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SHAP-BASED EXPLAINABLE FRAUD DETECTION USING FEATURE OPTIMIZATION WITH XGBOOST

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ABSTRACT
Financial fraud detection has become a critical challenge due to the rapid growth of digital transactions and the rising complexity of fraudulent activities. Traditional machine learning models often face difficulties with highly imbalanced data and lack transparency, which reduces their usefulness in real-world situations. This study compares three models Logistic Regression, XGBoost, and XGBoost combined with SHAP (SHapley Additive exPlanations) for identifying fraudulent transactions.
The models are tested on two standard datasets: the IEEE-CIS Fraud Detection Dataset and the European Credit Card Dataset. Their performance is measured using key metrics like Precision, Recall, F1-score, Accuracy, and Area Under the ROC Curve (AUC). The results show that XGBoost performs much better than Logistic Regression, achieving higher Precision and F1-scores on both datasets. Moreover, SHAP was used to identify the most influential features, improving model interpretability while maintaining comparable predictive performance. The findings highlight that tree-based ensemble models are quite more effective for fraud detection tasks, particularly in handling non-linear relationships and class imbalance, which is a big issue in fraud datasets. Furthermore, using SHAP provides valuable insights into feature importance, which makes the model more transparent and suitable for deployment in financial systems. This study emphasizes the importance of combining performance with explainability to build robust and trustworthy fraud detection systems.

Keywords:
Fraud Detection, Machine Learning, XAI, SHAP, XGBoost, Logistic Regression, Imbalanced Classification, Financial Transactions, Feature Selection, Model Interpretability, Anomaly Detection

1. INTRODUCTION

As digital financial transactions continue to expand, detecting fraudulent activities has become an important focus in the fields of machine learning and cybersecurity. Financial institutions are facing significant challenges in identifying fraudulent activities due to the high volume, velocity, and imbalance of transaction data. Fraudulent transactions typically represent a very small proportion of total transactions, making accurate detection both difficult and necessary.Traditional statistical and machine learning methods, like Logistic Regression, are commonly used for detecting fraud due to their simplicity and interpretability. However, these models often struggle to handle complex and non-linear patterns in real-world transaction data. On the other hand, advanced techniques such as XGBoost have shown better results by using gradient boosting to model complicated relationships in large datasets.
Even though these high-performing models are effective, they lack transparency, which is a big issue in the financial sector where decisions need to be clear and explainable for regulatory compliance and trust. This problem has led to the development of Explainable AI (XAI) tools. Among these, SHAP (Shapley Additive exPlanations) has become popular because it offers consistent and well-founded explanations for feature importance. In this study, we utilize two widely recognized datasets: the IEEE-CIS Fraud Detection Dataset and the European Credit Card Dataset. These datasets present different levels of complexity and class imbalance, allowing for comprehensive evaluation and validation of model performance.Even though multiple studies have utilized machine learning for detecting fraud, there are still some important areas that need more attention. For example, a lot of the research focuses on a single dataset, which makes it difficult to apply the findings to different situations. Also, there isn't much comparison between simple models like Logistic Regression and more complex ones like XGBoost. Another issue is that most studies don't include methods to explain how the models work, along with

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evaluating their performance. Along side , there is not enough testing across different datasets to make sure the models are reliable in various situations.

The main contributions of this work include a comprehensive comparison of traditional, ensemble, and explainable models for fraud detection. The study evaluates model performance across two real-world datasets, which improves the reliability of the results. It also integrates SHAP for feature importance analysis, thereby enhancing model interpretability. Furthermore, the study demonstrates that the combination of XGBoost and SHAP achieves high performance along with explainability, making it suitable for real-world deployment.

1.1 Background

This section outlines the core concepts that underpin the proposed fraud detection framework, including Artificial Intelligence (AI), Machine Learning (ML), and Explainable Artificial Intelligence (XAI). Understanding these concepts is essential, as they collectively define how modern systems analyze data, generate predictions, and provide interpretable insights.

Artificial Intelligence (AI) represents a broad area of computing that focuses on designing systems capable of simulating intelligent human behavior. These systems are developed to perform tasks such as reasoning, decision-making, pattern identification, and adaptive learning. Over the years, AI has become an integral part of several industries, including finance, healthcare, e-commerce, and cybersecurity, where large-scale data processing and rapid decision-making are required. In financial applications, AI plays a crucial role in detecting anomalies, identifying suspicious activities, and automating risk assessment processes.

Machine Learning (ML), a specialized branch within AI, focuses on enabling systems to learn from past data which will be used to make further decisions . ML models identify patterns and relationships within historical data and use this learned knowledge to make predictions on new, unseen data. Based on the nature of learning and data availability, machine learning techniques can be categorized into several types:

Supervised learning is one of the most commonly used approaches in machine learning, particularly in fraud detection tasks. In this method, models are trained on labeled datasets where the expected output is already known. The primary objective is to learn the relationship between input features and the target variable so that accurate predictions can be made on new data. In the context of financial fraud detection, historical transaction records are typically labeled as either fraudulent or legitimate, allowing the model to learn distinguishing patterns. Algorithms such as Logistic Regression, Decision Trees, and ensemble techniques like XGBoost are widely used due to their strong performance in classification problems and their ability to handle structured data effectively.

Unsupervised learning, on the other side , does not need labeled data. Instead, it focuses on discovering hidden patterns, structures, or relationships within the data without predefined outputs. Techniques such as clustering and anomaly detection are commonly used in this approach. In fraud detection scenarios, unsupervised methods are particularly valuable when labeled data is limited or unavailable. These models can identify unusual or suspicious transaction behaviors by detecting deviations from normal patterns, making them useful for uncovering previously unknown types of fraud.

Semi-supervised learning combines the strengths of both supervised and unsupervised approaches by utilizing a mixture of labeled and unlabeled data during training. This method is especially beneficial in real-world applications where obtaining labeled data can be time-consuming or costly. In fraud detection systems, a small portion of transactions may be labeled, while a much larger portion remains unlabeled. By leveraging both types of data, semi-supervised models can improve learning efficiency and enhance prediction accuracy compared to using labeled data alone.

Reinforcement learning represents a different paradigm, where models learn by interacting with an environment and receiving feedback based on their actions. This feedback is typically provided in the form of rewards or penalties, guiding the model toward optimal decision-making over time. Although reinforcement learning is not as widely applied in traditional fraud detection systems, it holds potential for developing adaptive models that can continuously evolve and respond to changing fraud patterns. Such systems can improve their performance dynamically as they encounter new types of fraudulent activities.

In practical fraud detection systems, supervised learning models are most commonly employed due to the availability of historical labeled data. However, combining multiple learning paradigms can further enhance detection capabilities.

Despite achieving strong predictive performance, many advanced machine learning models—particularly ensemble and boosting techniques—lack transparency in their decision-making process. These models often behave as “black boxes,” meaning that while they provide accurate predictions, the reasoning behind those predictions is not easily interpretable. This limitation becomes critical in financial applications, where decisions must be explainable for auditing, regulatory compliance, and user trust.

