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ENHANCING FINANCIAL FRAUD DETECTION IN THE UNITED STATES HEALTHCARE SYSTEMS USING EXPLAINABLE AI MODELS

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ABSTRACT
The United States healthcare system, the foundation of public welfare face challenges due to financial fraud, which causes waste of resources while also undermining trust in the system. Though their lack of transparency, often referred to as the "black-box" problem which raises questions regarding accountability, interpretability, and regulatory compliance, AI models have shown potential in identifying fraud through the analysis of large and complex information. However, in industries like healthcare, explainable AI (XAI) presents a viable approach. The purpose of this study is to investigate how XAI can improve financial fraud detection in healthcare systems. The study revealed that by providing clear, useful insights into AI-driven decisions, XAI dramatically increases the accuracy and effectiveness of fraud detection. It also suggests the need to balance model accuracy and interpretability, computational demands, and data quality challenges. XAI therefore presents as a revolutionary method of detecting financial fraud in United States healthcare systems that bridges the gap between advanced AI technology and the demands of accountability, transparency, and equity.

Keywords:
Artificial intelligence, AI models, financial fraud, healthcare, Explainable AI

1. INTRODUCTION

With its complex web of services and systems aimed at preventing illness, promoting health, and providing medical care, the global healthcare industry is essential to human development (Kruk et al., 2019). The industry is varied and complex, representing the particular difficulties and concerns of several geographical areas. While developing countries concentrate on tackling infectious diseases, expanding access to basic healthcare services, and building healthcare infrastructure, developed nations frequently highlight advanced medical technologies, ageing populations, and the management of chronic disorders (Sharma et al., 2022; Chowdhury & Ravi, 2022).
One of the most advanced and intricate healthcare systems in the world, the United States is distinguished by a combination of corporate and public finance, innovative medical research, and a strong focus on innovation (Allers et al., 2023). Despite its strengths, the United States healthcare system is threatened by the widespread problem of financial fraud. According to reports, fraudulent actions such as false patient data, service misrepresentation, and fraudulent billing cost billions of dollars annually (Hilal et al., 2021). These actions damage patient, provider, and insurer trust in addition to depleting resources. Beyond just causing monetary losses, fraud has a negative impact on treatment quality, restricts access to services, and exerts more financial strain on patients and trustworthy healthcare professionals (Villegas-Ortega et al., 2021; Stowell et al., 2020).
Generally, it is impossible to overestimate the importance of reliable financial fraud detection systems in the healthcare industry. Therefore, to identify fraudulent trends and prevent losses, advanced tools and technologies like artificial intelligence (AI) and data analytics are crucial. The complexity and scope of existing healthcare fraud render conventional fraud detection techniques which depend on manual audits and rule-based systems inadequate (Kumaraswamy et al., 2022). As such, Explainable AI (XAI) and other AI-driven solutions are viable options for improving detection skills while maintaining compliance and transparency (Saeed & Omlin, 2023). Owing to this, healthcare systems may reduce fraud and reallocate important resources to enhance patient outcomes and promote a more efficient and fair healthcare environment by utilizing these technologies.
In contrast to conventional AI models, XAI offers insights into the decision-making process, enabling stakeholders to comprehend, validate, and trust the results. Explainable models can help close the gap between advanced computer algorithms and medical experts' domain knowledge in financial fraud detection, guaranteeing that

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detection systems are precise and useful (Saranya & Subhashini 2023). In particular, more advanced detection techniques are required because financial fraud in the United States healthcare system remains an expensive and persistent problem (Sorum et al., 2023). These conventional methods of detecting fraud are becoming inadequate considering the growing complexity, scope, and adaptability of fraudulent schemes as the healthcare industry evolves. Therefore, to effectively address these issues, advanced fraud detection techniques especially those that utilize advanced technologies are essential. This review explores how XAI may transform healthcare fraud detection systems by integrating XAI models into the financial fraud detection framework within the United States healthcare systems.

