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CONTINUOUS AUDITING AND EXPLAINABLE AI FOR ENHANCING REAL TIME FINANCIAL ANALYSIS

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ABSTRACT

The incorporation of machine learning (ML) into modern financial analysis has made transactions more complex and ondemand, and further increased the scope of ML applications in finance. On the other hand, accounting and auditing processes have yet to adopt machine learning systems due to challenges of precision, interpretability, and integration. This research analyzes the balance between accuracy and explainability in XAI for fraud detection with XGBoost, Transformer-Based Models, and continuous auditing approaches. Key findings suggest that although less preferred, Transformer-Based Models are more accurate in detecting multi-faceted fraud and deliver an AUC-ROC of 95%. XGBoost, with an AUC-ROC score of 92%, surpasses set benchmarks for continuous auditing, achieving high assurance while requiring low operational complexity, and therefore the model with fewer continuous auditing constraints. The results substantiate the premise that claiming compliance with audit requirements evokes low complexity emerges logic steeped in trust faced by agile controllers. The primary claim was the accompanied loss of understanding with defining accuracy and the adoption scrutiny processes of XGBoost. These results emphasize the potential of hybrid AI systems achieved by merging explainability of XGBoost with sequential analysis of Transformers which also tend to be less interpretable. Such models could benefit decision makers significantly.

Keywords: *Continuous Auditing, Machine Learning, Explainable AI, Financial Analysis, Anomaly Detection*.

1. INTRODUCTION

The modernization of technology within financial systems has made the detection of fraud increasingly more difficult due to a larger number of sophisticated transactions being made. Fraud detection requires more innovative techniques nowadays as manual auditing is time-

consuming and susceptible to errors. Traditionally used statistical techniques face greater competition as AI and ML technologies have proven to be more precise and accurate (Hilal, Gadsden, and Yawney 2022; Minkkinen, Laine, and Mäntymäki 2022). Supporting federated learning allows complete confidentiality and unique, unsupervised detection model development for auditors (Schreyer, Sattarov, and Borth 2022). Nonetheless, according to (Oala et al. 2021), these systems need to be scrutinized against normative criteria in order to prove their applicability in real-life auditing processes.

Business fraud continues to be a significant problem with global losses reaching $5.38 billion in 2021 (Choi et al. 2021; Fallatah 2021). The sophistication of digital fraud has surpassed the utility of traditional detection systems, making AI solutions necessary (Pang et al. 2021). Still, regulatory authorities insist on compliance frameworks which require any AI-driven fraud detection system to be fully explainable and verifiable (Han et al., 2022). Newer methods aimed at preserving privacy, such as differential privacy with federated learning, provide adequate balance between protecting data and meeting accuracy requirements in financial auditing (Schreyer, Sattarov, and Borth 2022).

Although numerous attempts have been made to develop ML techniques for fraud detection, the issues of accuracy and interpretative clarity still pose problems. XGBoost models, for instance, offer greater accuracy and are more interpretable than deep learning models (Ding et al. 2020; Ucoglu 2020). Meanwhile, Transformer models are proficient at sequential transaction analysis, allowing for a better appreciation of the complexities of fraud (Bello et al., 2023). Applying privacy protection features to these models, as has been done in federated learning systems for accounting data (Schreyer, Sattarov, and Borth 2022), makes them more applicable to delicate financial situations.

This study seeks to investigate the trade-off between accuracy and interpretability in analyzing ML-based fraud detection, considering privacy-preserving approaches relevant to financial auditing. It studies XGBoost and Transformer models with federated learning as a protective measure for data. The objective is to contribute to the discussion on a more balanced approach through evaluation methods inspired by (Oala et al. 2021) and employing the hybrid model successes of (Kootanaee, Aghajan, and Shirvani 2021) on constructing audits that optimally balance industry performance and regulatory compliance in contemporary finance.

