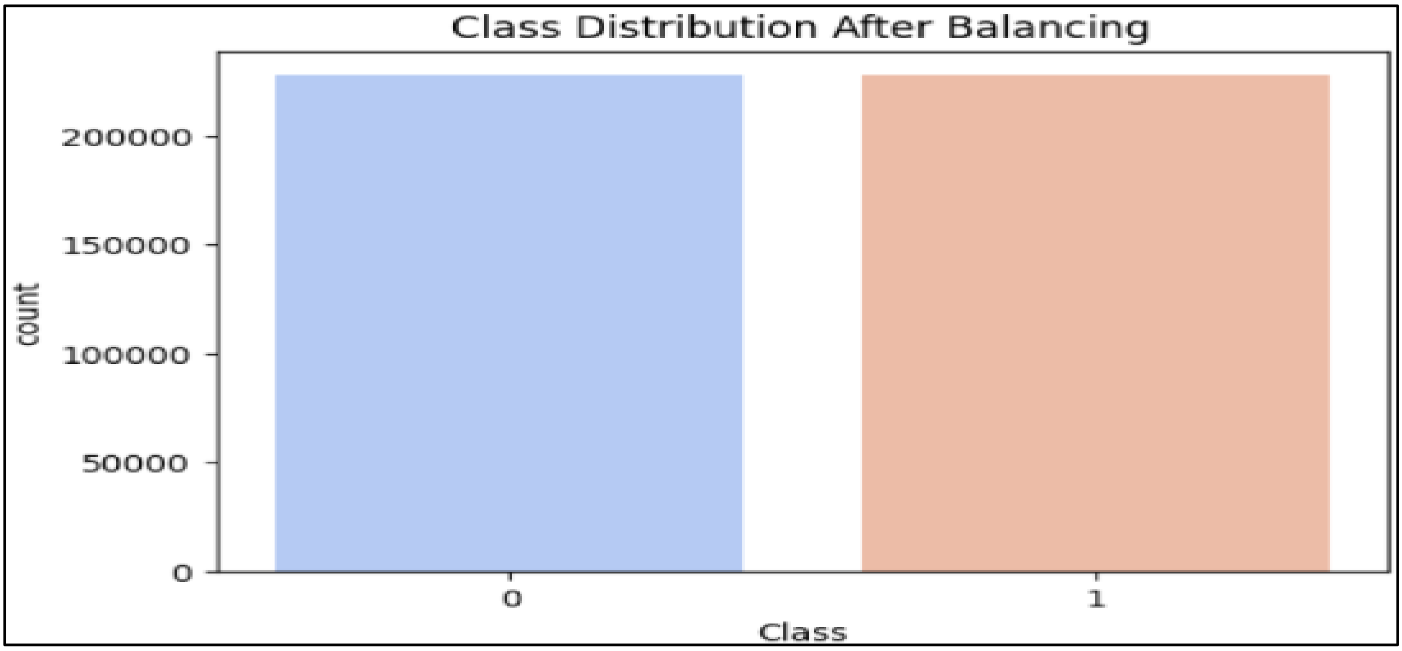

Fig 5 Class Distribution After Applying SMOTE to Achieve a Balanced Dataset.

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➢ *Data Splitting*

In the CCFD dataset is divided into two subsets: training subset, and testing subset, with 74% for training and 26% for testing.

➢ *Classification with Machine Learning and Deep Learning Models*

The suggested system employs the following categorization algorithms for output prediction:

- *Extra Trees Classifier (ETC)*

The ETC builds upon the ensemble learning approach that uses bagged decision trees. When it comes time to forecast the target class for a classification problem, the ETC mixes the results of several decorrelated DTs. This study used the ETC. Their suggested method for forecasting staff turnover is the Extra Trees Classifier [17]. Equation (2) shows the expression of the entropy that was computed for the Extra Trees Classifier:

$$Entropy(S) = \sum_{i=1}^{c} - pi \log_2(pi) \tag{2}$$

- *Artificial Neural Network*

This approach is based on a network of neurons that are all linked and each one has a part in making a decision. A combination of human intelligence and computer processing techniques and skills is used by ANN technology to provide predictions. Applying the same pattern it has learnt from past patterns observed in historical datasets, it predicts the likelihood of fraud in a current transaction [18]. The functions that are used for activation are hyperbolic tangent sigmoid. (according to the results of Equation (3):

$$f = \frac{1_{-e^{-2x}}}{1+e^{-2x}} \tag{3}$$

- *CatBoost Classifier*

CatBoost is a GBDT ensemble learning technique developed for fast processing of small sample data situations and categorical characteristics [19]. Several weak learners, often known as decision trees, make up CatBoost's training process. The current model's residual (the discrepancy between the actual and anticipated values) provides the basis for each subsequent decision tree. Through multiple rounds of iteration, the overall performance is gradually improved. (as shown in Equation (4):

$$Target\ Enc(x) = \frac{\sum_{i\epsilon past} y_i + \alpha}{N_{past} + \alpha} \tag{4}$$