2. FINANCIAL FRAUD IN HEALTHCARE

Financial fraud in healthcare is a persistent and widespread problem that threatens the sustainability, equity, and efficiency of healthcare systems worldwide (Glynn, 2022). In its broadest sense, healthcare fraud refers to dishonest practices intended to obtain unapproved benefits or payments, frequently at the expense of patients, government programs, and insurers. Examples of fraudulent activities in the healthcare industry include kickbacks, phantom billing, upcoding, and unbundling of services (Villegas-Ortega et al., 2021; Coustasse, 2021). These practices take advantage of the complexity of healthcare systems, where several stakeholders, providers, insurers, patients, and regulators operate within complex billing and reimbursement systems. The complex financial arrangements that define contemporary healthcare systems are the origins of healthcare fraud (Smith & Appelbaum, 2021; Stowell et al., 2020). The number of transactions and the variety of payers may present chances for exploitation in settings such as the United States, where a combination of public and private financing streams coexist. Due to their size and reliance on standardized billing codes, programs like Medicare and Medicaid, which serve millions of Americans, are especially vulnerable (Batko & Ślęzak, 2022). In a similar vein, private insurers encounter difficulties handling fraudulent claims while under pressure to expedite and streamline payment processing. While digitization and technological improvements have increased efficiency, they additionally provided new fraud opportunities. Fraudsters can now more easily modify data, automate dishonest tactics, and hide illegal activity inside large datasets as a result of the adoption of electronic health records (EHRs) and digital billing systems (Abernethy et al., 2022). Additionally, the COVID-19 epidemic has pushed the growth of telemedicine and online healthcare services, creating new avenues for fraud, such as billing for services that were never provided and abusing telehealth platforms (Giancola & Stedman, 2021).

Over time, efforts to prevent healthcare fraud have changed, combining a variety of legislative actions, technology advancements, and cooperative projects. Despite these initiatives, advanced and proactive detection and prevention techniques are required due to the scope and complexity of healthcare fraud (Vian, 2020). The advent of data analytics and artificial intelligence (AI) has opened up new avenues for combating healthcare fraud. AI-powered systems can detect fraudulent activity with unusual speed and accuracy by examining massive datasets and detecting unusual trends (Kaur et al., 2023). Adoption of these technologies must, however, address issues like scalability, bias, and transparency. A viable remedy is Explainable AI (XAI), which combines interpretability and AI analytical capabilities to improve responsibility, trust, and cooperation in fraud detection initiatives (Tiwari, 2023; Mill et al., 2023). Therefore, addressing financial fraud remains the primary concern as healthcare systems change to maintain sustainability, equity, and the provision of high-quality care.

Table 1. Variations of Healthcare Fraud

Types	**Description**	**References**
Billing for services not rendered	Fraudulent businesses file claims for medical treatments, tests, or supplies that were never supplied. This practice exploits weaknesses in regulation, leading to large financial losses for insurers.	Stowell et al., 2020; Griswold et al., 2022.
Unbundling	This technique inflates payments by billing individual parts of a bundled medical service.	Phillips & Cohen, 2016.
Upcoding	Fraudsters use higher-paying billing codes for services that were never actually rendered. A simple office visit, for instance, could be coded as a more involved and expensive consultation.	Coustasse, 2021; Cremeans et al., 2019.

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Phantom providers or patients	False patient or provider identities and frequently fabricated supporting paperwork are used to submit fraudulent claims.	Stowell et al., 2020; Hilal et al., 2021.
Kickbacks	Financial incentives are transferred between parties, such as suppliers and providers, to sway procurement choices or recommendations in violation of anti-kickback laws.	Dike-Minor, 2023.

Ultimately, healthcare fraud has far-reaching effects that extend beyond financial losses. In terms of finances, it raises the price of healthcare for both individuals and businesses, resulting in more out-of-pocket costs and insurance premiums. Operationally, fraud lowers the standard of patient treatment by taking funds away from actual medical needs. Furthermore, it damages public confidence in payers and providers, undermining trust in the healthcare system.