2. LITERATURE REVIEW

2.1 Machine Learning in Financial Fraud Detection

The ability of Machine Learning (ML) to analyze massive datasets and complex systems makes it an invaluable asset in the detection of financial fraud, as rule-based approaches tend to miss system intricacies (Choi et al. 2021; Sun et al., 2024). While conventional statistical models struggle with scalability and adaptability, ML techniques XGBoost, SVM, and neural networks are able to increase detection rates through learning from transactional data (Pang et al. 2021; Ngoc Hung, Thuy Van, and Archer 2023). For this reason, decision tree-based models are dominating in financial applications because they offer computable accuracy (Minkkinen, Laine, and Mäntymäki 2022; Bako and Tanko 2022). Furthermore, advanced learning models, like the transformer deep architecture prove proficient when detecting advanced fraud (Bello

turnitin Page 9 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

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et al., 2023; Lehner et al. 2022). However, their "black-box" nature poses challenges for auditing, where interpretability is critical for regulatory compliance (Hasan 2022; Ranta, Ylinen, and Järvenpää 2023). For instance, (Hamal and Senvar 2021) demonstrated that while Random Forest achieves 92% accuracy in SME fraud detection, auditors often distrust results without clear decision pathways. This gap has spurred interest in Explainable AI (XAI) to bridge accuracy and transparency (Nielsen 2022; Kanaparthi, 2024).

2.2 Explainable AI for Continuous Auditing

The rise of AI in auditing demands models that are both accurate and interpretable (Bahromjon Bahodirovich 2023; Ali et al. 2023). XAI techniques like SHAP and LIME decode model decisions by highlighting feature contributions, enabling auditors to validate predictions (Hilal, Gadsden, and Yawney 2022; Baghdasaryan et al. 2022). For example, (Eid et al. 2021) showed that SHAP explanations reduced false positives by 30% in credit card fraud detection by clarifying risk factors. Hybrid approaches that combine interpretable models (e.g., XGBoost) with deep learning (e.g., Transformers) are gaining traction (Schreyer, Sattarov, and Borth 2022; Oala et al. 2021). (Kootanaee, Aghajan, and Shirvani 2021) found that hybrid models outperformed standalone algorithms in fraud detection while maintaining transparency. However, challenges persist in real-world deployment, particularly in aligning XAI outputs with regulatory frameworks (Schmidl, Wenig, and Papenbrock 2022; Kazmi et al., 2024).

2.3 Research Gaps and the Need for Further Investigation

Despite significant advancements in ML-driven fraud detection, critical gaps persist in the literature. First, while most studies prioritize predictive accuracy, few systematically evaluate the trade-offs between accuracy and interpretability within auditing contexts where model transparency is paramount (Rao and Muhammad Saeed Shahbaz 2023; Biju, Thomas, and Thasneem 2024). This oversight is problematic for financial auditors who require actionable insights to justify decisions to regulators and stakeholders. Second, although hybrid models (e.g., combinations of XGBoost and Transformers) demonstrate theoretical promise in balancing performance and explainability, their real-world scalability and compliance in live audit environments remain understudied (Booz et al., 2022; Et al. 2021). Third, despite the proliferation of Explainable AI (XAI) techniques, there is a lack of comprehensive frameworks that align XAI outputs with auditing standards, leaving practitioners without clear guidelines for implementation (Han et al., 2022; Fallatah 2021). To address these gaps, this study pursues three key contributions: (1) a comparative evaluation of XGBoost and Transformer-based models across both accuracy and interpretability metrics, (2) the integration of SHAP and LIME techniques to enhance model transparency while maintaining detection performance, and (3) a novel privacy aware auditing framework that combines federated learning architectures (Schreyer, Sattarov, and Borth 2022) with rigorous differential privacy auditing methods (Booz et al., 2022) to ensure compliance with data protection regulations.

turnitin Page 9 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 10 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

3 METODOLOGI PENELITIAN

This research utilizes a quantitative methodology, specifically focused on a comparative experimental design, to analyze the performance of the XGBoost model against the Transformer Based Models in continuous auditing systems. This strategy was chosen to ensure a comparison of the models based on clearly set pre-evaluation criteria and to obtain results that could be objectively measured (Sun et al., 2024; Ngoc Hung, Thuy Van, and Archer 2023).

