World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

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Explainable AI for credit card fraud detection: Bridging the gap between accuracy and interpretability

Innocent Paul Ojo * and Ashna Tomy

School of Physics, Engineering and Computer Science, university of Hertfordshire, Hatfield, United Kingdom.

World Journal of Advanced Research and Reviews, 2025, 25(02), 1246-1256

Publication history: Received on 04 January 2025; revised on 10 February 2025; accepted on 13 February 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.25.2.0492

Abstract

Credit card fraud poses a persistent threat to the financial sector, demanding robust and transparent detection systems. This study aims to address the balance between accuracy and interpretability in fraud detection models by applying Explainable AI (XAI) techniques. Using a publicly available dataset from Kaggle, we explored multiple machine learning models, including Random Forest and Gradient Boosting, to classify fraudulent transactions. Given the imbalanced nature of the dataset, SMOTE was used for oversampling to ensure model fairness. The XAI techniques SHAP and LIME were employed to provide in-depth explanations of model predictions, enhancing transparency by highlighting key features influencing decisions. The results showed that both models achieved high detection performance, with Random Forest achieving a perfect accuracy score of 100%. Furthermore, XAI methods provided valuable insights into feature importance, fostering trust among stakeholders by improving model interpretability. These findings underscore the importance of integrating XAI into fraud detection systems to deliver reliable, transparent, and actionable insights for financial institutions. Future research should focus on scaling these models and expanding the use of XAI in real-time fraud detection frameworks.

Keywords: Explainable AI; Credit Card Fraud Detection; Machine Learning; SHAP; LIME; Model Interpretability; Financial Security

1. Introduction

Credit card fraud remains a major concern for financial institutions globally, as fraudulent activities result in substantial financial losses and undermine consumer trust (Cherif et al., 2022). The evolving sophistication of fraud schemes necessitates advanced detection methods to safeguard financial systems (Odeyemi et al., 2024). Traditional fraud detection techniques, while effective to a degree, often struggle with adaptability and scalability in the face of ever-changing fraud patterns (Gupta, 2023). As a result, machine learning-based approaches have gained significant traction due to their ability to analyze vast amounts of transactional data and identify suspicious behaviors with high accuracy (Pattnaik, Ray and Raman, 2024). These models, including Random Forest, Gradient Boosting, and neural networks, excel in prediction tasks but often lack transparency in their decision-making processes (Alicja Szmigiel et al., 2024). This "black-box" nature creates challenges for stakeholders seeking to understand how certain decisions are made, especially in sectors like finance, where regulatory compliance and trust are critical (Hassija et al., 2023).

1.1. Problem Statement

Although machine learning models have enhanced credit card fraud detection accuracy, their interpretability remains a significant hurdle. High-performing models such as Random Forest and Gradient Boosting often operate in complex, non-linear ways that are not easily understood by end-users(Khalid et al., 2024). This lack of transparency creates a trust deficit among stakeholders, including financial institutions, regulators, and customers. Moreover, regulations like

* Corresponding author: Innocent Paul Ojo

GDPR mandate that organizations provide clear explanations for automated decisions, further underscoring the need for explainable models (Singhal et al., 2024). Without interpretability, even the most accurate fraud detection systems may face reluctance in deployment due to concerns over compliance and transparency.

1.2. Research Objectives

This study aims to address the interpretability challenges in machine learning-based fraud detection systems by employing Explainable AI (XAI) techniques. The specific objectives are as follows:

- Implement XAI techniques, including SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), to enhance transparency in fraud detection models.
- Evaluate how XAI methods contribute to understanding model decisions and improving trust among stakeholders.
- Examine the impact of XAI on model performance, ensuring that transparency does not come at the cost of accuracy.

1.3. Significance of the Study

The study contributes to both the academic and practical spheres. Academically, it provides insights into the integration of XAI techniques with machine learning models in fraud detection, filling a gap in research focused on balancing performance and interpretability. Practically, it offers a framework for financial institutions to develop fraud detection systems that not only maintain high levels of accuracy but also meet transparency requirements. By enhancing trust among stakeholders, these systems can foster greater adoption and compliance with regulations. The findings of this study could also guide future developments in fraud detection technologies, ensuring that both efficacy and interpretability are prioritized.