➢ *Evaluation Metrics*

The proportion of transactions that were successfully identified is called Accuracy, and it is used to compare different approaches. It is a widely used and very effective assessment measure. The number of legitimate or fraudulent transactions that were accurately identified is called the detection rate, which is also called precision [20]. Recall is the percentage of suspicious records (those with the highest likelihood of being fraudulent) that the system properly identifies as such, whereas F1 measures the percentage of legitimate records (those with the lowest likelihood of being fraudulent) that the system correctly identifies as such.

The various metrics for evaluation are shown in Equations (5-8):

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \tag{5}$$

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

$$F1 - Score = \frac{2(Precision * Recall)}{\text{Precision +Recall}} \tag{8}$$

The AUC measures a classifier's performance by evaluating the trade-off between TPR and FPR across various thresholds. The Recurve plots FPR (x-axis) vs. TPR (y-axis), and the AUC represents its overall effectiveness.

"True Positive" (TP) measures how many fraudulent transactions were also detected by the system. The True Negative (TN) is the total number of correctly identified and legitimately categorized transactions. A "False Positive" (FP) is the number of valid transactions that were incorrectly identified as fraudulent. A False Negative (FN) occurs when the system incorrectly identifies fraudulent transactions as legal ones.

➢ *Explainable AI (Lime and Shap)*

The created models will be made more interpretable by using XAI techniques:

- SHAP (SHapley Additive exPlanations): This approach will enable stakeholders to comprehend how attributes influence predictions by offering both local and global interpretability of the model's conclusions.
- LIME (Local Interpretable Model-agnostic Explanations): This method will be used to give instance-level explanations, which will give information about specific predictions.

➢ *Experimental Setup*

Hardware and cloud resources were used to support the experimental setup. The local computer has been equipped with an Intel(R) Core (TM) i5-2520M CPU with a speed of 2.50 GHz and 12GB of RAM, which will be efficient in carrying out the intended tasks.

IV. RESULT ANALYSIS AND DISCUSSION

Table 1 provides the performance of Extra Trees, ANN and CatBoost on the basis of Acc, Prec, Rec and F1Score. Extra Trees was the highest performing system with the highest overall acc of 99.97%, 99.95% prec, 99.99% recall, and 99.97% F1score. CatBoost was also very close to Extra Trees with 99.74% acc, 99.75% prec, 99.73% rec, and 99.74% F1score. ANN was effective but with relatively low scores 98.12% accuracy, 97.61% precision, 98.68% recall, and 98.15% F1-score. Generally, Extra Trees and CatBoost appeared to be the most powerful and stable, whereas ANN slightly lagged behind them in all measures.

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Table 1 Performance of Machine Learning Models on Credit Card Fraud Transaction Dataset

Performance Measures	Extra Trees	ANN	CatBoost
Accuracy	99.97	98.12	99.74
Precision	99.95	97.61	99.75
Recall	99.99	98.68	99.73
F1-score	99.97	98.15	99.74