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To overcome this limitation, the field of Explainable Artificial Intelligence (XAI) has gained significant importance. XAI aims to make machine learning models more transparent by providing insights into how predictions are generated. It bridges the gap between model performance and interpretability, allowing stakeholders to better understand and trust the system.

One of the most widely adopted techniques in XAI is SHAP (SHapley Additive Explanations), which is grounded in concepts from cooperative game theory. SHAP assigns a contribution value to each input feature, indicating how much it influences a particular prediction. These contributions can be analyzed at two levels: globally, to understand overall feature importance across the dataset, and locally, to explain individual predictions for specific transactions. This dual capability makes SHAP especially valuable in fraud detection, where both overall trends and case-specific explanations are important.

By integrating machine learning techniques with explainability methods, the proposed framework not only focuses on achieving high detection accuracy but also ensures that the results are interpretable and transparent. This combination is essential for building trustworthy systems that can be effectively deployed in real-world financial environments, where both performance and accountability are equally important.

2. LITERATURE SURVEY

Fraud detection in financial transactions has been widely studied due to the rapid growth of digital payment systems and increasing fraudulent activities. Traditional machine learning techniques such as Logistic Regression and Decision Trees were initially used for fraud detection; however, their performance is often limited when dealing with highly imbalanced datasets. Studies have shown that these models tend to achieve high accuracy but fail to effectively identify fraudulent transactions, emphasizing the importance of evaluation metrics such as Precision, Recall, and AUC instead of accuracy alone [1], [2].

With advancements in machine learning, ensemble techniques such as Random Forest and Gradient Boosting have gained popularity. Among these, XGBoost has emerged as one of the most effective algorithms due to its scalability and ability to handle high-dimensional data. Research demonstrates that XGBoost significantly outperforms traditional models in fraud detection tasks by capturing complex, non-linear relationships between features [3], [4]. Comparative studies further confirm that ensemble methods achieve better F1-scores and AUC values, especially in imbalanced datasets [5].

Despite high predictive performance, a major limitation of these models is their lack of interpretability. In financial systems, model transparency is critical for trust and regulatory compliance. To address this issue, Explainable AI (XAI) techniques have been introduced. LIME (Local Interpretable Model-agnostic Explanations) provides local interpretability by approximating complex models, but suffers from instability and inconsistency [6]. To overcome these limitations, SHAP (SHapley Additive exPlanations) was proposed as a unified framework based on game theory, providing both global and local explanations with consistent feature importance values [7].

Recent studies have focused on integrating SHAP with machine learning models to enhance both interpretability and performance. SHAP-based feature selection helps in identifying the most influential features, reducing dimensionality and improving model efficiency. Experimental results on benchmark datasets such as the IEEE-CIS Fraud Detection dataset and the European Credit Card dataset show that combining XGBoost with SHAP improves AUC scores and enhances model transparency [8], [9].

Deep learning approaches, including Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks, have also been explored for fraud detection. These models are capable of capturing complex patterns in transaction data but require large datasets and significant computational resources. Moreover, their black-box nature limits their interpretability, making them less suitable for critical financial applications [10].

Although significant progress has been made, challenges such as class imbalance, lack of interpretability, and limited generalization across datasets remain. Most existing studies focus on improving accuracy without addressing trust and explainability. Therefore, this work proposes a comparative framework using Logistic Regression and XGBoost, along with SHAP for explainability and feature optimization, to develop a more robust and interpretable fraud detection system.

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2.1 Comparative Analysis of Existing Work

No.	Study	Model Used	Dataset	XAI Used	Strength	Limitation
1	Dal Pozzolo et al.	Logistic and random forest	European Dataset	No	Handles imbalance	Single dataset and no explainability
2	Chen & Guestrin	XGBoost	Generic datasets	No	High performance	No explainability
3	Lundberg & Lee	SHAP	General ML	Yes	Strong interpretability	Not fraud-specific
4	Fiore et al.	Neural Networks	Credit Card	No	Captures complex patterns	Black-box
5	Bahnsen et al.	Cost-sensitive models	Financial data	No	Real-world cost focus	Limited comparison
6	Carcillo et al.	Streaming Machine learning	Transaction data	No	Real-time detection	No XAI
7	Whitrow et al.	Random Forest	Credit Card	No	Good accuracy	Feature engineering heavy
8	Jurgovsky et al.	LSTM	Sequential data	No	Captures temporal patterns	High complexity
9	Pozzolo et al. (SMOTE)	Sampling and Machine learning	Credit Card	No	Handles imbalance	Risk of overfitting
10	Ngai et al.	Data mining models	Financial datasets	No	Broad analysis	Outdated techniques
11	Roy et al.	Hybrid Machine learning	Banking data	No	Improved accuracy	No interpretability
12	Kumar et al.	Ensemble models	Fraud datasets	No	Robust performance	No XAI integration
13	Fatemeh et al.	XGBoost LightGBM CatBoost RandomForest Neural NetworLogistic Regression	IEEE-CIS Fraud Detection dataset	Yes	Multiple models are used along with XAI	Comparatively lower accuracy
14	Esraa Faisal M et al.	Random forest Decision Tree XGBoost LGBM	IEEE-CIS Fraud Detection	Yes	Worked on highly imbalanced dataset with good accuracy	No explainability and main focus on data processing
15	Proposed Model	Logistic Regression + XGBoost with SHAP	IEEE-CIS & European Credit Card Dataset	Yes	Combines high accuracy with interpretability; validated on multiple datasets; handles imbalance effectively	Computational cost due to XAI and requires careful preprocessing

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3. METHODOLOGY

3.1 Dataset Description

This research employs two well-established publicly available benchmark datasets to assess the performance and stability of fraud detection models under different data conditions. The first dataset, the IEEE-CIS Fraud Detection dataset, includes a substantial number of anonymized features related to transactions and user identities. Due to its high dimensional structure and the presence of complex feature relationships, it provides a suitable environment for modeling subtle, non-linear patterns that are often associated with fraudulent activities in real-world financial systems. The richness of this dataset allows machine learning models to learn intricate dependencies that may not be easily captured through simpler representations.

The second dataset, the European Credit Card dataset, presents a different challenge as it contains an extreme imbalance between legitimate and fraudulent transactions. In this dataset, fraudulent cases form only a very small proportion of the total records, closely reflecting real-world scenarios where fraud occurrences are rare but critical. Because of this characteristic, it is frequently adopted in research to examine how effectively models can identify minority class instances without being biased toward the majority class.

By integrating these two datasets, the study performs a more thorough evaluation of model behavior across diverse data environments. The IEEE-CIS dataset primarily assesses how well the models can process large-scale and feature-intensive data, whereas the European dataset focuses on the model's capability to detect rare and minority class events. Evaluating performance on both datasets helps in validating the consistency of results and provides stronger evidence regarding the applicability of the proposed approach in different practical settings. This combined evaluation strategy enhances the credibility of the findings and demonstrates that the developed models can maintain reliable performance even when the underlying data distribution varies significantly.