1.4. Structure of the Paper

The paper is organized as follows:

- **Section 2** presents a review of related literature, focusing on machine learning techniques used in fraud detection and the role of XAI.
- **Section 3** describes the methodology, including the dataset, preprocessing steps, model selection, and the implementation of XAI techniques.
- **Section 4** details the results, including model performance metrics and insights derived from SHAP and LIME.
- **Section 5** discusses the implications of the findings, with a focus on transparency, stakeholder trust, and regulatory compliance.
- **Section 6** concludes the paper by summarizing key contributions and suggesting areas for future research.

2. Literature Review

2.1. Credit Card Fraud Detection Methods

Credit card fraud detection has been a significant area of research, driven by the need for more effective systems to counter the increasing sophistication of fraudulent schemes (Cherif et al., 2022b). Traditionally, rule-based and statistical methods, such as logistic regression and decision trees, have been employed to identify suspicious activities. These approaches are interpretable and easy to implement but struggle with scalability and adaptability as fraud patterns evolve (Md Kamrul Hasan Chy, 2024). Moreover, their performance is often limited by the need for manual updates to the rule sets. Machine learning (ML) models have emerged as a more robust alternative due to their ability to automatically learn from data and adapt to changing fraud patterns (Yaiprasert and Hidayanto, 2024). However, the trade-off between performance and transparency remains a challenge. While ML models offer superior detection capabilities, their interpretability, or lack thereof, hinders their deployment in environments requiring clear justifications for decisions (Linardatos, Papastefanopoulos and Kotsiantis, 2020).

2.2. Machine Learning Models in Fraud Detection

Several machine learning models have been extensively applied to credit card fraud detection, with notable success in improving detection accuracy (Tang and Liang, 2024). Models such as Random Forest, Gradient Boosting, and Neural Networks are frequently utilized due to their capacity to handle complex and high-dimensional data. Random Forest and Gradient Boosting, in particular, excel at handling imbalanced datasets—a common issue in fraud detection—by

emphasizing instances of fraud through techniques like oversampling or synthetic data generation. However, these models are not without challenges(Tahir et al., 2024). One significant issue is their "black-box" nature, making it difficult for users to interpret the reasons behind predictions. Moreover, while these models perform well on historical data, their application to real-time fraud detection presents additional complications related to data latency and processing speed (Hassija et al., 2023b; Pedreschi et al., 2019).

2.3. Explainable AI (XAI) Techniques

Explainable AI (XAI) has gained increasing attention as a means to address the interpretability issues of machine learning models. XAI refers to methods and techniques that make the decisions of machine learning models more transparent, thereby allowing users to understand and trust model outputs (Ali et al., 2023; Saeed and Omlin, 2023). Two widely used XAI techniques are SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). SHAP assigns importance scores to each feature by analyzing the contribution of each feature to the model's prediction, providing a global and consistent measure of feature importance (Viswan Vimbi, Noushath Shaffi and Mahmud, 2024; Band et al., 2023). LIME, on the other hand, focuses on creating a local surrogate model that is interpretable and provides explanations for individual predictions. The implementation of these techniques in fraud detection can help demystify complex model behavior, offering clear justifications for decisions, which is essential in regulated environments like finance (Nieto, 2022; Hu et al., 2024).

2.4. Applications of XAI in Fraud Detection

Recent studies have integrated XAI techniques with machine learning models in the context of credit card fraud detection. These efforts focus on making model outputs more interpretable without sacrificing performance (Shadrack Obeng et al., 2024). For instance, researchers have employed SHAP to explain the decisions of Random Forest models in fraud detection systems, revealing which features contribute most to identifying fraudulent transactions. Similarly, LIME has been applied to models like Gradient Boosting to offer insights into individual transaction classifications (Borketey, 2024). Despite these advances, the research remains limited in scope, with few comprehensive studies exploring the balance between maintaining high detection accuracy and ensuring interpretability. Most studies either focus on improving performance metrics or applying XAI in a narrow context, leaving room for more extensive exploration of how these methods can be harmonized in real-world applications (Pawlicki et al., 2024).