3. EVOLUTION OF AI IN FRAUD DETECTION

Fraud detection has been transformed from a reactive procedure to a proactive and predictive discipline by AI (Jada & Mayayise, 2023). Rule-based methods, which used preset criteria and patterns to indicate questionable activity, were a major component of early fraud detection systems. Although these algorithms were good at identifying well-known forms of fraud, they were not flexible enough to adjust to new schemes (Pourhabibi et al., 2020). A crucial shift occurred with the introduction of machine learning (ML), which allowed models to examine enormous datasets, identify intricate patterns, and detect slight irregularities that might be signs of fraud (Afriyie et al., 2023). Therefore, AI systems were able to forecast possible fraud more precisely than conventional approaches due to techniques including supervised learning, unsupervised learning, and anomaly detection. While unsupervised models investigate unlabeled data to find novel fraud trends, supervised models employ labelled data to differentiate between genuine and fraudulent claims.
Recent developments in deep learning have considerably improved the ability to detect fraud. In addition to its capacity to handle high-dimensional data, neural networks have proven very useful for examining intricate datasets, including billing transactions and electronic medical records (Cherif et al., 2022). These models can reveal complex correlations between variables that conventional approaches may disregard. Furthermore, AI systems can now examine unstructured data, such as patient histories and provider notes, to find discrepancies by using natural language processing (NLP). Notwithstanding these developments, the emergence of AI has also brought attention to the necessity of accountability and transparency, especially as models become increasingly complex (Juhn & Liu, 2020). As such, XAI was developed, aiming to improve fraud detection systems and ensure they are more reliable and useful by fusing interpretability with the predictive capabilities of advanced AI.

4. ROLE OF EXPLAINABLE AI (XAI) IN FRAUD DETECTION

The use of AI in fraud detection has grown because of its capacity to analyze enormous volumes of data, detect irregularities, and make accurate predictions about fraudulent activity (Afriyie et al., 2023; Aslam et al., 2022). However, conventional AI models often referred to as "black-box" models function in ways that are difficult for human users to comprehend (Mytnyk et al., 2023). These models present a serious problem in high-stakes sectors like healthcare and finance because they produce results without providing explicit justifications for their choices. This drawback is addressed by XAI, which makes AI systems more transparent and interpretable by offering insights into their decision-making processes (Saeed & Omlin, 2023). Therefore, XAI remains more than just a technical improvement; it is essential in settings where accountability, trust, and regulatory compliance are critical.

Resolving the Opacity of Black-Box AI Models

Deep neural networks and other black-box AI models are excellent at deciphering intricate datasets and identifying minute patterns that may be overlooked. However, there are problems associated with their lack of interpretability, particularly in situations when judgements have broad ramifications (Band et al., 2023). For example, in fraud detection, human auditors or compliance officials may frequently need to investigate a reported transaction or claim further. Investigators can find it difficult to confirm or take action on the findings if they do not have a clear explanation regarding why AI reported the case. This opacity may result in ineffective fraud investigations, a lack of confidence in the AI system, and possible legal and reputational issues if outcomes are contested.

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By dissecting intricate models into easily comprehended parts, XAI lessens these problems. Users can see which features influenced a model's decision and to what degree by using techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) (Nohara et al., 2019). In fraud detection, XAI might show that contradictory patient demographics or abnormally high billing amounts were the cause of a flagged claim. Therefore, by bridging the gap between machine intelligence and human expertise, these explanations enable fraud investigators to comprehend, trust, and act upon AI-generated outputs.

Interpretability and Transparency in High-Stakes Sectors

Errors can have a huge financial, ethical, and reputational cost in high-stakes sectors including healthcare, banking, and law enforcement. Interpretability and transparency are essential needs, not simply desired ones. Upcoding, phantom billing, and bogus claims are examples of fraudulent practices in the healthcare industry that not only drive up expenses but also take resources away from providing actual patient care (Coustasse, 2021). In order to foster trust among stakeholders, such as insurers, regulators, and healthcare providers, AI systems that are employed to detect fraud in such situations must make their decisions clear.