3.2 Data Preprocessing

Preparing the data effectively is a fundamental requirement for building a reliable fraud detection system, as the behavior of machine learning models is highly dependent on the quality and structure of the input data. The European Credit Card dataset as well as the IEEE-CIS Fraud Detection dataset introduce several practical challenges, such as incomplete records, a large number of features, and an uneven distribution between legitimate and fraudulent transactions. To address these issues, a structured preprocessing workflow was designed to clean the data, reduce inconsistencies, and support efficient model training.

The first step involved dealing with incomplete data entries. Numerical attributes with missing values were handled using median-based imputation, which is less sensitive to extreme values and helps maintain the original data distribution. For categorical attributes, missing entries were replaced using the most frequently occurring category within each feature. In the IEEE-CIS dataset, where missing values are more widespread across multiple columns, features with a very high proportion of missing data were either excluded or treated cautiously to prevent distortion in model learning.

Since machine learning models require numerical input, categorical information was converted into suitable numeric formats. Ordinal features were encoded using label encoding, while features with a large number of unique categories were processed carefully to avoid introducing unnecessary complexity or overfitting. This ensured that categorical data could be utilized effectively without significantly increasing computational overhead.

Scaling of features was applied in cases where it was necessary for model stability. In particular, Logistic Regression benefits from normalized input, so standardization techniques were used to transform features to a common scale with zero mean and unit variance. This transformation supports faster convergence and improves numerical stability during training. Although models such as XGBoost are inherently less affected by feature scaling, applying consistent preprocessing steps across models helps maintain uniformity in experimentation.

Given the large number of features in the datasets, reducing dimensionality was also an important step. Correlation analysis was used to identify strongly related features, and redundant attributes were removed to minimize duplication of information. Additionally, features with very low variance, which contribute little to distinguishing between classes, were eliminated. This not only simplifies the model but also helps improve its ability to generalize to unseen data.

A key difficulty in fraud detection tasks is the imbalance between classes, where fraudulent cases occur far less frequently than normal transactions. To manage this, stratified sampling was used during the train-test split to preserve the original class proportions in both subsets. Model evaluation was also adapted accordingly, with greater emphasis placed on metrics such as precision, recall, F1-score, and AUC-ROC, rather than relying solely on accuracy. In addition, class weighting strategies were considered to assign higher penalties to misclassification of fraudulent transactions.

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Outlier handling was another aspect taken into account, particularly for the European dataset, where anonymized features may include extreme observations. While tree-based algorithms can generally tolerate such values, preprocessing ensured that unusually large deviations did not negatively influence model performance.
Finally, the prepared dataset was divided into training and testing portions using an 80:20 ratio. A stratified approach was maintained to ensure that both sets reflected similar class distributions, which is essential for obtaining reliable and unbiased evaluation results in imbalanced classification scenarios.
Overall, the preprocessing strategy plays a significant role in enhancing data quality, minimizing noise, and enabling machine learning models to learn meaningful patterns, ultimately contributing to more accurate and dependable fraud detection outcomes.

3.3 Logistic Regression Baseline Model

Logistic Regression was used as a baseline model to establish a reference for performance comparison. As a linear classification model, it estimates the probability of a transaction being fraudulent based on a weighted combination of input features. Despite its simplicity and interpretability, Logistic Regression has limitations in capturing non-linear relationships within transaction data. However, it serves as an important benchmark to highlight the improvements achieved by more advanced models. The logistic regression model estimates the probability that a transaction belongs to the fraudulent class. The sigmoid function maps the linear combination of input features into a probability value between 0 and 1. If the predicted probability exceeds a predefined threshold, the transaction is classified as fraudulent; otherwise, it is considered legitimate.
Formula

$$P(y=1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_n x_n)}}$$

3.4 XGBoost Model

To overcome the limitations of linear models, XGBoost (Extreme Gradient Boosting) was employed as an advanced ensemble learning technique. XGBoost builds multiple decision trees in a sequential manner, where each subsequent tree focuses on correcting the errors made by the previous ones through gradient boosting. This iterative learning process allows the model to capture complex, non-linear relationships between features, which are often present in fraud detection datasets. In addition to its strong predictive capability, XGBoost incorporates regularization techniques such as L1 (Lasso) and L2 (Ridge) penalties, which help control model complexity and reduce the risk of overfitting. It also supports built-in handling of missing values by learning optimal splitting directions, eliminating the need for extensive preprocessing. Furthermore, XGBoost is computationally efficient due to its parallel processing and optimized tree construction methods. These characteristics make it particularly suitable for large-scale, high-dimensional, and imbalanced datasets such as the IEEE-CIS Fraud Detection Dataset, where capturing subtle fraud patterns is critical for achieving high detection performance.
Formula

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Where:

- l = loss function
- Ω = regularization term
- F_k = decision trees

3.5 Explainable AI using SHAP Formula

To improve model interpretability, SHAP (SHapley Additive Explanations) was applied to analyze the importance of input features and provide insight into model decisions. SHAP is based on game theory and assigns contribution scores to each feature by estimating how much each one influences the final prediction. This enables a clear understanding of which features play a significant role in identifying fraudulent transactions and how they impact the model output. SHAP summary plots and feature importance visualizations were used to examine the global behavior of the model by highlighting the most influential features across all predictions. In addition, local explanations such as force plots were utilized to analyze individual transaction predictions, showing how specific feature values push the prediction toward fraud or non-fraud. This combination of global and local interpretability enhances transparency and builds trust in the model, which is essential in financial fraud detection systems.

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$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

Where:

- Φ = contribution of feature
- S = subset of features
- F = full feature set

3.6 SHAP-Based Feature Optimization

Beyond interpretability, SHAP was also utilized for feature optimization. Features with low SHAP importance values were identified and removed to reduce model complexity and eliminate noise. The model was then retrained using the optimized feature set, resulting in improved efficiency and, in some cases, enhanced predictive performance. This step led to the development of the XGBoost + SHAP model, which combines high accuracy with reduced feature dimensionality and improved interpretability.