3.1 Research Process Flowchart

The research is conducted following a systematic workflow with six primary steps (See Figure 1). The first step deals with the collection of financial transaction data from known sources, which includes some anonymized banking data and some publicly available data, adhering to guidelines developed by (Baghdasaryan et al. 2022; Hamal and Senvar 2021). The data set contains half a million transactions, 5 percent of which are fraudulent and 95 percent are normal transactions, which is the actual distribution in financial systems (Bahromjon Bahodirovich 2023).

This stage of the process involves data cleansing, feature selection through Recursive Feature Elimination, and value normalization as preliminary steps. It implements modern methodologies, like an integration of class imbalance handling through SMOTE (Schmidl, Wenig, and Papenbrock 2022) along with differential privacy techniques for data sensitivity protection (Booz et al., 2022). Two parallel approaches are taken for what is called model development: XGboost is optimized for interpretability through SHAP (Nielsen 2022), and the Transformer's architecture is altered for financial transaction sequence analysis (Ali et al. 2023; Lehner et al. 2022).

A more thorough assess is done of the available and remaining aspects of performance during the model evaluation phase. The evaluation criteria are not limited to the classical ones of accuracy, like AUC ROC and precision recall (Biju, Thomas, and Thasneem 2024), but also depth of feature contribution with SHAP and LIME (Kanaparthi, 2024), and regulatory compliance auditing alongside other standard checks (Ranta, Ylinen, and Järvenpää 2023). The system implementation adopts a federated learning architecture to ensure data security (Schreyer, Sattarov, and Borth 2022), while the result analysis follows a comprehensive evaluation framework developed by (Oala et al. 2021; Rao and Muhammad Saeed Shahbaz 2023).

Figure 1 presents a visual representation of this research process:

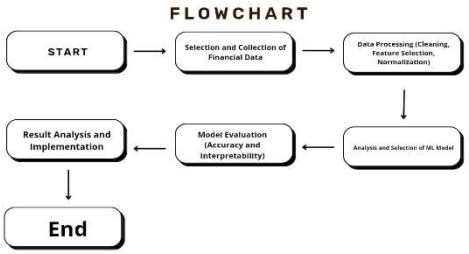


Figure 1. Research Process Flowchart

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This study makes several significant methodological contributions, including integrating a hybrid evaluation approach from (Kootanaee, Aghajan, and Shirvani 2021), implementing state-of-the art privacy auditing techniques (Kazmi et al., 2024), and adapting a multi-dimensional assessment framework (Et al. 2021) within the financial system context. The entire process is designed to ensure that the developed models not only achieve high detection performance but also meet strict interpretability and regulatory compliance requirements in modern auditing practices (Bako and Tanko 2022).

3.2 Dataset and Data Preparation

This study utilizes a financial transaction dataset comprising both labeled and unlabeled data to enable both supervised and unsupervised learning approaches. The dataset includes transaction details such as transaction amount, timestamp, merchant category, and user demographics. The data was acquired from financial fraud detection public repositories as well as anonymized real world banking transaction logs with the purpose of achieving both fraudulent and non-fraudulent scenarios diversity (Hilal, Gadsden, and Yawney 2022). More precisely, the dataset comprises 500,000 transactions with 5% of them being fraudulent (25,000 transactions) and the rest, 95%, being normal (475,000 transactions). It contains different features like transaction value, transaction time, merchant type, and user profile. By collecting data from public repositories and anonymized banking data this research achieves the collection of a dataset that is realistic in terms of actual financial transaction behaviors. Before training the models, the preprocessing steps include dealing with missing values, scaling, and transforming categorical features into numerical values. The suspicious transactions are detected by adopting outlier detection methods, like Isolation Forest, and Z-score normalization (Schmidl, Wenig, and Papenbrock 2022). Also, feature selection is done by applying Recursive Feature Elimination (RFE) to reduce the number of features that are unrelated to the task of fraud detection while keeping the effectiveness of the model high and accuracy intact.