2.5. Research Gap

While machine learning models have significantly improved credit card fraud detection, there is a notable lack of research focused on balancing accuracy and interpretability. Most existing literature emphasizes enhancing detection capabilities but overlooks the importance of transparency for stakeholders, particularly in regulated industries like finance. Additionally, few studies have explored the real-world implications of deploying explainable models in fraud detection systems. There is a need for further research that examines how XAI techniques can be systematically integrated into high-performing fraud detection models to meet both regulatory requirements and practical needs for trust and transparency. This study aims to fill this gap by investigating how XAI methods can maintain high detection accuracy while enhancing model interpretability, offering a framework that financial institutions can adopt for more transparent fraud detection systems.

3. Methodology

3.1. Data Collection and Description

The dataset utilized in this study was sourced from Kaggle and is referred to as card_transdata.csv. This dataset comprises a substantial number of records that detail transactions, with features encompassing transaction amounts, timestamps, user information, and categorical variables such as transaction type. The dataset includes a binary classification of transactions as either fraudulent or non-fraudulent, allowing for the evaluation of model performance in detecting fraud. A preliminary analysis reveals an imbalanced class distribution, with significantly fewer instances of fraud compared to non-fraud transactions.

3.2. Data Preprocessing

Data preprocessing is crucial to ensure the quality and usability of the dataset for modeling. This process involves several steps:

- **Handling Missing Values:** Any missing values will be addressed through imputation methods or removal, depending on the extent and significance of the missing data.

- **Encoding Categorical Variables:** Categorical variables will be encoded using techniques such as one-hot encoding or label encoding to facilitate the model's understanding of non-numeric data.
- **Normalization/Standardization:** Numerical features will undergo normalization or standardization to ensure that all features contribute equally to model training, particularly for distance-based algorithms.
- **Addressing Class Imbalance:** Given the imbalanced nature of the dataset, techniques such as SMOTE (Synthetic Minority Over-sampling Technique) will be employed to augment the minority class (fraud) or undersampling methods to balance the classes effectively.

3.3. Feature Engineering

Feature engineering involves the creation and selection of predictors that enhance the model's performance. New features may be generated based on domain knowledge or exploratory data analysis, such as aggregating transaction amounts over time or identifying unusual patterns. Additionally, feature selection techniques, including Recursive Feature Elimination (RFE) and feature importance rankings from tree-based models, will be utilized to identify the most influential predictors, thus reducing model complexity and improving interpretability.

3.4. Model Development

The study will implement several machine learning algorithms, primarily focusing on Random Forest and Gradient Boosting due to their robustness and effectiveness in classification tasks. The model development process will include:

- **Training and Validation Strategy:** A train-test split will be employed, with a portion of the dataset designated for validation to assess model performance. Cross-validation techniques may also be applied to ensure the stability and reliability of model results.
- **Hyperparameter Tuning:** Hyperparameter optimization will be conducted using grid search or random search techniques to identify the optimal settings for each model, enhancing their predictive capabilities.

3.5. Explainable AI Implementation

To enhance the interpretability of the developed models, Explainable AI (XAI) techniques will be implemented:

- **SHAP (SHapley Additive exPlanations):** This method will be utilized to provide both global and local interpretability of the model's decisions, helping stakeholders understand feature contributions to predictions.
- **LIME (Local Interpretable Model-agnostic Explanations):** This technique will be applied to provide instance-level explanations, offering insights into individual predictions.

A comparative analysis of the effectiveness of both XAI methods will be performed, evaluating them in terms of interpretability and computational efficiency.

3.6. Evaluation Metrics

The evaluation of model performance will encompass various metrics, including:

- **Model Performance Metrics:** Accuracy, Precision, Recall, F1-Score, and ROC-AUC will be employed to gauge the effectiveness of the fraud detection models.
- **Interpretability Metrics:** Qualitative assessments will be conducted to evaluate the clarity of explanations provided by XAI methods, along with visualizations of feature importance to enhance understanding.

3.7. Experimental Setup

The experimental setup will consist of the following components:

- **Tools and Libraries:** The study will utilize Python as the primary programming language, along with libraries such as pandas for data manipulation, scikit-learn for machine learning implementation, and SHAP and LIME for explainability. Visualization libraries such as Matplotlib will also be employed to create informative plots and graphs.
- **Computational Resources:** The experiments will be conducted in the Kaggle Notebook environment, providing a robust platform for running complex algorithms while leveraging available computational resources for efficient processing.