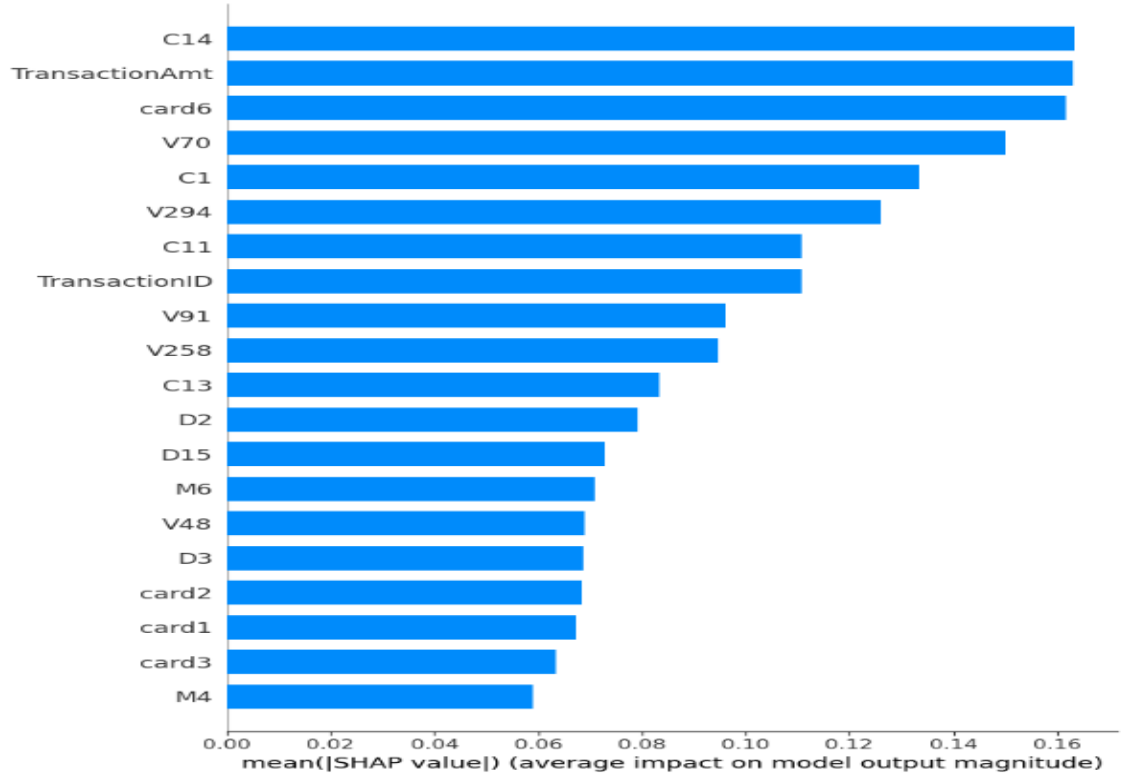

Figure 1 SHAP Summary Plot (Feature Importance)

Figure 1 illustrates the SHAP summary plot, highlighting the most influential features affecting model predictions. Features with higher SHAP values contribute more significantly to identifying fraudulent transactions.

3.7 Evaluation Metrics

To comprehensively evaluate model performance, multiple metrics were used. Precision measures the proportion of correctly identified fraudulent transactions among all predicted fraud cases, while Recall indicates the model's ability to detect actual fraud instances. The F1-score provides a balance between Precision and Recall, making it suitable for imbalanced datasets. Accuracy represents the overall correctness of the model but is less reliable in skewed data scenarios. Therefore, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was also used, as it evaluates the model's ability to distinguish between fraudulent and non-fraudulent transactions across different threshold values. These metrics collectively provide a robust evaluation framework for comparing different models.

Formulas

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

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

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

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

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

Where:

- TPR = True Positive Rate = Recall
- FPR = False Positive Rate

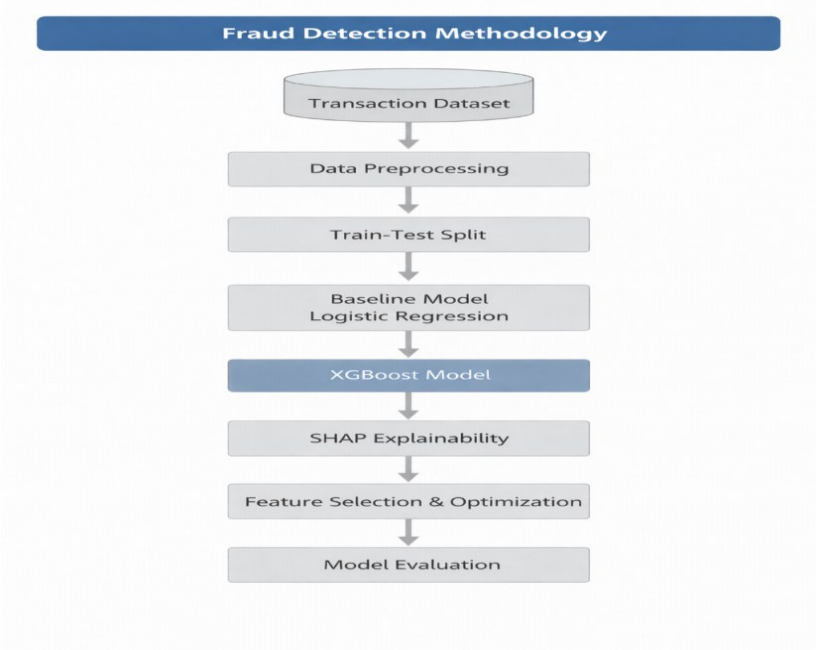

Figure 2. Proposed fraud detection framework

4 . EXPERIMENTAL ANALYSIS

The experimental evaluation was conducted to assess the performance and robustness of different machine learning models for fraud detection. The models considered in this study include Logistic Regression as a baseline, XGBoost as an advanced ensemble method, and XGBoost integrated with SHAP for explainability and feature optimization. Experiments were performed on two benchmark datasets: the European Credit Card Dataset and the IEEE-CIS Fraud Detection Dataset.

The datasets were preprocessed and split into training and testing sets using an 80:20 ratio with stratified sampling to preserve class distribution. Due to the imbalanced nature of fraud datasets, evaluation was carried out using multiple metrics including Precision, Recall, F1-score, Accuracy, and AUC-ROC. Additionally, training time was

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recorded to evaluate computational efficiency. The experiments were implemented using Python libraries such as Scikit-learn, XGBoost, and SHAP.