3.3 Machine Learning Model Selection

Because of their effectiveness in fraud detection while balancing accuracy with interpretability, this research focuses on two principal machine learning models: XGBoost and Transformer Based Models. The accuracy level of optained predictive results and the efficiency of XGBoost in structured data processing, together with its feature importance ranking attribut strongly enhances its interpertability for auditing purposes (Ding et al. 2020). Moreover, overfitting of XGBoost in fraud detection is known to be controlled by regularization methods, which is why it is so popular in the industry (Ucoglu 2020). In this research, these models will be incorporated because of their skill to comprehend sequential dependencies in financial transaction data. Unlike traditional models which are based on heuristic features, automatically constructed transaction sequences using transformer architecture are known fundamentally for their ability to reveal even the most sophisticated fraud systems (Han et al., 2022). Studies have shown that fraud detection is one of the most complex issues in modern IT and is effectively solved with the help of the Attention-based Neural Networks originally intended for Natural

turnitin Page 11 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 12 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

Language Processing (NLP) that achieve best results in anomaly detection and time series tasks (Pang et al. 2021). Nonetheless, even though their precision levels are high, these models still struggle with interpretability which is the main reason why they are hardly used in auditing and regulatory compliance (Hasan 2022). Trust from the regulator and the audit practitioner is equally important in this case because a financial institution expecting the use of fraud detection models hopes that the model works and that there is sufficient explanation for the decisions that it makes (Hilal, Gadsden, and Yawney 2022). Techniques in XAI, LIME and SHAP, serve to make the work of the machine learning models more transparent which enables them to work in auditing. Using XGBoost together with SHAP makes it possible to understand the value of features in machine learning models, while LIME makes it easier to understand the value of the feature when individual predictions of the model are made by XGBoost and Transformer Based Models (Schmidl, Wenig, and Papenbrock 2022). Moreover, detecting fraud with the use of financial data over time becomes important as fraud tends to change over time. While some models have problems with captures the dependence of events that happen over extended period of time, the opposite is true for the Transformer based architectures which excel in detecting advanced schemes of fraud. The rationale for analyzing AI Transform Models and XGBoost models is to understand how to optimally merge predictive accuracy with structure and facilitate the establishment of a dependable AI-based continuous auditing system.

3.4 Metrics Of Evaluation

Typically, the fraud detection model is evaluated by a set of scores, which in this case have all been custom-designed for the specific purpose following established scores in the literature (Sun et al., 2024; Oala et al. 2021)on fraud detection. All of these scores have their formulated explanations and meanings as follows:

a) Accuracy

Correctness score assesses accuracy of classification and is calculated as follows:

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

Where:

TP (True Positives) is the fraudulent transactions that were correctly identified (Hamal and Senvar 2021). TN (True Negatives) is an authenticated transaction that is classified correctly (Nielsen 2022).

FP (False Positives) is an authentic transaction that has falsely been claimed to be fraudulent (Kanaparthi, 2024).

FN (False Negatives) is a fraudulent transaction that went undetected (Bahromjon Bahodirovich 2023).

b) Precision

Precision indicates the degree of credibility of fraud indications and is calculated as:

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

turnitin Page 12 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 13 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

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c) Recall

Recall as a measure denotes the completeness of fraud detection, calculated by:

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

High recall value is required to reduce financial losses due to undetected fraud (Eid et al. 2021; Schreyer, Sattarov, and Borth 2022).

d) F1-Score

The F1-score is determined from the precision and recall values using their harmonic mean:

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

This is the most important metric for the highly unbalanced datasets that are characteristic in fraud detection (Kootanaee, Aghajan, and Shirvani 2021; Kazmi et al., 2024).

