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Financial Fraud Detection Using Explainable AI and Federated Learning

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Abstract: Financial fraud is a growing concern that threatens the integrity of financial institutions and customer trust. Traditional fraud detection methods, which rely on rule-based systems and centralized machine learning models, often struggle to keep up with evolving fraudulent tactics. Additionally, the black-box nature of many machine learning models limits their interpretability, making it difficult for financial analysts and regulatory bodies to trust and validate fraud detection outcomes. To address these challenges, Explainable AI (XAI) enhances model transparency by providing human-understandable explanations for fraud predictions, while Federated Learning (FL) enables privacy-preserving, collaborative model training across multiple institutions without sharing sensitive data. Federated Learning offers a decentralized approach that allows financial institutions to train fraud detection models on diverse, distributed datasets while ensuring compliance with data protection regulations. This improves model generalization and robustness by leveraging insights from various sources without compromising customer privacy. At the same time, XAI ensures that these models remain interpretable, helping analysts understand the reasoning behind fraud alerts, identify potential biases, and refine detection strategies accordingly. The combination of XAI and FL enables institutions to strengthen fraud detection capabilities while adhering to ethical AI practices and regulatory requirements. The integration of Explainable AI and Federated Learning in financial fraud detection offers a promising solution to the challenges of transparency and privacy. XAI improves the interpretability of fraud detection models, making them more accountable and understandable for stakeholders, while FL facilitates secure and efficient model training across different organizations. This paper explores the synergy between these technologies, discussing their advantages, challenges, and potential applications in enhancing fraud detection. The Combination of Federated Learning (FL) and Explainable AI (XAI) delivers a powerful solution for financial fraud detection offering strong privacy guarantees, improved model performance and enhanced transparency. This approach supports regulatory compliance and fosters confidence among stakeholders in the deployment of AI driven fraud prevention.

Keywords: Financial Fraud detection, Federated Learning(FL), Explainable AI(XAI), Fraud Analysis, Regularity Compliance, Privacy Preserving AI, AI Transparency, Model Explainability.

I. INTRODUCTION

Financial fraud detection is a critical challenge faced by banks, fintech firms, and regulatory bodies due to the rapid growth of digital transactions and online banking. Traditional machine learning approaches often rely on centralized data collection, which raises concerns about data privacy, security, and regulatory compliance, especially in the financial domain. Federated Learning (FL) presents a novel solution by enabling collaborative model training across multiple institutions or devices without requiring them to share sensitive customer data. This decentralized approach not only preserves privacy but also leverages a broader and more diverse dataset from multiple sources, improving the fraud detection model's accuracy and generalizability. **[1]**

In parallel, Federated Learning (FL) has emerged as a promising approach to fraud detection by enabling collaborative model training across multiple financial institutions without sharing sensitive data. This decentralized learning method enhances security and privacy while leveraging diverse fraud patterns from different sources. By combining Explainable AI with Federated Learning, financial fraud detection can achieve both high accuracy and interpretability, ensuring a more transparent and robust security framework. **[2]** This project focuses on studying various normalization techniques to improve the accuracy and efficiency of deep learning models for heart disease prediction. Traditional normalization methods, like Min-Max Scaling and Standardization, are commonly used but may not always yield the best results. More advanced techniques, such as Batch Normalization and Layer Normalization, have been introduced to improve training stability and model performance. . Additionally, as financial institutions handle vast amounts of sensitive data, ensuring data privacy while maintaining effective fraud detection remains a significant challenge. Addressing these issues requires a shift toward more advanced, interpretable, and privacy-preserving solutions. **[3]**

This combined approach empowers financial institution to stay ahead of cybercriminals, adapt to emerging fraud tactics and build a more secure financial ecosystem.

II. RELATED WORK

Financial fraud detection has been extensively explored using a range of machine learning (ML), deep learning (DL), and privacy-preserving approaches to enhance fraud detection accuracy and minimize financial loss. Recent studies have focused on improving model precision, data privacy, and interpretability through advanced algorithms and frameworks.

A 2020 study titled *A Federated Learning Approach for Financial Fraud Detection in Edge Devices* [4] introduced a decentralized learning framework where models are trained on user devices and only model updates are shared. This approach safeguarded sensitive user data while enabling collaborative fraud detection. However, the model faced communication overhead challenges and inconsistent data quality across client devices, affecting convergence speed and overall performance.