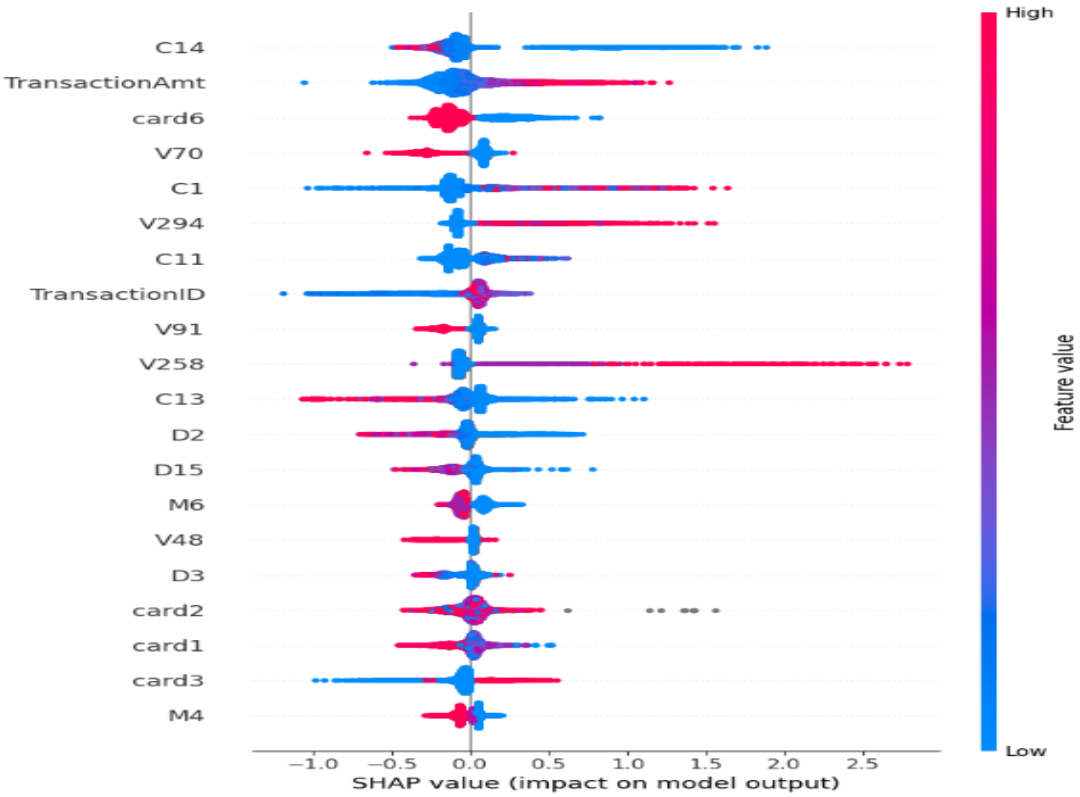

Figure 3: SHAP Summary Plot Showing Feature Importance for Fraud Detection

Figure 3 presents the SHAP summary plot, which illustrates the global feature importance and their impact on model predictions. Each point represents a feature value for a specific instance, with color indicating the feature magnitude. Features at the top of the plot have the highest influence on the model output. Positive SHAP values indicate a higher likelihood of a transaction being classified as fraudulent, while negative values correspond to non-fraudulent predictions. This visualization helps in identifying the most critical features contributing to fraud detection and enhances the interpretability of the model.

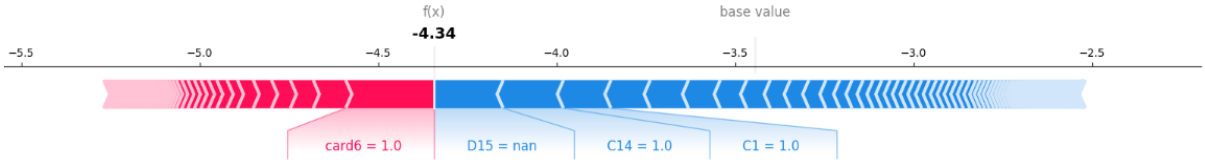

Figure 4: SHAP Force Plot Explaining Individual Transaction Prediction

Figure 4 illustrates the SHAP force plot for an individual transaction, providing a local explanation of the model's prediction. The plot shows how different features contribute to pushing the prediction towards either the fraudulent or non-fraudulent class. Features highlighted in red increase the likelihood of fraud, while features in blue decrease it. The magnitude of each feature's contribution is represented by the size of the corresponding bar. The base value represents the average model output, and the final prediction is obtained by summing the contributions of all features. This visualization provides detailed insight into the decision-making process of the model at an instance level, enhancing transparency and trust.

4.1 Results on European Credit Card Dataset

The European Credit Card dataset presents a highly imbalanced classification problem, where fraudulent transactions constitute a very small portion of the data. As a result, model evaluation requires careful consideration of performance metrics beyond accuracy.

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The performance of the proposed models was evaluated using multiple metrics, including precision, recall, F1-score, accuracy, and AUC, to ensure a comprehensive assessment on the imbalanced fraud detection dataset.
The Logistic Regression model achieved a high recall of 0.918, indicating its ability to identify most fraudulent transactions. However, its precision was extremely low (0.061), suggesting that a large number of legitimate transactions were incorrectly classified as fraud. This imbalance resulted in a low F1-score, highlighting the limitation of Logistic Regression in handling highly skewed datasets despite achieving high overall accuracy.
In comparison, the XGBoost model demonstrated significantly improved performance across all evaluation metrics. It achieved a precision of 0.882 and a recall of 0.837, indicating a strong balance between detecting fraudulent transactions and minimizing false alarms. This balance is further reflected in its high F1-score of 0.859. Additionally, XGBoost achieved the highest accuracy (0.99952) and AUC (0.9745), confirming its effectiveness in distinguishing between fraudulent and non-fraudulent transactions.
To enhance interpretability, SHAP-based feature selection was applied to identify the most influential features. The XGBoost model trained on the top selected features produced performance comparable to the full-feature model, with only a marginal reduction in precision , F1-score and AUC. This indicates that a reduced set of features can still retain most of the predictive power while improving model transparency.
Overall, the experimental results demonstrate that XGBoost outperforms Logistic Regression for fraud detection tasks, and the integration of SHAP provides an effective approach to balancing model performance with interpretability.

Model	Precision	Recall	F1-Score	Accuracy	AUC
Logistic Regression	0.06097	0.918367	0.114358	0.97552	0.9720
XGBoost	0.88172	0.836735	0.858639	0.99952	0.9745
XGBoost + SHAP	0.863158	0.836735	0.849741	0.99949	0.9737

Table 2 Performance on European Credit Card Dataset

Overall, the results confirm that ensemble methods outperform traditional models in handling imbalanced fraud detection tasks.