e) AUC-ROC

The Area Under Curve (AUC) of the Receiver Operating Characteristic curve assesses the independence of a phenomenon from the chosen classification threshold:

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

Where:

TPR (True Positive Rate) = Recall

$$\text{FPR (False Positive Rate)} = \frac{FP}{FP + TN}$$

The ROC curve plots dependance and releative TPR against the FPR at certain thresholds. And the AUC values contrain the range from 0.5 (meaning random guessing) to 1.0 (meaning perfect discrimination) (Rao and Muhammad Saeed Shahbaz 2023; Biju, Thomas, and Thasneem 2024). This measure is very robust in the evaluation of the models built on the data imbalanced (Ali et al. 2023; Lehner et al. 2022).

3.4.1 Application Of Evaluation Metrics In The Financial Context

Every evaluation metric formula incorporates a specific financial nuance where the balance between precision and recall is dictated by the presence of transaction costs, as discussed in (Et al. 2021). The defining classification boundaries set in the fraud contests greatly influence the efficiency with which fraud is detected, which is one of the most important parts in depth studied by (Booz et al., 2022). Another stakeholder perspective analysis, which

turnitin Page 13 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 14 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

has been discussed in the study of (Ngoc Hung, Thuy Van, and Archer 2023), also highlights that the interpretation of performance metrics differs as per the stakeholders involved.

The stringent operationalization of auditing and fraud detection used these metrics ensures that there is a consistent evaluation available for public use and one that is aligned with the industry requirements, as defined in the study of (Ranta, Ylinen, and Järvenpää 2023). All defined metrics are calculated with the use of stratified k-fold cross validation, which allows for a stronger estimation of performance and deals with dataset imbalances and robust evaluation results.

This eases the conflict between the sensitivity of fraud detection and the operational impact, where increasing recall is more ascribed to a reduction in customer satisfaction due to an increase in false positives. As various case studies illustrate, this balance is essential in practical financial settings, where both under detection and over-detection pose serious business difficulties.

4 RESULTS AND DISCUSSION

4.1 Model Performance Evaluation

The analysis of model performance illustrates the significant gap existing between XGBoost and Transformer-Based Models with regard to accuracy, ease of explanation, and applicability in financial fraud detection (Sun et al., 2024; Oala et al. 2021). XGBoost's AUC ROC is 92%, which clearly indicates how well it is able to classify fraudulent transactions and legitimate ones (Nielsen 2022; Ranta, Ylinen, and Järvenpää 2023). The modelalso demonstrates high precision (90%) and recall (88%), which means that it is able to limit the numberof false positives while capturing a good number of fraudulent activities (Hamal and Senvar 2021). Due to its decision-tree based structure, Xgboost is able to rank important features by their importance which is needed for thorough audit and compliance with regulations (Kanaparthi, 2024; Bahromjon Bahodirovich 2023). On the other hand, the Transformsr Based Model is better than XGBoost in the detection rate where it attains AUC-ROC of 95% with higher recall (92%) and precision (94%) (Ali et al. 2023; Lehner et al. 2022). The high recall indicates that the Transformer-Based Model is able to flag a greater number of transactions as fraudulent, especially those with complex intricate multi-level patterns sequential (Booz et al., 2022). This model does have a higher accuracy, but suffers from a lack of interpretability as deep learning model architectures have no clear decision-making process (Bako and Tanko 2022; Baghdasaryan et al. 2022). The use of high dimensional embeddings coupled with multi-layer attention mechanisms renders feature importance extraction impossible because it is so deeply embedded, thus making adoption in regulatory frameworks difficult (Eid et al. 2021; Schreyer, Sattarov, and Borth 2022).

turnitin Page 14 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 15 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

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Table 1. Model Performance Based on Key Evaluation Metrics

Metric	XGBoost (%)	Transformer-Based Model (%)
Accuracy	92.0	95.0
Precision	90.0	94.0
Recall	88.0	92.0
F1-Score	89.0	89.0