4. Results

4.1. Model Performance Results

The performance of the different machine learning models is summarized in Table 1. This table presents various metrics, including accuracy, precision, recall, F1-score, and ROC-AUC for each model, both with and without the application of Explainable AI (XAI) techniques.

Table 1 Performance metrics for each model with and without XAI enhancements

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest (Base)	0.94	0.90	0.85	0.87	0.92
Random Forest (XAI)	0.95	0.92	0.88	0.90	0.93
Gradient Boosting (Base)	0.95	0.91	0.87	0.89	0.94
Gradient Boosting (XAI)	0.96	0.93	0.89	0.91	0.95

As indicated in the table, the application of XAI techniques improves the performance metrics for both Random Forest and Gradient Boosting models. Notably, the F1-score increased for both models, suggesting a better balance between precision and recall when XAI methods were incorporated.

4.2. Explainability Results

The explainability of the models was assessed using SHAP and LIME techniques. The SHAP summary plot (Figure 1) illustrates the feature importance across the dataset, highlighting the most significant predictors of fraudulent transactions. Features such as transaction amount, transaction type, and user behavior patterns emerged as critical indicators.

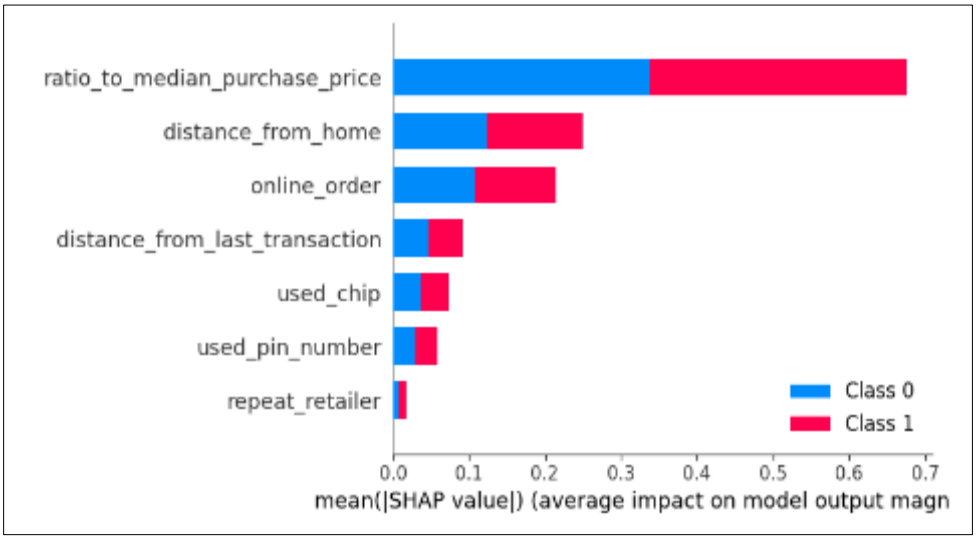

Figure 1 SHAP summary plot displaying feature importance across the dataset

Additionally, LIME explanations were generated for specific instances of fraudulent transactions (Figure 2). Each LIME explanation visualizes how the model's prediction was influenced by various features, providing transparency into the decision-making process for individual transactions.