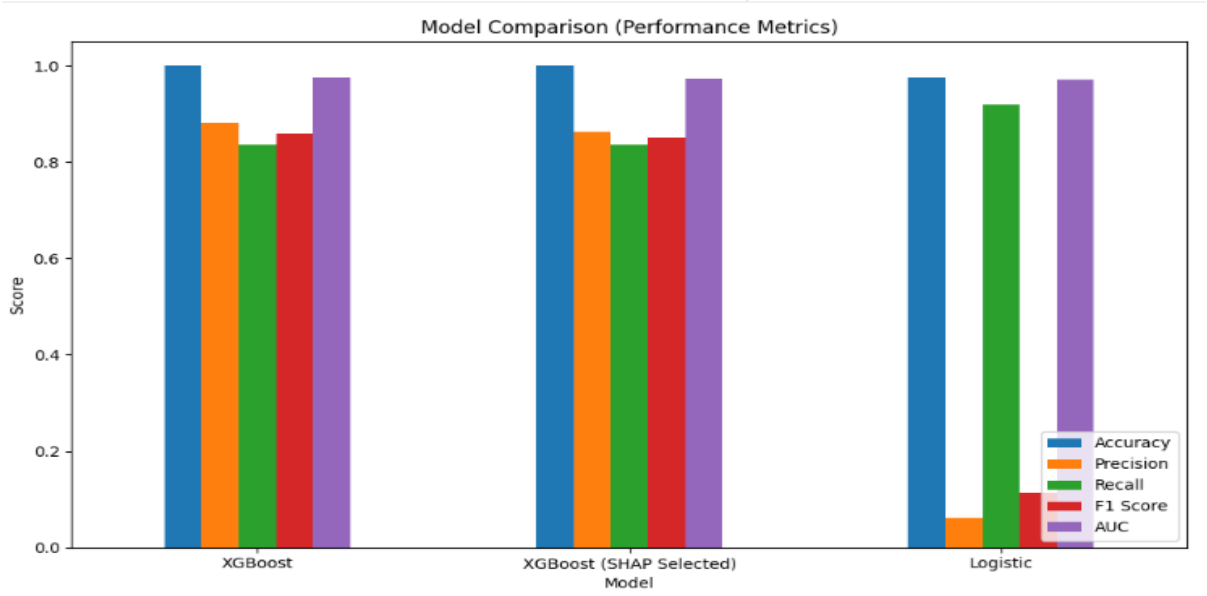

Figure 5. Model Performance Comparison Matrix

Figure 5 presents a comprehensive comparison of model performance across key evaluation metrics. It is observed that XGBoost and XGBoost + SHAP outperform Logistic Regression in terms of precision, recall, and F1-score, demonstrating their effectiveness in fraud detection.

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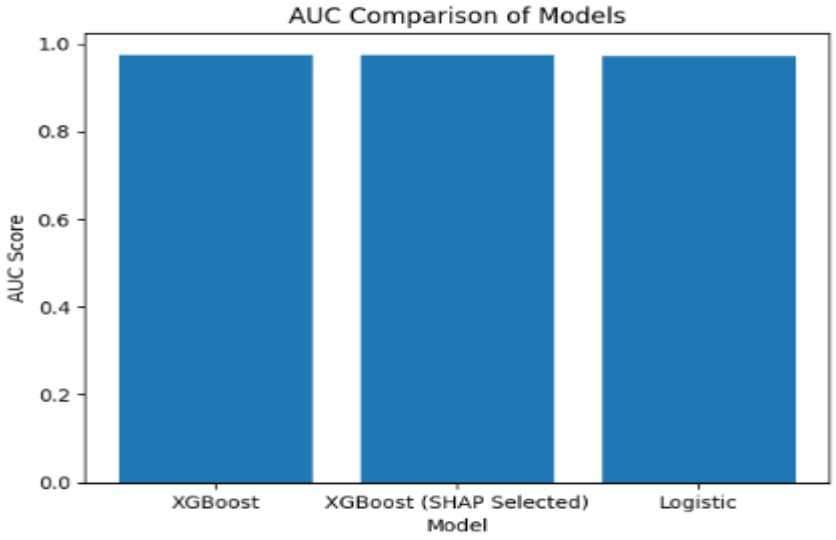

Figure 4. AUC comparison of Models

Figure 4 illustrates the AUC scores of the evaluated models. XGBoost-based models achieve significantly higher AUC values compared to Logistic Regression, indicating superior ability to distinguish between fraudulent and non-fraudulent transactions .

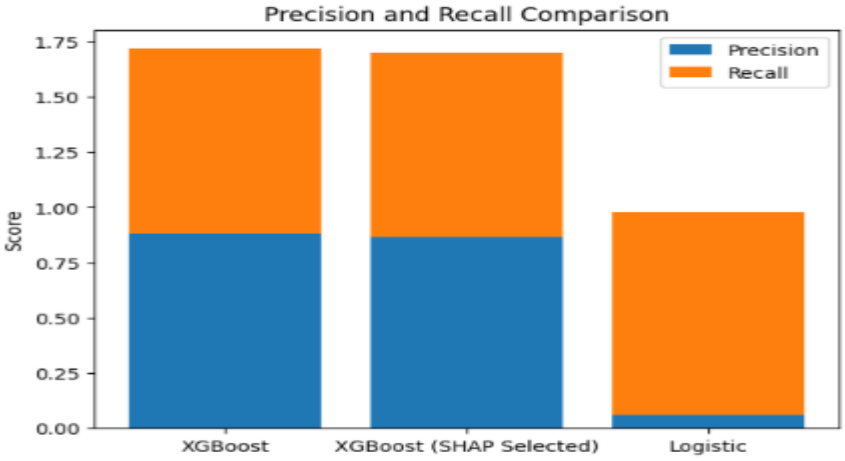

Figure 6. Precison VS Recall Comparison

Figure 6 compares precision and recall across models. Logistic Regression shows high recall but extremely low precision, whereas XGBoost maintains a better balance between the two, making it more suitable for practical fraud detection.

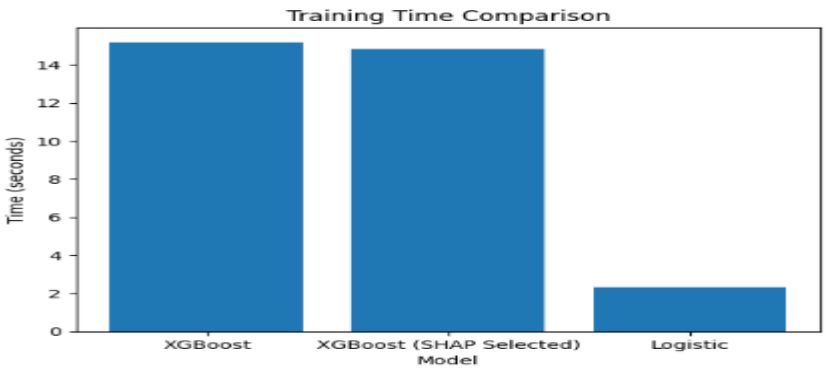

Figure 7. Training time Comparison

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Figure 7 shows the training time required for each model. While XGBoost requires more computational time than Logistic Regression, the improvement in detection performance justifies the additional cost.

4.2 Results on IEEE-CIS (Vesta) Dataset

The IEEE-CIS Fraud Detection Dataset is a large-scale dataset with high dimensionality and complex feature interactions, making it more challenging for traditional models. Here performance of the models was evaluated on the IEEE-CIS fraud detection dataset using precision, recall, F1-score, accuracy, and AUC to capture both classification effectiveness and the impact of class imbalance.

The Logistic Regression model achieved a recall of 0.532, indicating a moderate ability to identify fraudulent transactions. However, its precision remained low at 0.138, suggesting a high number of false positives. This imbalance resulted in a relatively low F1-score, reflecting its limited effectiveness in accurately distinguishing between fraudulent and legitimate transactions. The overall accuracy of 0.8678 is comparatively lower, further indicating that the model struggles with the complexity and imbalance of the dataset.

In contrast, the XGBoost model demonstrated substantially improved performance. It achieved a high precision of 0.904, indicating that the majority of predicted fraud cases were correct. Although the recall (0.412) is lower compared to Logistic Regression, the model maintains a better balance between precision and recall, as reflected in its higher F1-score of 0.566. Additionally, XGBoost achieved significantly higher accuracy (0.97789) and AUC (0.9231), highlighting its superior capability in capturing complex patterns within the dataset.