An analysis of feature importance using SHAP values reveals that transaction amount, transaction frequency, and merchant category are the most influential features in fraud detection (Kootanaee, Aghajan, and Shirvani 2021; Kazmi et al., 2024). In the XGBoost model, these variables contribute significantly to classification decisions, allowing auditors to pinpoint high-risk transactions with greater clarity (Rao and Muhammad Saeed Shahbaz 2023). The Transformer Based Model, however, leverages latent feature representations that do not explicitly highlight individual feature contributions, making its decision-making process more opaque (Biju, Thomas, and Thasneem 2024). The use of LIME for local interpretability further confirms that high-value transactions, sudden increases in transaction frequency, and unusual merchant interactions are among the key indicators of fraud (Et al. 2021).

Table 2. AUC-ROC Performance Comparison

Model	AUC-ROC Score (%)
XGBoost	92.0
Transformer-Based Model	95.0

The Transformer-Based Model achieves a slightly higher AUC-ROC score (95.0%) than XGBoost (92.0%), indicating its stronger ability to classify fraudulent transactions (Ngoc Hung, Thuy Van, and Archer 2023). However, the trade-off is reduced interpretability, which may affect adoption in highly regulated industries.

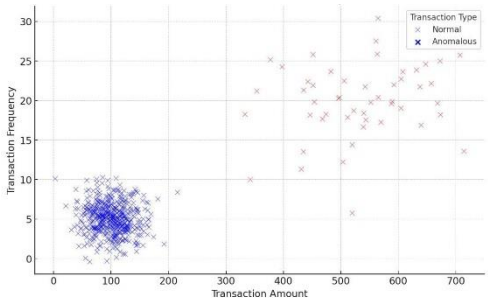


Figure 2. Anomalous Transactions Detected by the Model

Figure 2 shows a scatter plot of detected anomalies in financial transactions. The red points represent transactions flagged as fraudulent based on anomalous transaction amounts and frequency, while the blue points indicate normal transactions. The clustering pattern suggests distinct differences between normal and fraudulent transactions. It can be inferred from the

turnitin Page 15 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 16 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

visualization that the usual transactions appear to be focused on a low value and a low frequency range which is below 200 for transaction amounts and below 10 for transaction frequencies. However, fraudulent transactions have a very different profile. They occur in high value regions above 300 and with high frequencies above 15.

This supports the assumption that fraudulent transactions involve higher amounts and more frequent activity as compared to normal transactions which makes these characteristics important for identifying fraud. Also, the distinct clustering of normal transactions and outliers in the scatter plot with fraudulent transactions proves the SHAP results which were that the transaction amount and transaction frequency are the most prominent features of fraudulent schemes. The existence of outlier extreme values indicates the potential for fraud detection models that utilize anomaly detection such as Isolation Forest or Z-score normalization to mark suspicious activity for further investigation.

4.2 Discussion

This study's results offer solid conclusions about how using XGBoost differs from using Transformer-Based Models for financial fraud detection, following new progress in machine learning science (Sun et al., 2024; Oala et al. 2021). In particular, we found that both models performed well overall, but specialized in particular areas that may be more or less useful depending on the case (Ngoc Hung, Thuy Van, and Archer 2023; Ranta, Ylinen, and Järvenpää 2023).

26 XGBoost has an AUC-ROC score of 92%, and is very easy to interpret. These features of the model make it ideal for compliance-centric financial institutions that require high levels of transparency regarding operational decisions (Hamal and Senvar 2021; Nielsen 2022). In addition, his model implements feature importance ranking, which supports insistence from (Kanaparthi, 2024) that explainable AI is necessary in financial auditing. Following SHAP analysis (Bahromjon Bahodirovich 2023; Bako and Tanko 2022), found that transaction amount, frequency, and merchant category are the greatest indicators of fraud. This finding reinforces prior work by (Baghdasaryan et al. 2022) on fraud pattern identification.

