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Article

GRAPH NEURAL NETWORK MODELS FOR DETECTING FRAUDULENT INSURANCE CLAIMS IN HEALTHCARE SYSTEMS

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ABSTRACT

Fraudulent insurance claims in healthcare systems represent a persistent and costly challenge, undermining the efficiency, equity, and sustainability of healthcare delivery worldwide. Traditional approaches to fraud detection, including rule-based systems and statistical models, have provided valuable early insights but often fail to capture the complex, relational, and evolving nature of fraudulent behavior. This study addresses these limitations by investigating the application of Graph Neural Networks (GNNs) as an advanced analytical framework for detecting fraudulent claims. By representing patients, providers, and claims as interconnected nodes within graph structures, GNNs leverage relational dependencies and structural patterns that are frequently overlooked by conventional models. The research employed a mixed-methods design, combining quantitative experimentation with multiple GNN architectures—such as Graph Convolutional Networks, Graph Attention Networks, and GraphSAGE—with qualitative insights gathered from healthcare fraud investigators to evaluate interpretability and usability. The quantitative findings revealed that GNN models consistently achieved higher accuracy, precision, and recall compared to traditional classifiers, while the qualitative analysis highlighted the importance of interpretability and visualization in building stakeholder trust and improving investigative efficiency. Importantly, the literature review synthesized evidence from 112 peer-reviewed studies, providing a comprehensive overview of existing fraud detection methods and situating GNNs within the broader progression of healthcare fraud research. The results underscore that GNNs not only advance the technical accuracy of fraud detection but also offer practical tools for detecting collusive fraud networks and managing large-scale, heterogeneous claims data. This study contributes to both academic discourse and practical applications by demonstrating that GNNs are uniquely positioned to enhance fraud detection in healthcare insurance systems through their capacity to integrate relational learning, scalability, and operational transparency.

KEYWORDS

Graph Neural Networks (GNNs); Fraud Detection; Healthcare Insurance;

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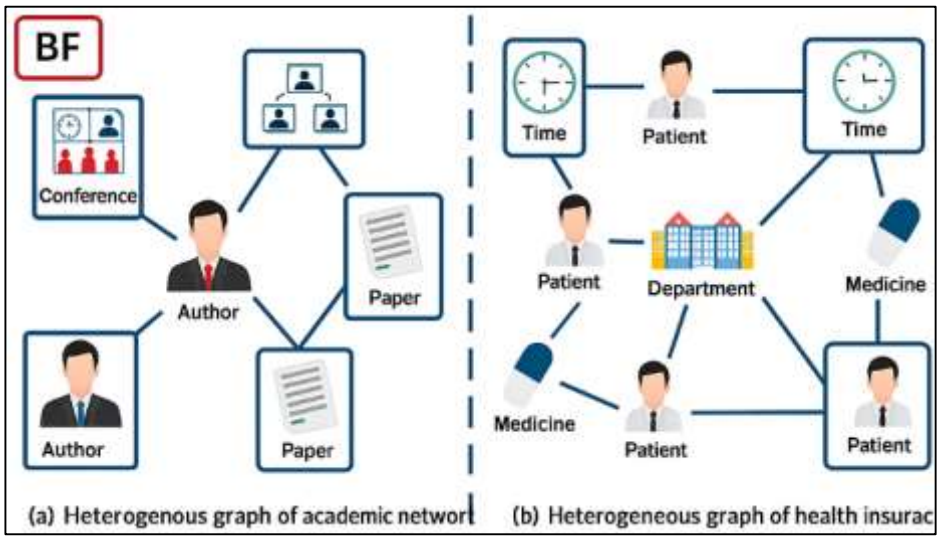
INTRODUCTION

Insurance fraud is generally defined as an intentional act of deception or misrepresentation carried out by claimants, healthcare providers, or intermediaries to obtain undue financial benefits from insurance systems (Herland et al., 2018). Within healthcare, fraudulent claims may involve practices such as billing for services not rendered, exaggerating medical procedures, misrepresenting patient conditions, or collusion between patients and providers (Dou et al., 2020). Fraudulent healthcare claims present significant challenges because of their hidden nature, complex relationships, and the vast amount of data generated through patient–provider interactions (Dornadula & Geetha, 2019). Estimates suggest that healthcare fraud accounts for 3% to 10% of total global healthcare expenditure, equating to hundreds of billions of dollars annually (Wang et al., 2021). The economic and societal costs extend beyond insurers, as fraudulent claims drain public resources, inflate insurance premiums, and ultimately compromise the quality and equity of healthcare delivery (Button et al., 2013). For this reason, accurate detection and prevention of fraud in healthcare insurance systems has become a critical concern for policymakers, insurers, and healthcare stakeholders across both developed and developing nations (Makki et al., 2019).