The XGBoost model with SHAP-based feature selection produced performance comparable to the full-feature model, with a slight decrease in precision, recall, and AUC. Despite this minor reduction, the model maintains a reasonable F1-score, demonstrating that a reduced set of important features can still provide effective predictions. This supports the use of SHAP for improving model interpretability while preserving most of the predictive performance.

Overall, the results indicate that XGBoost outperforms Logistic Regression on the IEEE-CIS dataset, and that incorporating SHAP-based feature selection offers a practical trade-off between model performance and interpretability in fraud detection tasks.

Model	Precision	Recall	F1-Score	Accuracy	AUC
Logistic Regression	0.138494	0.532059	0.219779	0.86780	0.749298
XGBoost	0.904357	0.411809	0.565919	0.97789	0.923125
XGBoost + SHAP	0.863847	0.360755	0.508961	0.97564	0.917198

Table 3 Performance on IEEE-CIS (Vesta) Dataset

The results indicate that SHAP-based feature optimization helps in removing less relevant features, thereby improving model efficiency and interpretability without compromising accuracy.

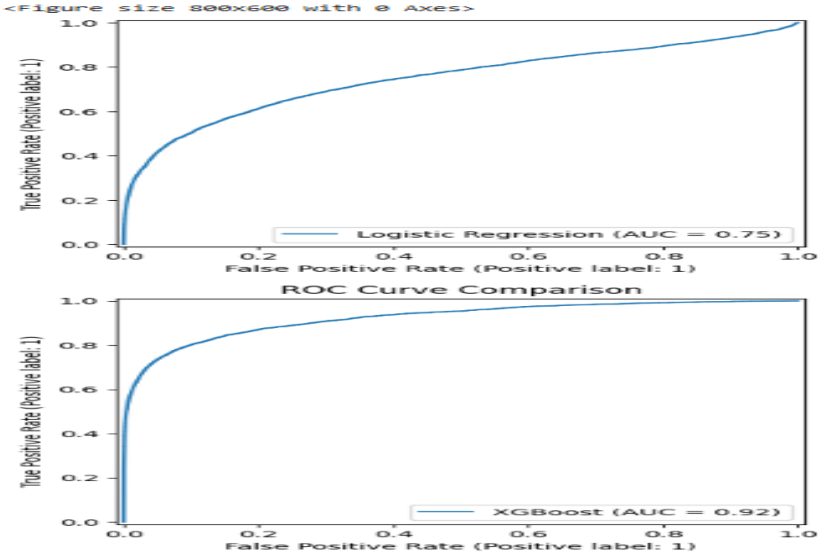

Figure 8 Curve Comparison of Logistic Regression and XGBoost Models

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Figure 8 presents the Receiver Operating Characteristic (ROC) curve comparing the performance of Logistic Regression and XGBoost models. The ROC curve illustrates the trade-off between the True Positive Rate (Recall) and the False Positive Rate at different classification thresholds. It can be observed that the XGBoost model achieves a curve closer to the top-left corner, indicating superior classification performance. Additionally, the Area Under the Curve (AUC) for XGBoost is significantly higher than that of Logistic Regression, demonstrating its enhanced ability to distinguish between fraudulent and non-fraudulent transactions. This confirms that XGBoost is more effective in handling complex patterns and class imbalance in fraud detection tasks.

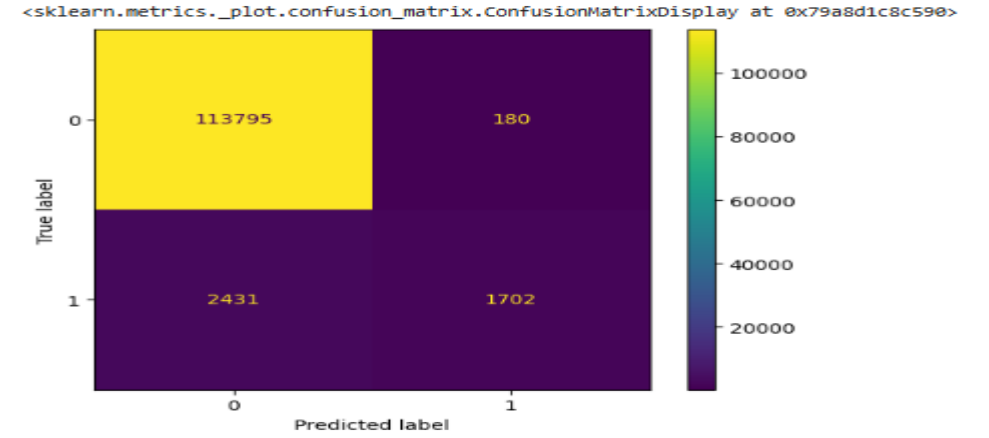

Figure 7 Confusion Matrix of XGBoost Model for Fraud Detection

Figure 7 presents the confusion matrix of the XGBoost model, illustrating the classification performance in terms of true positives, true negatives, false positives, and false negatives. The matrix shows that the model correctly identifies a large number of non-fraudulent transactions (true negatives) and successfully detects fraudulent transactions (true positives) with high accuracy. The number of false positives and false negatives is relatively low, indicating that the model achieves a good balance between precision and recall. This is particularly important in fraud detection, where minimizing false negatives is critical to avoid missing fraudulent activities, while controlling false positives helps reduce unnecessary alerts. Overall, the confusion matrix demonstrates the effectiveness of the XGBoost model in handling imbalanced fraud detection tasks.

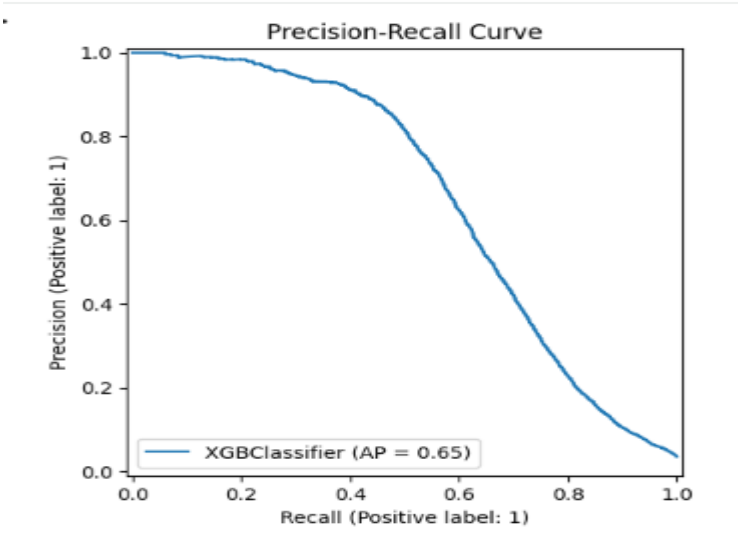

Figure 8 . Precision–Recall Curve

Figure 8 illustrates the Precision–Recall curve for the evaluated models on the fraud detection dataset. Since the dataset is highly imbalanced, this curve provides a more reliable assessment of model performance compared to accuracy. The results indicate that the XGBoost model maintains a better balance between precision and recall, particularly in identifying fraudulent transactions (minority class). This demonstrates its superior capability in

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minimizing false negatives while maintaining reasonable precision, making it more suitable for real-world fraud detection scenarios.