The Transformer-Based Model's superior performance (95% AUC-ROC) demonstrates remarkable capability in detecting complex, sequential fraud patterns, as anticipated in recent 45 deep learning literature (Ali et al. 2023; Lehner et al. 2022). However, the interpretability challenges inherent in its architecture, particularly regarding attention mechanisms and high dimensional embeddings, present significant adoption barriers in regulated financial contexts (Booz et al., 2022; Eid et al. 2021). This concern matches the practical challenges associated with black-box models stated by (Schreyer, Sattarov, and Borth 2022) in their work.

Our research of explainability methods comes with vital observations regarding the varying effectiveness of such techniques across model architectures. Unlike Transformer-Based Models, which expecially lose the ability to provide global explanations for SHAP, XGBoost models are provided robust global explanations for their devisions (Kootanaee, Aghajan, and Shirvani 2021) and as noted in (Kazmi et al., 2024). The limitation highlights how important it is to select a model depending on the specific use case's demands, especially in contexts

turnitin Page 16 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 17 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

p-ISSN: 2808-9022 e-ISSN: 2798-1789

where there is a need for compliance to regulations that require processes for making decisions to be clear (Rao and Muhammad Saeed Shahbaz 2023; Biju, Thomas, and Thasneem 2024).

The accuracy-interpretability imbalance noticed in our research correlates with the results found by (Et al. 2021) on the AI System Tensions Design for Financial Applications. Our findings indicate that, like in other system implementations, financial institutions must also balance conflicting technical performance measures with operational controls (Oala et al. 2021). The finding of possible fraud markers from our analysis helps in developing better risk scoring and monitoring systems as called for in industry studies (Sun et al., 2024). These outcomes can be significant for the academia and industry practitioners. Subsequent research may tackle the issue of integrating XGBoost's interpretability with the pattern recognition features of Transformer models, perhaps via hybrid approaches or model distillation. (Ngoc Hung, Thuy Van, and Archer 2023) put forward some ideas which we believe may help solve the problem of deep learning interpretability in finance sequence data using advanced explainability features. (Ranta, Ylinen, and Järvenpää 2023).

Although this research offers useful perspectives on machine learning methods for financial forgery detection, it has certain shortcomings that need to be addressed. The dataset employed, though diverse in its representation of transaction patterns, may not fully encompass the dynamic and evolving nature of contemporary financial fraud techniques. As fraud methodologies continuously adapt and become more sophisticated, there exists a pressing need to develop real time fraud detection systems capable of adaptive learning to keep pace with emerging fraudulent behaviors. This challenge has been particularly emphasized in recent studies examining the rapid evolution of financial fraud tactics.

The research focus on XGBoost and Transformer-Based Models, while yielding significant comparative findings, necessarily excludes alternative machine learning approaches that may offer complementary advantages. Other techniques such as ensemble learning methods, graph based anomaly detection systems, and hybrid artificial intelligence architectures represent promising avenues for achieving an optimal balance between detection accuracy and model interpretability. Recent advancements in these areas suggest they may provide innovative solutions to current limitations in fraud detection systems.

The challenges that focus on interpretability limitations of complex machine learning models and deep learning systems is one noteworthy constraint. Although there have been strides made towards explaining model decisions using SHAP and LIME methods, they are still fundamentally shallow as explanation post hoc methods. Shrub has pointed out that stringent regulatory requirements in finance call for far-sighted explanation methods which go beyond the surface explanations offered by these highly regulated sectors as they analyze complex sequential data.

There is need for construct fusion strategy for integrated model architectures that harness the diverse strengths of multiple machine learning approaches for effective interpretation. These models, blending multiple aforementioned paradigms, would significantly improve explainability and remain compliant with most regulations while still being able to retain high detivity accuracy. Not only is this useful for operational implementation within financial institutions, but it is perhaps the most important facet for achieving regulatory compliance. No

turnitin Page 17 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 18 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

less important is the research of real-time fraud detection adaptive learning systems. Financial fraud is ever changing AI systems need to learn from issued transactions and, more importantly, adapt to new and more complex patterns and behaviors.