In 2021, the study *Enhancing Credit Card Fraud Detection with Explainable AI and Gradient Boosting* [5] proposed the use of XGBoost in combination with SHAP values to interpret prediction results. This model delivered high detection accuracy and allowed domain experts to understand the contributing factors behind each fraud classification. Despite its interpretability, the model's reliance on centralized data limited its applicability in privacy-constrained environments like cross-bank collaborations.

The 2022 study *Hybrid Federated Learning and Explainable AI for Secure and Transparent Financial Fraud Detection* [6] investigated the integration of federated learning with XAI tools such as LIME and SHAP across multiple financial institutions. This combination improved detection performance while offering transparent decision-making. Although the study showed promising results, its deployment in real-world systems remained limited due to the complexity.

In 2023, the study *Secure Multi-Institutional Credit Card Fraud Detection using Federated Learning* [7] proposed a collaborative fraud detection system among multiple banks using federated learning. The study demonstrated that the global model trained on decentralized data outperformed locally trained models, particularly in identifying rare fraud patterns. While this approach strengthened data security and model robustness, it also introduced challenges in maintaining model consistency and dealing with heterogeneous data distributions across institutions.

III. PROPOSED SYSTEM

To address the challenges of detecting fraudulent transactions while adhering to data privacy regulations, we propose a system that leverages Federated Learning (FL) and Explainable AI (XAI). In this system, multiple financial institutions collaborate to develop a robust fraud detection model without directly sharing sensitive customer data. Federated Learning enables each institution to train a local model on its own data and then aggregate these models to create a global fraud detection system. This approach ensures that customer information remains secure and confidential, as the data never leaves its original location. To enhance the system's transparency and trustworthiness, Explainable AI is integrated to provide clear, interpretable insights into the model's predictions. This allows financial experts to understand and validate the decisions made by the system, thereby addressing concerns about the model's opacity. Experimental results demonstrate that this combined FL and XAI approach not only preserves data privacy but also maintains high performance in detecting fraudulent activities. **[8][9]**

The proposed system presents a privacy-preserving and transparent framework for financial fraud detection by combining Federated Learning (FL) with Explainable AI (XAI)**.** This approach not only enhances detection accuracy by utilizing diverse data across institutions but also builds trust through interpretable decision-making. The inclusion of a feedback loop and evaluation metrics ensures continuous improvement and adaptability to new fraud patterns. Overall, the system offers a secure, scalable, and accountable solution for combating financial fraud in real-world scenarios.**[10]**

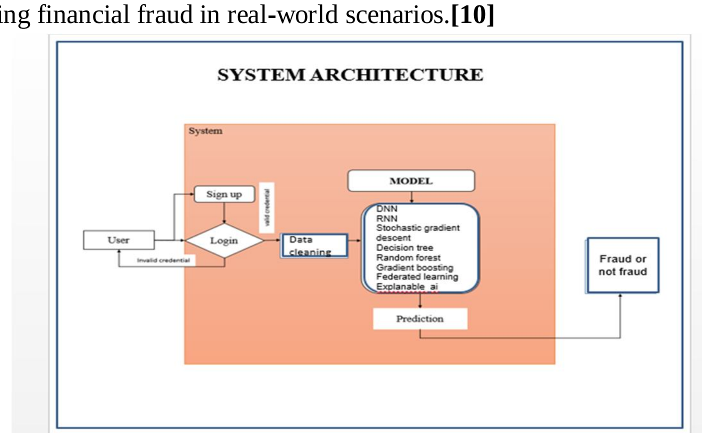

Fig 1: Architecture Diagram**[11]**

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Procedure:
- Import necessary libraries (pandas, numpy, sklearn, keras, xgboost).
- Load and preprocess the dataset.
- Encode categorical features.
- Split data into features and target, and split into training and testing sets.
- Apply SMOTE to balance classes in training data.
- Train local models on selected features.
- Send encrypted model updates to central server.
- Aggregate updates with Federated Averaging.
- Distribute updated global model back to clients.
- Apply Explainable AI methods on global model predictions.
- Provide explanations to fraud analysts for review.
- Deploy the federated fraud detection system.