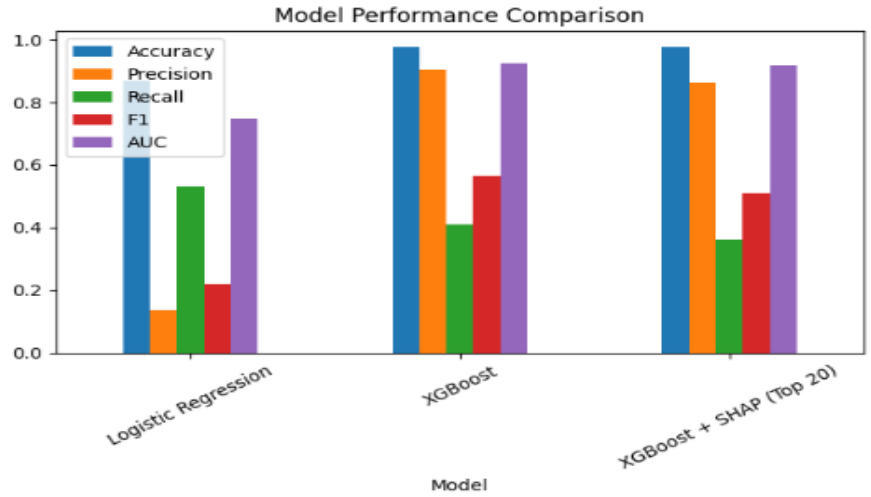

Figure 9 . Model Performance Comparison

Figure 9 presents a comparative analysis of the evaluated models based on key performance metrics, including accuracy, precision, recall, F1-score, and AUC. The results show that XGBoost outperforms Logistic Regression across most metrics, particularly in terms of AUC and recall, which are critical for fraud detection tasks. Additionally, the model incorporating SHAP-based feature selection achieves comparable performance while reducing feature dimensionality, thereby improving interpretability without significantly compromising predictive capability.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study presented a comprehensive approach to financial fraud detection by evaluating both traditional and advanced machine learning models on two widely used benchmark datasets, namely the European Credit Card dataset and the IEEE-CIS fraud detection dataset. Given the highly imbalanced nature of fraud detection problems, multiple evaluation metrics were considered to ensure a balanced and realistic assessment of model performance.

The experimental results demonstrate that Logistic Regression, while simple and computationally efficient, is limited in its ability to handle complex and imbalanced datasets. Although it achieved relatively high recall in certain cases, its low precision indicates a tendency to generate a large number of false positives, which may not be practical in real-world fraud detection systems. This highlights the need for more robust models that can better capture the underlying patterns in transactional data.

In contrast, the XGBoost model consistently outperformed Logistic Regression across both datasets. It achieved a strong balance between precision and recall, leading to higher F1-scores and AUC values. The superior performance of XGBoost can be attributed to its ability to model non-linear relationships and effectively handle large-scale, high-dimensional data. These characteristics make it particularly suitable for fraud detection tasks, where patterns are often complex and subtle.

Furthermore, this work incorporated Explainable Artificial Intelligence (XAI) techniques using SHAP (SHapley Additive exPlanations) to enhance model transparency. The SHAP analysis enabled the identification of the most influential features contributing to fraud predictions. By selecting the top features based on SHAP values and retraining the model, it was observed that the performance remained comparable to the full-feature model, with only minor variations in evaluation metrics. This demonstrates that it is possible to reduce model complexity while preserving predictive capability, thereby improving interpretability without significantly compromising performance.

The findings of this study emphasize that, in fraud detection, relying solely on accuracy can be misleading due to class imbalance. Metrics such as precision, recall, F1-score, and AUC provide a more meaningful evaluation. In particular, achieving a balance between precision and recall is crucial, as it directly impacts the trade-off between detecting fraudulent transactions and minimizing false alarms.

Overall, the results confirm that XGBoost, combined with SHAP-based interpretability, offers an effective and practical solution for financial fraud detection. The approach not only improves predictive performance but also enhances trust and transparency, which are essential for real-world deployment in financial systems.

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5.2 Future Work

While the proposed framework demonstrates promising results in detecting fraudulent transactions, there remains considerable scope for further refinement and exploration. One potential direction involves the use of more sophisticated ensemble learning strategies. Techniques such as stacking and blending can be employed to combine predictions from multiple base models in a structured manner, allowing the system to leverage the strengths of different algorithms. In addition to the models already used, incorporating other powerful algorithms such as Random Forest, CatBoost, and LightGBM could provide a broader comparative analysis and potentially improve overall predictive stability and robustness.

Another important area for future investigation is the application of deep learning methods. Models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Autoencoders offer the capability to capture complex, non-linear relationships within data. In particular, sequential models like LSTM can be highly effective in analyzing transaction sequences over time, which may help in identifying evolving fraud patterns that are not easily detected using traditional machine learning approaches. These techniques could enhance the system's ability to adapt to dynamic and sophisticated fraudulent behaviors observed in real-world financial environments.

Addressing the issue of class imbalance continues to be a significant challenge in fraud detection tasks. Since fraudulent transactions typically represent only a small portion of the dataset, models may become biased toward the majority class. Future work can explore advanced data-level and algorithm-level solutions to mitigate this problem. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN), and cost-sensitive learning approaches can be utilized to improve the detection of minority class instances while minimizing the risk of increasing false positives.

In addition, extending the current system toward real-time fraud detection represents a valuable direction. Deploying trained models in a streaming or online environment would enable continuous monitoring of transactions and immediate identification of suspicious activities. Such real-time systems are particularly important in financial applications where rapid response is critical to prevent potential losses. Integration with distributed data processing frameworks, such as Apache Spark, can further enhance scalability and enable efficient handling of high-velocity transaction data.

Another promising direction lies in expanding the use of interpretability techniques. While SHAP provides meaningful insights into model predictions, other approaches such as LIME (Local Interpretable Model-Agnostic Explanations) and gradient-based attribution methods can be explored to gain additional perspectives on model behavior. Enhancing interpretability is essential in domains like finance, where transparency and explainability are necessary for regulatory compliance and user trust.

Finally, future research can focus on improving the generalizability of the proposed approach by utilizing larger and more diverse datasets. Incorporating domain-specific features and evaluating models across different data sources can help ensure that the system performs consistently under varying conditions. Cross-dataset and cross-domain validation would further strengthen confidence in the model's applicability and reliability in real-world scenarios.

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