For regulatory compliance in particular, transparency is crucial. Strict control of healthcare billing and claims procedures is required in the United States by regulations including the Health Insurance Portability and Accountability Act (HIPAA) and the False Claims Act. Organizations must be able to explain how and why an AI system came to the decision that a claim may be fraudulent (McGraw & Mandl, 2021). This is made possible by XAI, which produces interpretable results that can be examined, audited, and contested in regulatory settings. Therefore, this feature lowers the possibility of fines and legal issues while also improving compliance.

Furthermore, preserving equality and fairness in fraud detection depends on interpretability. Biases may be unintentionally encoded in black-box models' decision-making, producing discriminating results (Pagano et al., 2023). For example, biassed training data may result in disproportionately high-risk flagging for specific demographic groups. By identifying and addressing these biases, XAI enables organizations to guarantee that fraud detection systems are equitable and efficient.

Importance of XAI's in the United States Healthcare System

With regard to its complexity, high expenses, and wide range of stakeholders, the healthcare system in the United States is especially susceptible to financial fraud, thereby loosing resources because of fraudulent practices including upcoding, unbundling, and phantom billing, which put a burden on government programs like Medicare and Medicaid and raise patient rates (Kumaraswamy et al., 2022; Glynn, 2022). Hence, to ensure the financial stability of the system and to guarantee that resources are only used for legitimate medical requirements, it is critical to mitigate these practices.

Enhancing fraud detection in the United States healthcare system is made possible by XAI. XAI makes it easy for healthcare organizations to evaluate findings and take corrective action by giving interpretable insights into the logic behind flagged claims (Mill et al., 2023). An XAI model that detects phantom billing, for instance, can point out that some providers routinely bill for services rendered outside of regular business hours or for operations that differ from patient data (Owens et al., 2022). These justifications encourage cooperation between AI systems and human auditors while also increasing the effectiveness of fraud investigations. Additionally, XAI increases confidence among those involved in the healthcare system in the United States such that when choices are clear and easy to understand, AI systems are more likely to be adopted and relied upon by insurers, regulators, and providers (Bajwa et al., 2021). Therefore, by offering interpretable results that can withstand scrutiny in audits and legal actions, XAI complies with the United States regulatory requirements.

Table 2. Relevance of XAI in High-Stakes Situations

Elements	Relevance	References
Transparency and Trust	Decisions must be transparent and defendable in high-stakes industries including healthcare, financial fraud detection, and legal systems. By guaranteeing that each decision is supported by an explanation, XAI promotes user trust. Explainable models, for example, assist administrators in understanding the reasons behind the flagging of specific claims in healthcare fraud detection, ensuring that actions are justifiable and equitable.	Kiseleva et al., 2022.
Error Mitigation	Errors can have broad consequences, such as misclassifying valid claims as fraudulent or failing to recognize actual fraud,	Nabrawi & Alanazi, 2023.

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	because of the stakes involved in the healthcare and financial industries. By empowering stakeholders to recognize and rectify misclassifications, XAI lowers these risks. Over time, XAI also aids in improving and refining model performance by bringing transparency to decision-making processes.	
Regulatory Compliance	Decision-making procedures in many high-stakes domains must be accountable and explicable due to strict regulatory frameworks. By offering transparent, auditable justifications for model predictions, XAI facilitates compliance. XAI can assist organizations in proving compliance with laws such as the False Claims Act in the U.S. healthcare system by guaranteeing that fraudulent acts that are reported are backed up with comprehensible proof.	Rane et al., 2023.
Stakeholder Collaboration	AI systems and domain experts frequently need to work together in high-stakes sectors. This is made possible by XAI, which produces interpretable results that professionals can examine and verify, creating a feedback loop that improves model accuracy and confidence. This partnership guarantees that ideas in fraud detection are practical and based on real-world experience.	Hoffman et al., 2023.
Social Responsibility and Ethics	High-stakes decisions can have significant social and ethical ramifications. By guaranteeing that judgements are not only correct but also in line with moral principles, XAI encourages the responsible use of AI. This is especially important in fields like healthcare, where choices have a direct impact on individuals' financial security and general well-being.	De Cremer & Narayanan, 2023.