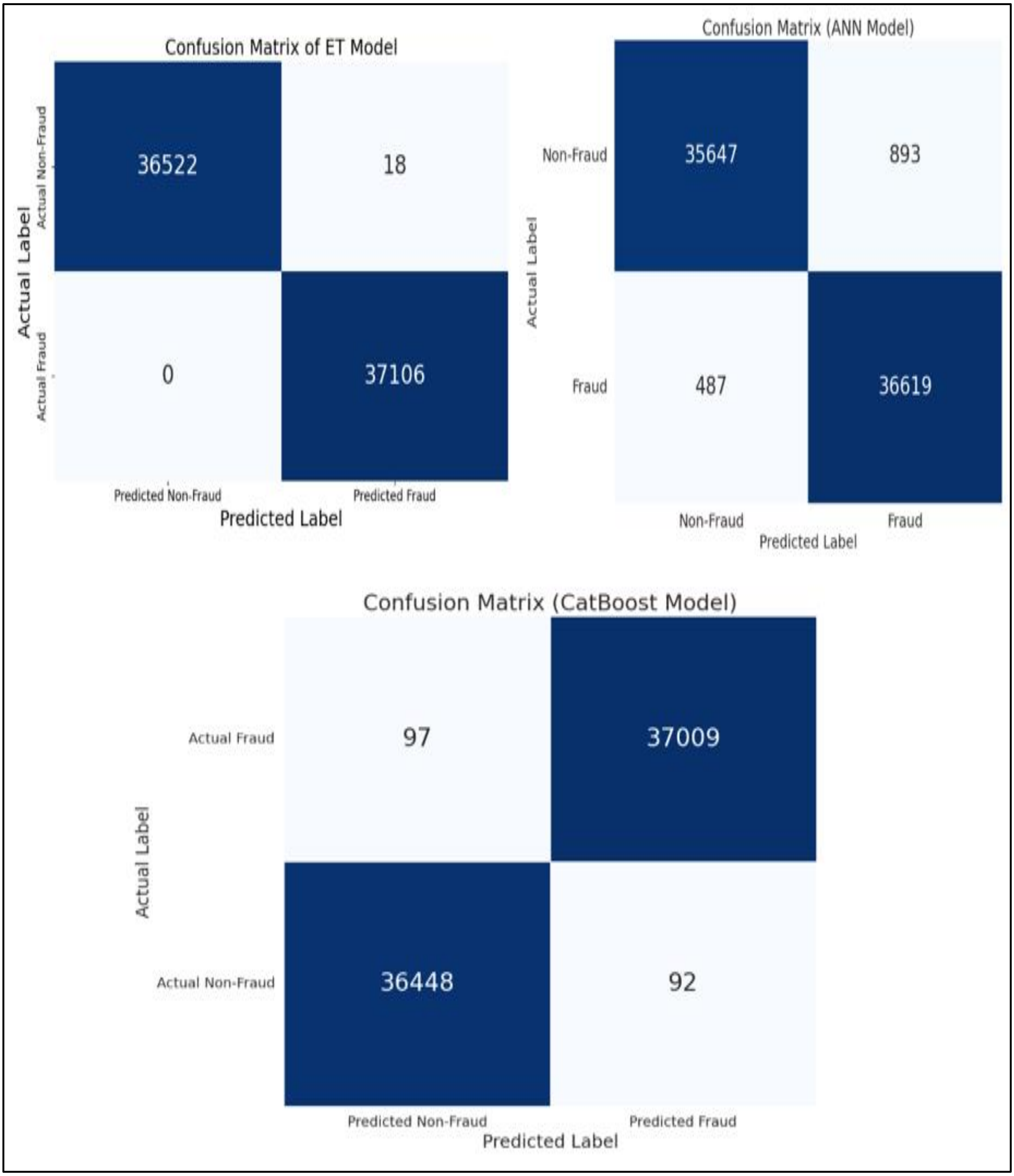

Fig 6 Confusion Matrix of Extra Trees, ANN and Catboost Model