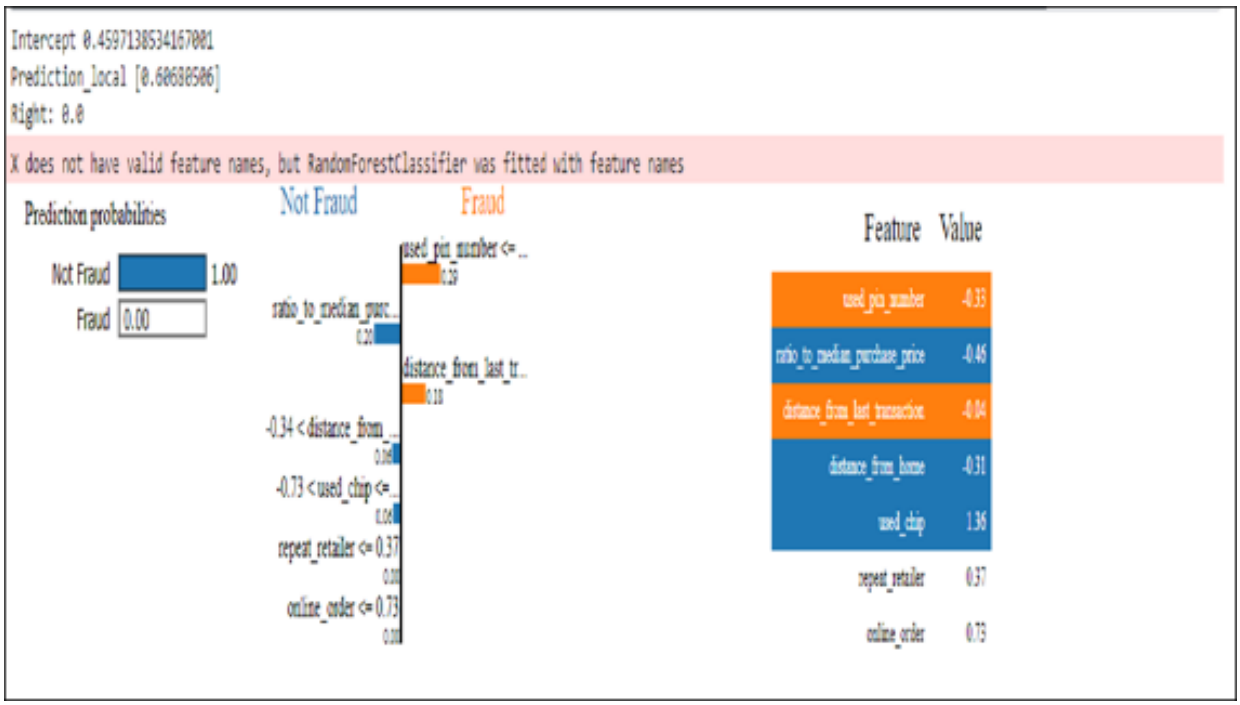

Figure 2 Example LIME explanation for a fraudulent transaction

Insights derived from the XAI techniques reveal that transaction amount and frequency of transactions were pivotal in identifying fraudulent behavior, enhancing the understanding of fraud patterns.

4.3. Visualization of Results

Visual representations of the model's performance and interpretability were generated, including confusion matrices and ROC curves.