4.1 Explainable AI (XAI) Techniques

SHapley Additive exPlanations (SHAP) is a popular method for deciphering machine learning models which give each feature a contribution score for a particular prediction. SHAP analyses how the forecast changes when a feature is added or removed in order to calculate the marginal contribution of each feature based on cooperative game theory (He et al., 2023). For example, in healthcare fraud detection, SHAP might emphasize variables like unusually high billing amounts or atypical service frequency to explain why a specific claim was marked as suspect.

Local Interpretable Model-Agnostic Explanations (LIME) approximate a complex model using a more straightforward, interpretable surrogate model to produce explanations within a local region of interest (Nieto, 2022). It enables users to comprehend the decision-making process for individual scenarios by altering the input data around a particular prediction and tracking the effects on the output. For instance, LIME can explain which characteristics like the procedure type or the provider's history had the biggest impact on the system's determination to detect fraudulent claims and it may be used with any machine learning model, increasing its usefulness because LIME functions as a model-agnostic (Abdollahi & Pradhan, 2023).

Advanced machine learning models and the human need for accountability, transparency, and trust are linked by explainable AI. Methods such as SHAP, LIME, and counterfactual explanations are useful instruments for enabling AI systems to be interpreted and used. XAI is not only an improvement but also a requirement in high-stakes areas like healthcare fraud detection, allowing stakeholders to make difficult decisions with clarity and confidence (Yang et al., 2023). Therefore, the role of XAI will continue to expand as AI systems become more widespread, guaranteeing that innovation is supported by accountability, fairness, and trust.

5. APPLICATION OF XAI IN FINANCIAL FRAUD DETECTION

In healthcare systems, XAI has become an essential tool for financial fraud detection, addressing the demands of accountability, accuracy, and transparency (Rane et al., 2023). Though their opacity frequently leaves consumers unsure of the reasoning behind their choices, conventional AI models are effective at finding patterns and anomalies within large datasets.

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XAI systems examine transaction histories, claims information, and other financial documents in order to identify questionable activity in the detection of financial fraud. For example, XAI can pinpoint the precise elements that led to a claim being reported as possibly fraudulent, such as irregular billing patterns, odd transaction frequency, or discrepancies between patient data and services provided (Zhu et al., 2021). Investigators can prioritize high-risk cases, validate findings, and improve detection models. Additionally, XAI encourages cooperation between human auditors and AI systems, which builds accountability and trust in efforts to avoid fraud (Mill et al., 2023). To scale XAI for wider use, it is necessary to overcome resource and technological issues and promote a collaborative and educational culture. Therefore, to effectively capitalize on the disruptive potential of XAI in mitigating financial crime across sectors, policymakers, regulators, and industry players must collaborate (Ridley, 2022). As XAI develops further, it will be a vital instrument for preserving trust in vital services like healthcare and protecting financial integrity.

6. CONCLUSION

AI models have demonstrated potential in detecting fraudulent activities; however, their interpretability has limited their effectiveness, especially in high-stakes industries like healthcare where accountability, trust, and regulatory compliance are crucial. The integration of Explainable AI (XAI) models into financial fraud detection in United States healthcare systems represents a significant advancement in addressing one of the major challenges in the sector.

In the process of offering insights into how AI systems make decisions, XAI remains relevant by offering a vital solution. By using methods like SHAP, LIME, and counterfactual explanations, XAI helps stakeholders validate, improve, and act upon AI-generated outputs by bridging the gap between machine intelligence and human comprehension. In addition to improving efficiency and transparency, the use of XAI in healthcare fraud detection complies with ethical and regulatory requirements, building confidence among providers, insurers, and regulators.

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