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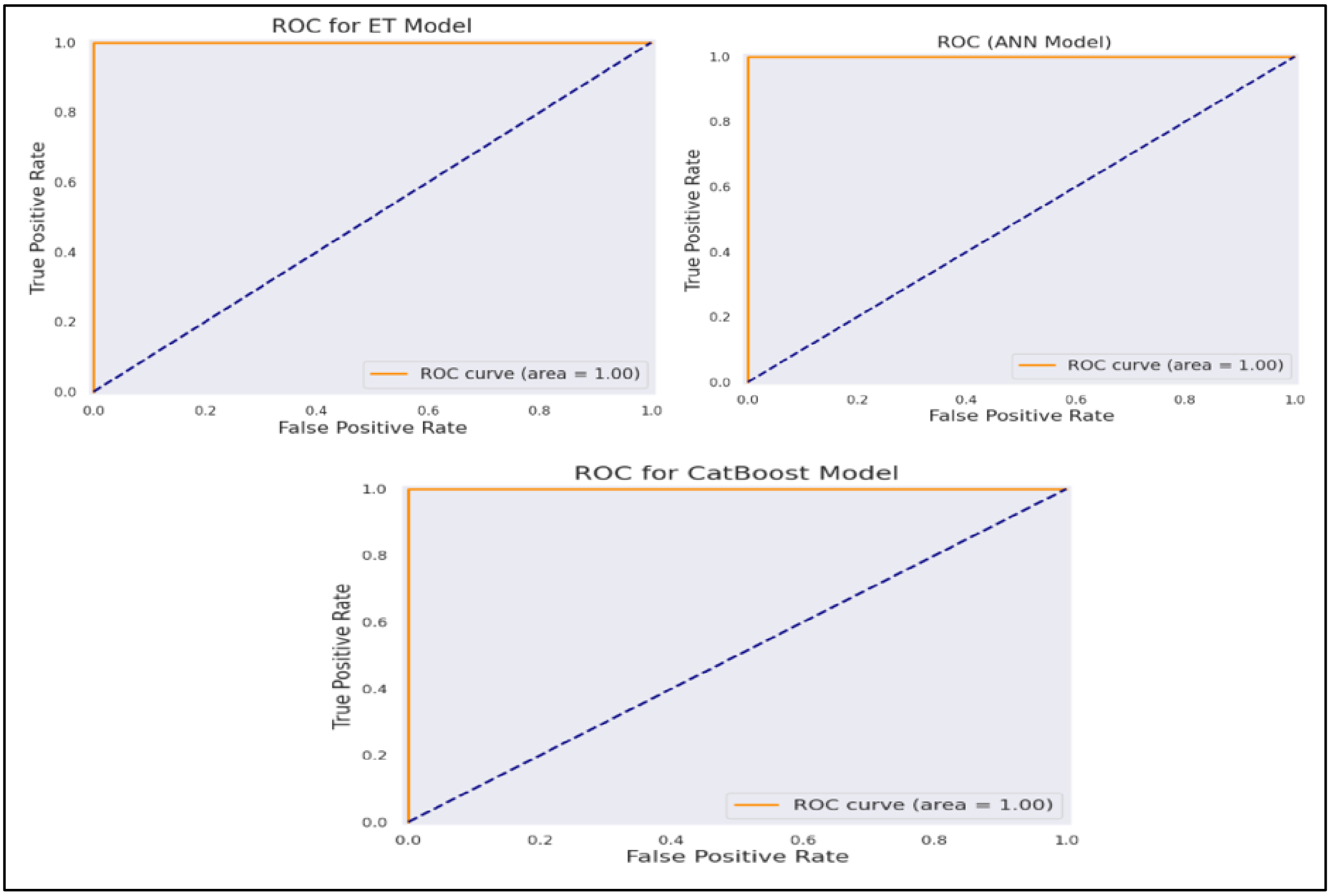
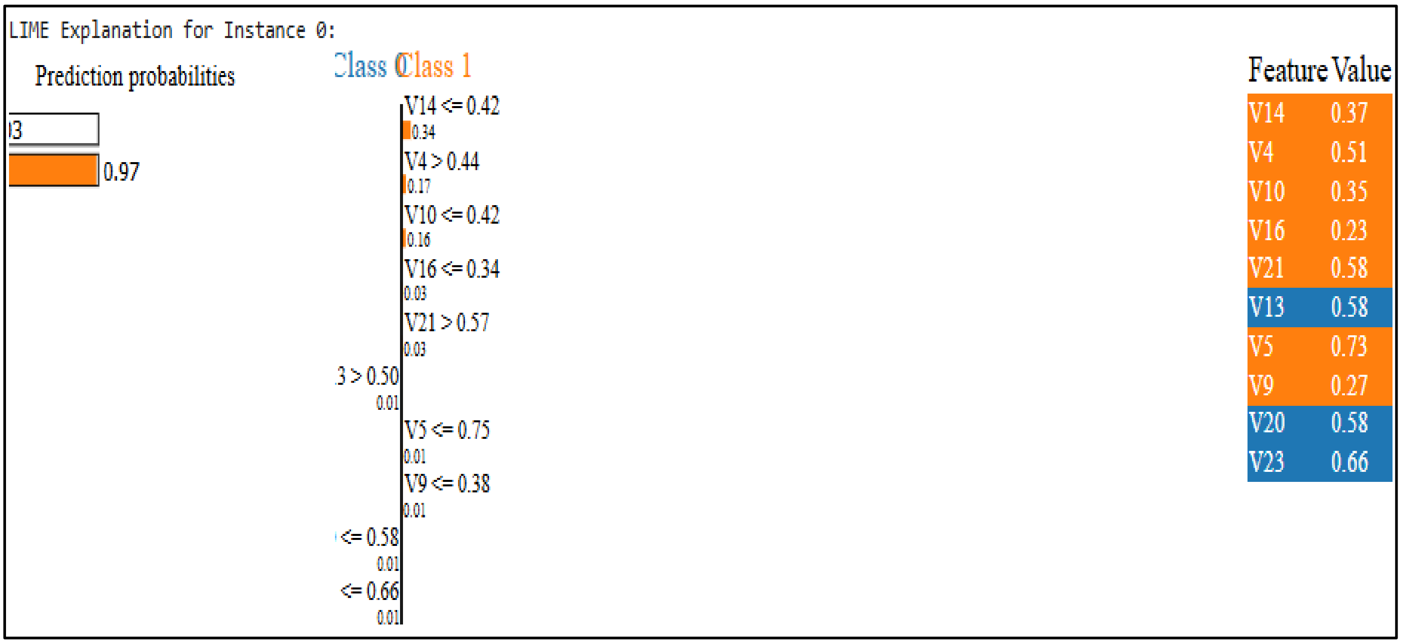