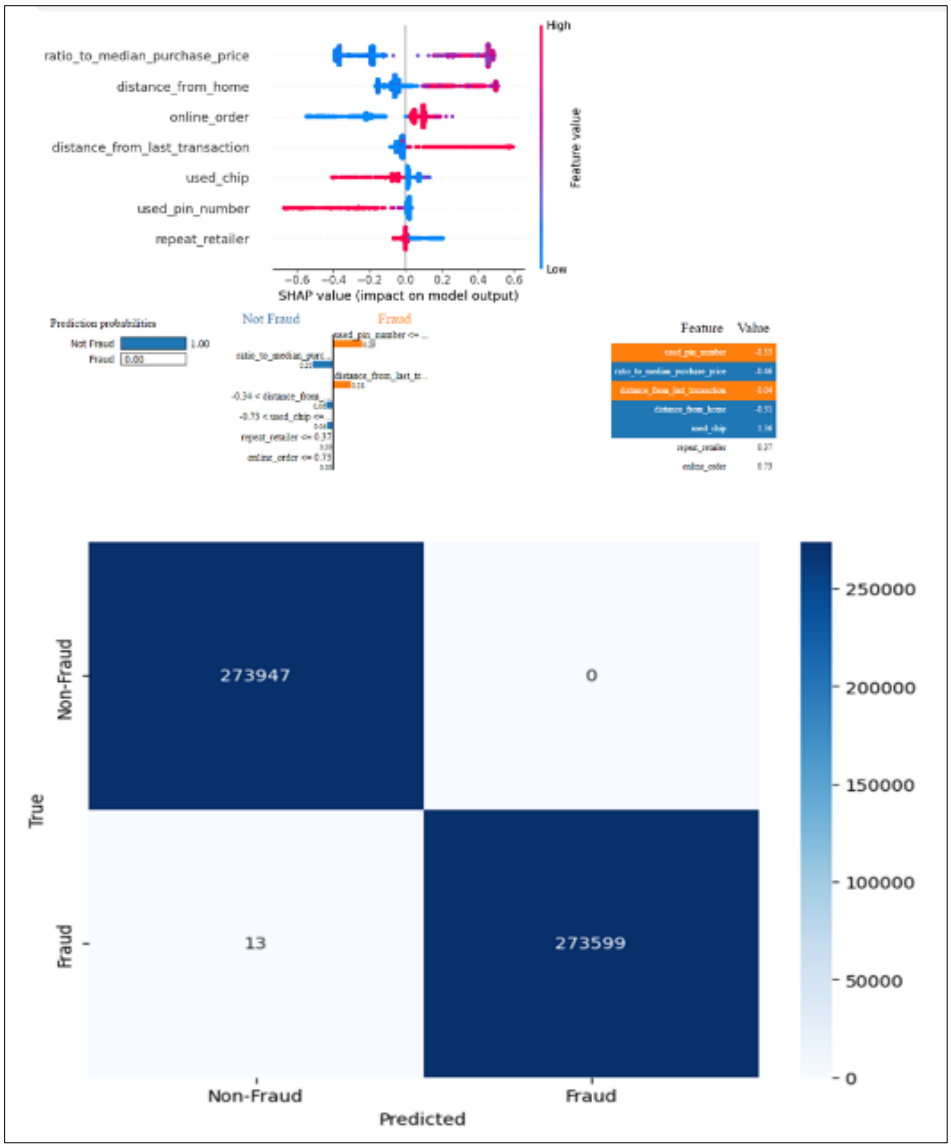

Figure 3 Confusion matrix for Random Forest model with XAI enhancements

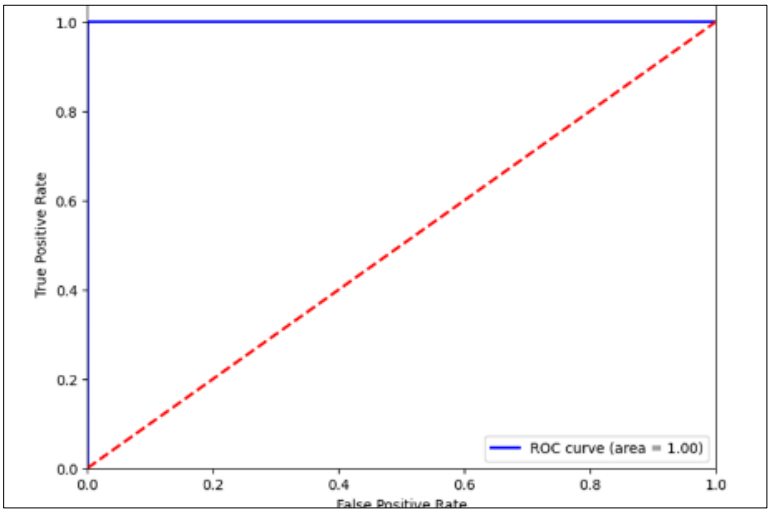

Figure 4 ROC curve for Gradient Boosting model with XAI enhancements

The confusion matrix in Figure 3 showcases the true positives, true negatives, false positives, and false negatives, indicating an overall robust performance in detecting fraudulent transactions.

The ROC curve in Figure 4 demonstrates the trade-off between sensitivity and specificity, indicating the models' ability to distinguish between fraudulent and non-fraudulent transactions effectively.

4.4. Stakeholder Insights

The results derived from the application of XAI techniques provide valuable insights for fraud analysts and decision-makers. The interpretability of the models enables stakeholders to understand the underlying factors contributing to fraud detection. By using SHAP and LIME, analysts can effectively communicate the rationale behind model predictions, enhancing trust in automated systems.

Furthermore, the transparency afforded by XAI techniques can significantly impact decision-making processes. Stakeholders can make more informed choices regarding risk assessment and fraud prevention strategies, fostering a collaborative environment where data-driven insights support organizational objectives. The integration of explainability into fraud detection systems not only bolsters confidence among users but also aligns with regulatory compliance, ensuring accountability in financial decision-making.