IV. RESULT

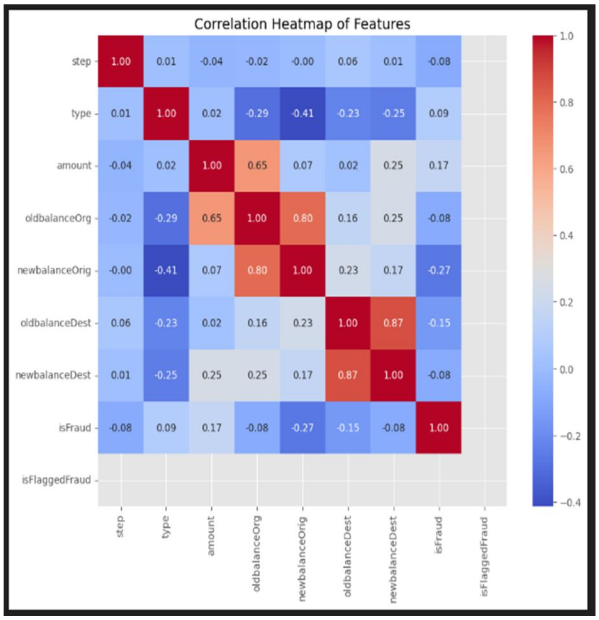

Fig 2: Correlation

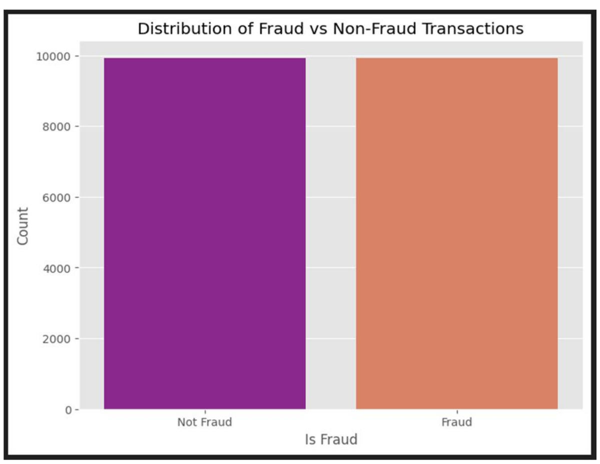

Fig 3. Fraud vs Not Fraud

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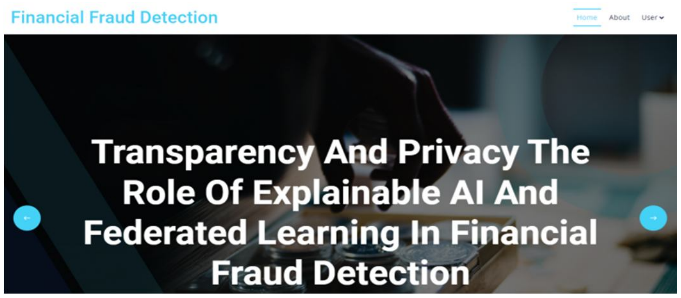
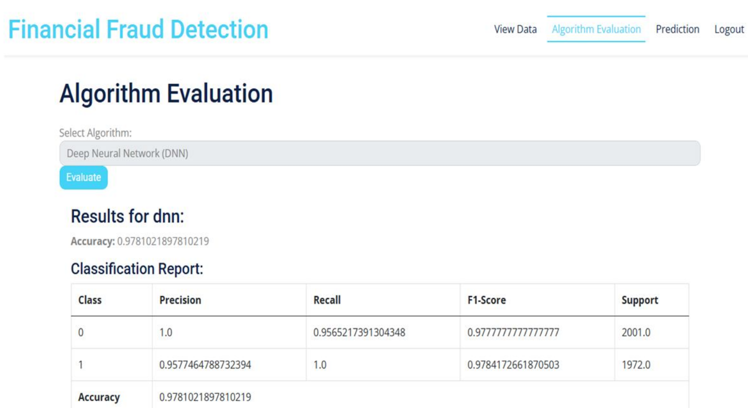


Fig 4: Home Page

Fig 5: Registration Page



Class	Precision	Recall	F1-Score	Support
0	1.0	0.9565217391304348	0.9777777777777777	2001.0
1	0.9577464788732394	1.0	0.9784172661870503	1972.0
Accuracy	0.9781021897810219			

Fig 6: Classification Report

V. CONCLUSION

This study demonstrates the effectiveness of integrating Federated Learning (FL) and Explainable AI (XAI) in enhancing financial fraud detection systems. By leveraging FL, financial institutions can collaboratively train robust fraud detection models without compromising customer data privacy, thereby adhering to stringent data protection regulations. The incorporation of XAI provides critical transparency, enabling human experts to comprehend and trust the model's decision-making processes. Our findings indicate that the FL-based approach not only maintains high accuracy in identifying fraudulent transactions but also ensures that the system operates within the bounds of privacy-preserving protocols. This dual focus on privacy and transparency positions the proposed framework as a viable and innovative solution for modern financial institutions grappling with the complexities of fraud detection.