Fig 7 ROC Graph for Extra Trees, ANN and CatBoost Models

Figure 6 shows the confusion matrices for the ET, ANN, and Cat Boost models. The ET model achieved close to perfect classification, with minimal misclassification, resulting in most TP and TN. The ANN model performed well but had a higher number of FP and FN, whereas the Cat Boost model produced balanced results, with slightly more misclassifications than ET.

Figure 7 shows the ROC curves for the ET, ANN, and CatBoost models in fraud detection. The three models had an AUC of 1.00, the ideal value, indicating that can achieve perfect classification without any trade-off between FPR and TPR. The depiction of each model's ROC curve on the upper left edge shows that each model effectively distinguishes between fraudulent and non-fraudulent transactions.



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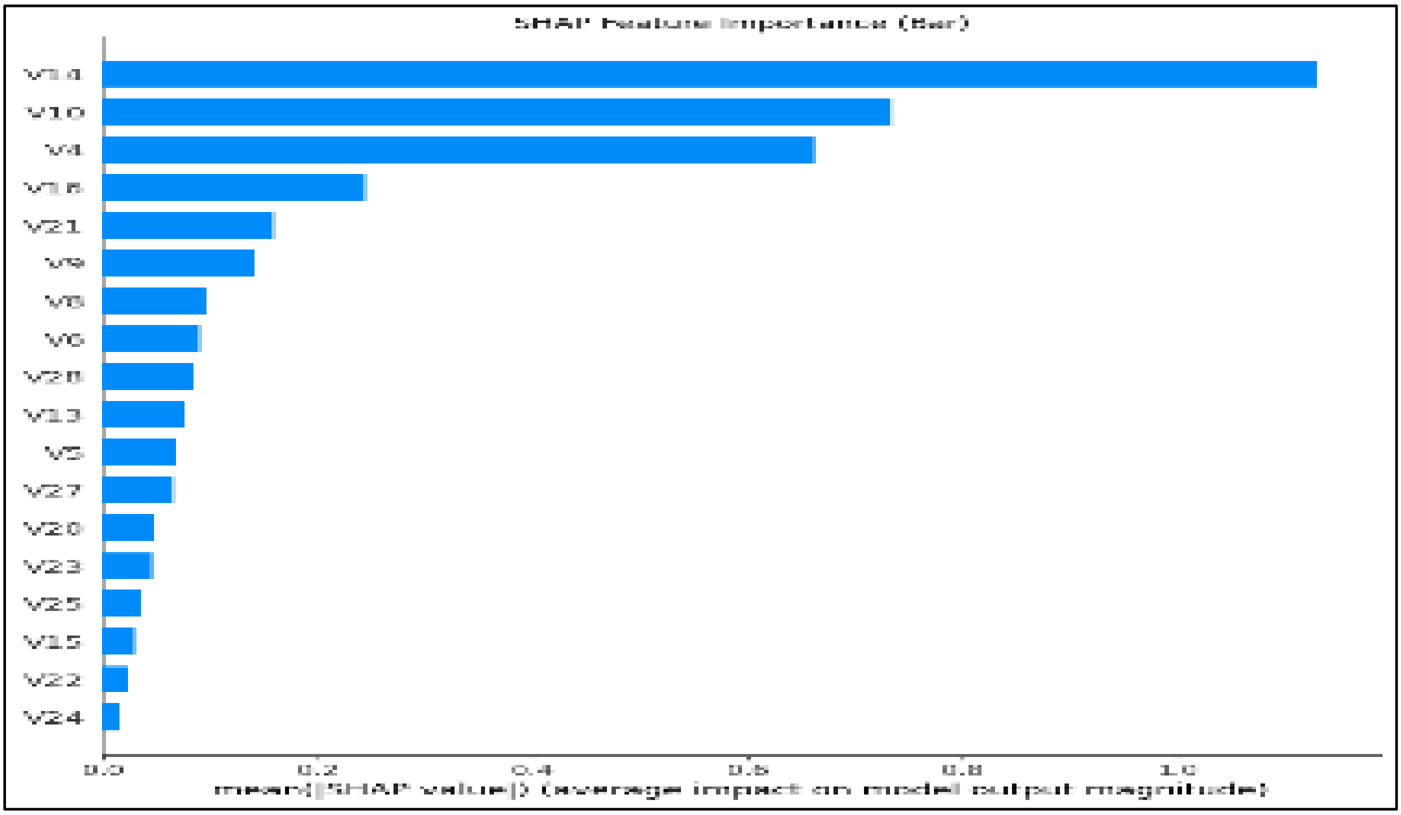