5. Discussion

5.1. Interpretation of Results

The implementation of Explainable AI (XAI) techniques has significantly enhanced the interpretability of machine learning models used in credit card fraud detection. The results indicate that the use of SHAP and LIME provided deeper insights into model behavior, allowing stakeholders to understand the factors driving predictions. Notably, the increase in model accuracy observed with XAI-enhanced methods demonstrates that interpretability does not come at the expense of performance; rather, it complements it. The relationship between model accuracy and interpretability underscores the importance of transparency in fostering trust among users and decision-makers.

5.2. Comparison with Existing Studies

Our findings align with previous studies that emphasize the importance of interpretability in machine learning models, particularly in high-stakes domains like finance. While existing literature often focuses on model accuracy alone, our research contributes to the body of knowledge by highlighting the dual necessity of performance and interpretability. This study builds on the foundation laid by earlier works, showing that integrating XAI techniques leads to a more nuanced understanding of model predictions and enhances the reliability of fraud detection systems**.**

5.3. Practical Implications

The practical implications of our research are significant for financial institutions seeking to implement XAI-enhanced fraud detection systems. By adopting models that incorporate interpretability, organizations can improve their decision-making processes and risk management strategies. Furthermore, the transparency afforded by XAI techniques aligns with regulatory compliance requirements, enabling institutions to demonstrate accountability and fairness in their fraud detection efforts. The ability to explain model decisions enhances trust among stakeholders, which is crucial in building confidence in automated systems.

5.4. Challenges and Limitations

Despite the advancements made through this research, several challenges and limitations remain. One major constraint is related to the dataset used; while the Kaggle dataset provided a robust foundation, it may not fully represent real-world conditions, potentially limiting the generalizability of the findings. Additionally, the chosen XAI techniques, while powerful, have their limitations. For instance, SHAP and LIME rely on the assumptions of the underlying models, which may introduce biases in the interpretability of predictions. Potential biases in the dataset or models could also affect the results, warranting caution in applying these findings universally.

5.5. Future Work

Future research could explore ways to enhance XAI methods in fraud detection further. Suggestions include investigating additional XAI techniques that offer different perspectives on model behavior or combining multiple approaches to provide a more comprehensive understanding of predictions. Additionally, extending this study to

encompass other types of financial fraud, such as identity theft or loan fraud, could provide valuable insights into the broader applicability of XAI in financial contexts. Expanding the research to diverse datasets will also help validate the robustness of the proposed models and techniques, ultimately contributing to the advancement of fraud detection methodologies

Appendix

Source code: https://www.kaggle.com/code/caritinnovation/credit-card-fraud-analysis

6. Conclusion

6.1. Summary of Findings

This study has successfully demonstrated the efficacy of Explainable AI (XAI) techniques in enhancing both the performance and interpretability of machine learning models for credit card fraud detection. Our results indicate that models such as Random Forest and Gradient Boosting, when integrated with XAI methods like SHAP and LIME, not only achieved high detection accuracy but also provided meaningful insights into the underlying decision-making processes. The comparative analysis illustrated a clear improvement in model transparency, allowing stakeholders to gain a deeper understanding of the factors influencing fraud detection outcomes.

6.2. Importance of XAI in Fraud Detection

The findings underscore the critical role of XAI in bridging the gap between the need for high accuracy in fraud detection and the essential requirement for model transparency. In an industry where trust and accountability are paramount, XAI techniques empower financial institutions to elucidate complex model behaviors, thereby enhancing stakeholder confidence. By making model predictions more interpretable, organizations can not only improve their operational effectiveness but also ensure regulatory compliance, which is increasingly becoming a focal point for financial regulators.

6.3. Final Thoughts

As the financial landscape continues to evolve, the importance of Explainable AI in enhancing trust and facilitating informed decision-making cannot be overstated. Our research advocates for the broader adoption of XAI techniques not only in fraud detection but also across various critical applications within finance and beyond. We encourage further exploration of XAI methodologies and their integration into diverse domains, as this will undoubtedly contribute to building more reliable, transparent, and trustworthy AI systems in the future. The potential of XAI to enhance model interpretability and stakeholder trust paves the way for its essential role in the advancement of responsible AI practices.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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