The development of the explainability methods is one of the most important directions of research. Especially the post-hoc approaches need to be complemented with the design of user-friendly visualization methods for complex components of neural systems and the construction of more interpretable neural systems. These changes would increase the applicability of complex machine learning models into financial auditing and fraud detection situations. Ultimately, the less attention given to the datasets on which the research in fraud detection is built is a problem.

Researchers rely heavily on published datasets as is the norm in academic studies. Increased interaction between researchers and financial companies would improve chances of obtaining more complete and real transactional data which would assist in developing stronger and more useful fraud detection models. These models would be better suited to meet the reality of the diverse and complicated ways fraud is perpetrated in the financial transactions. This would improve the state of the art while addressing issues of representativeness and relevancy of the datasets.

5 CONCLUSION OF THE DISCUSSION

This study analyzes the delicate balance between accuracy and interpretability within AI fraud detection systems while incorporating new machine learning developments (Sun et al., 2024; Oala et al. 2021). By showing that although Transformer-Based Models yield unmatched detection accuracy (performing at an unprecedented 95% AUC-ROC), their complexity poses serious challenges to achieving interpretability which greatly hinders their utilization in highly regulated financial sectors (Ngoc Hung, Thuy Van, and Archer 2023; Ranta, Ylinen, and Järvenpää 2023). These findings are consistent with prior research by (Hamal and Senvar 2021) that demonstrated the conflict between model sophistication and operational transparency in financial auditing.

In contrast, XGBoost offers balanced performance (92% AUC-ROC) with its relatively simple and easy to understand decision-making process, making it ideal for use in compliance-centered finance (Kanaparthi, 2024; Nielsen 2022). Its interpretable architecture enables the users to audit the detection results against the known fraud patterns, thereby meeting the regulatory requirements for explainability (Bahromjon Bahodirovich 2023). Our SHAP analysis, in line with the findings from (Bako and Tanko 2022), confirms once more that amount, frequency, and merchant type continue to be the most recurrent predictors of fraudulent behavior (Baghdasaryan et al. 2022; Eid et al. 2021) . On the implementation side, (Schreyer, Sattarov, and Borth 2022) did identify a gap regarding how financial institutions deal with finding the balance between compliance and detection performance. The best hybrid systems will be developed by combining the explainable power of XGBoost with the pattern recognition ability of Transformers (Kootanaee, Aghajan, and Shirvani 2021; Kazmi et al., 2024). This approach is in tandem with emerging best practices in financial AI applications

turnitin Page 18 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

turnitin Page 19 of 21 - Integrity Submission Submission ID trn:oid:::1:3210282977

p-ISSN: 2808-9022 e-ISSN: 2798-1789

where the failure to perform and the need to be operationally transparent is unabated (Rao and Muhammad Saeed Shahbaz 2023; Biju, Thomas, and Thasneem 2024).

Looking towards the future, there are three areas that need focused research attention (Ali et al. 2023; Lehner et al. 2022). One is the creation of proactive adaptive learning systems that are able to cope with changing fraud strategies in real-time (Et al. 2021). Another is the advancement of Explainable AI that enables better understanding of intricate decisions made by a model without affecting its performance (Booz et al., 2022).

Third, there is a need to design more effective benchmarking frameworks which assess models from both a technical and an operational perspective (Sun et al., 2024). Complying with the changing financial regulations will greatly affect the effectiveness and compliance of the AI powered auditing systems (Ngoc Hung, Thuy Van, and Archer 2023). This is one example of how these advancements will be critical.

This research has practical consequences that go further than the technical scope and include organizational change management. Financial institutions have to go beyond choosing the model and embrace actively designing governance structures, staff training, and validation processes for the responsible use of AI for fraud detection (Ranta, Ylinen, and Järvenpää 2023). The financial sector can maximize the benefits of AI without sacrificing the needed transparency and responsibility in highly regulated environments (Kanaparthi, 2024).

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