Fig 8 Lime and Shap Features Important Bar Chart

In Figure 8 below explainable AI Lime SHAP model interpretability results: the top figure displays a local explanation of a single prediction, meaning, it is confident in Class 1 (probability 0.87), and the bottom figure is a summary of the importance of each feature, showing that V14, V10, and V4 are the largest contributors to model predictions on average across the dataset.

➢ *Comparative Analysis and Discussion*

This section presents the data analysis in terms of comparison. Table II compares the performance of ML and DL models (Extra Trees, ANN, Cat Boost, Logistic Regression, and KNN) based on acc, prec, rec, and F1score results. An accuracy of 99.97 per cent made Extra Trees the top model for detecting individual fraudulent transactions. The Cat Boost model also showed tremendous performance, with an accuracy of 99.74, and the ANN came in second, with an accuracy of 98.12. Conversely, other conventional ML algorithms, such as LR, KNN, and AdaBoost, had lower accuracies of 94.65%, 93.68%, and 97%, respectively. Ensemble and Deep Learning techniques were the best and most accurate with a precision of 98.2 compared to Hybrid Random Forest using AdaBoost.

Table 2 Comparison with Existing Studies for Credit Card Fraud Detection

Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Extra Trees	99.97	99.95	99.99	99.97
ANN	98.12	97.61	98.68	98.15
CatBoost	99.74	99.75	99.73	99.74
Logistic Regression [21]	94.65	97.32	91.85	94.51
KNN[22]	93.68	94.50	94.20	94.20
AdaBoost[23]	97	98	96	97
Random Forest+Adaboost[24]	98.2	94	78	85

The proposed model that combines Extra Trees, ANN, and Cat Boost models proved to be the best in CCFD. The models were able to demonstrate high classification accuracy and strength by being capable of modelling complex data patterns and nonlinear relationships. Extra Trees ensemble nature, deep feature learning of ANN, and robust gradient boosting of Cat Boost all helped in the boost of detection accuracy, the decrease in misclassification rates, and the general enhancement of the handling of the class imbalance.

V. CONCLUSION AND FUTURE WORK

Finance fraud has been a major issue in the digital economy especially in the use of credit cards and online banking due to the sophisticated methods that are used by the fraudsters. The paper presented a comprehensive AI-based fraud detection model using the CCFD dataset, which involves the latest ML and DL models, such as Extra Trees, ANN, and Cat Boost. Based on systematic pre-processing, feature selection, min-max scaling and SMOTE data balancing. The results of the experiment revealed that the Extra Trees model had the highest overall performance with the close second being Cat Boost that was very accurate, had high prec, recall, and F1score. The description of AI algorithms like LIME and SHAP also contributed to the creation of a transparent enough model as the most influential features in predicting fraud were identified.

The proposed framework can be extended to real-time fraud detection systems in the future, which are integrated within online banking systems for adaptive learning and lifelong model improvement. Besides, alternative hybrid deep learning models, such as CNN-LSTM or Transformer-based models, could be examined to enhance temporal pattern recognition in sequential transaction data. "

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