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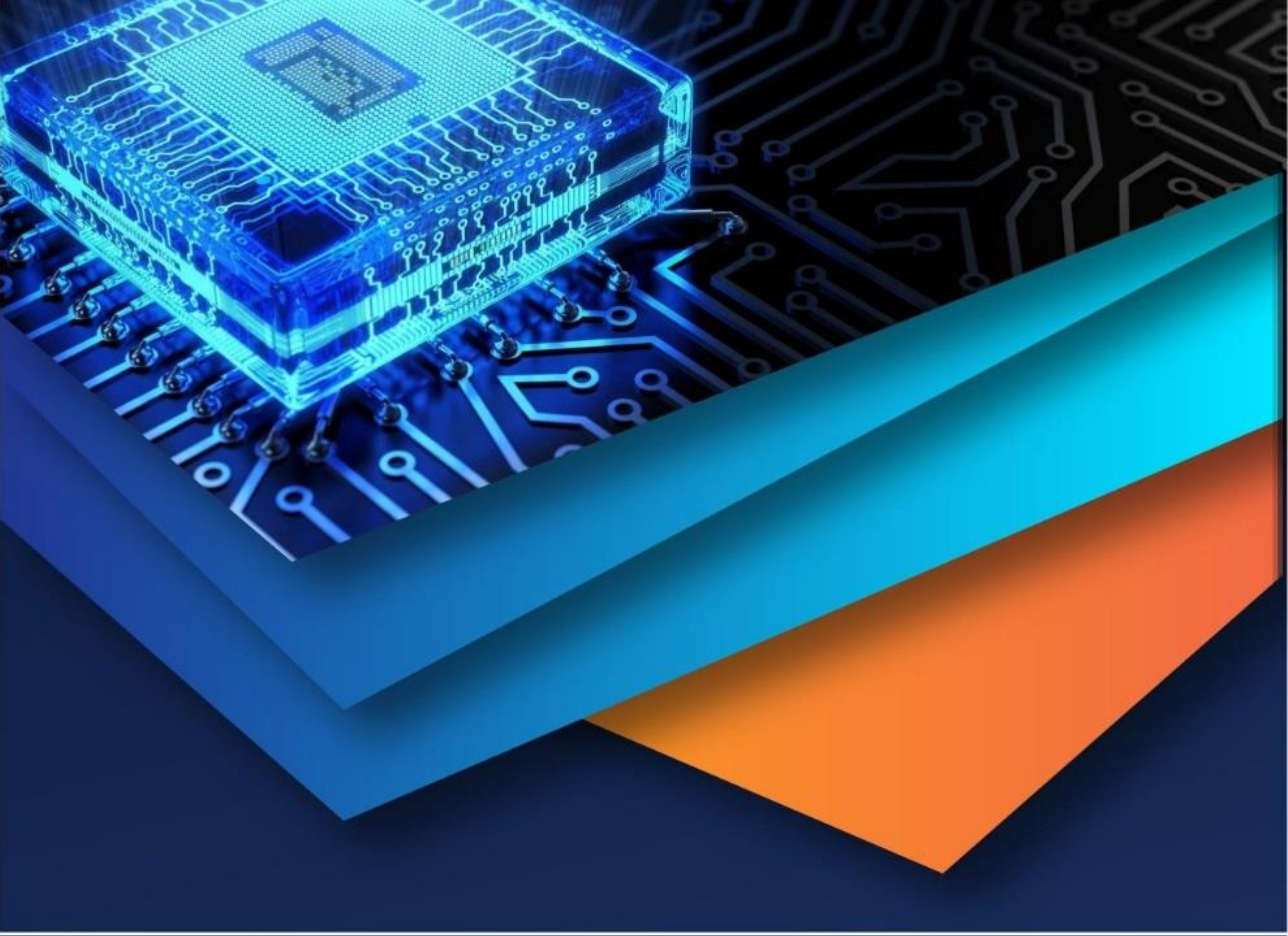

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