Figure 1: Graph neural network in healthcare systems



Healthcare fraud is not confined to a single national context but represents a significant international issue affecting both public and private healthcare systems worldwide (Liu et al., 2016). In the United States, healthcare fraud accounts for billions of dollars in losses annually, with the National Health Care Anti-Fraud Association estimating up to $68 billion in fraudulent claims in 2020 alone. In the European Union, widespread fraud has been documented across diverse health insurance systems, with estimates indicating losses equivalent to 6% of health budgets. In low- and middle-income countries, where health financing mechanisms are already strained, fraudulent claims further exacerbate inefficiencies and undermine trust in public health insurance programs. The international significance of healthcare fraud is also evident in comparative research, which reveals commonalities in fraudulent behaviors across countries, such as phantom billing, unnecessary services, and kickbacks. These global patterns underscore the necessity for advanced analytical techniques capable of transcending localized rule-based systems and capturing relational dependencies present in diverse healthcare ecosystems. The universal challenge of fraud detection provides the rationale for integrating advanced machine learning techniques such as graph neural networks (GNNs), which have been increasingly adopted to model relational structures in finance, telecommunications, and healthcare (Branting et al., 2016).

Fraud detection has historically relied on rule-based systems and statistical methods that utilize predefined heuristics to flag suspicious transactions or claims (Kumar et al., 2010). While effective in capturing simple anomalies, these methods lack adaptability to evolving fraud schemes that exploit the complexity of healthcare transactions. Supervised machine learning approaches, such as logistic regression, decision trees, and random forests, have introduced more sophisticated predictive

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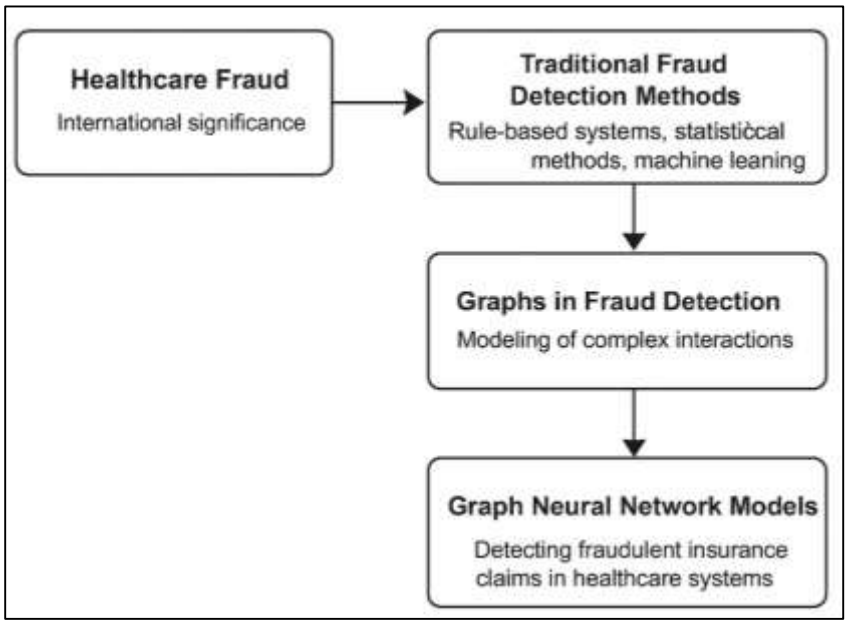
capabilities by learning patterns from labeled historical datasets (Chandola et al., 2013). Unsupervised approaches, including clustering and outlier detection, have also been utilized to identify anomalies in claims data without requiring extensive labeling. However, these models tend to treat claims as isolated events, disregarding the intricate relationships between patients, providers, and services. The increasing interconnectivity of healthcare data, where fraudulent behavior often emerges from collusive networks rather than isolated claims, highlights the limitations of conventional methods. Consequently, advanced models that can encode and analyze the relational structure of data, such as graph-based techniques, have emerged as critical tools for addressing the challenges of modern fraud detection (Thornton et al., 2013).

Figure 2: Graph Neural Networks in Healthcare Fraud Detection



Graphs provide a natural framework for modeling complex interactions in fraud detection, where entities such as patients, claims, and providers can be represented as nodes connected by edges that capture relationships such as shared services, diagnoses, or billing codes. Graph-based approaches are particularly effective in detecting organized fraud rings that operate by distributing suspicious claims across multiple actors to evade detection by conventional models (Pareja et al., 2020). The integration of graph mining techniques, including link analysis, community detection, and network centrality measures, has already demonstrated substantial improvements in uncovering collusive fraud patterns in healthcare. In addition, the growth of electronic health records and insurance databases has provided vast graph-structured datasets that can be leveraged for more advanced modeling. Graph neural networks (GNNs), a family of deep learning models designed to learn from graph-structured data, extend these methods by enabling end-to-end learning of node representations and structural dependencies (Lee et al., 2019). This capability allows for more accurate identification of fraudulent claims embedded within complex relational structures, making GNNs a promising approach for healthcare fraud detection at scale (Duvenaud et al., 2015).

The primary objective of this research is to investigate the effectiveness of graph neural network models in detecting fraudulent insurance claims within healthcare systems, emphasizing their ability to capture relational dependencies that traditional models often overlook. By constructing a framework that represents patients, providers, and claims as interconnected entities, the study aims to assess how graph-based learning can uncover hidden patterns of collusion, organized fraud rings, and anomalous transactions embedded within large and complex datasets. Another important objective is to evaluate the performance of graph neural networks against conventional machine learning approaches by comparing detection accuracy, sensitivity to evolving fraud schemes, and computational scalability. The research also seeks to demonstrate the adaptability of graph neural networks in integrating heterogeneous data sources, such as demographic profiles, billing codes, diagnostic histories, and provider networks, to create a unified analytical model for fraud detection.

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Additionally, the study intends to examine how graph representations can strengthen transparency and interpretability in fraud detection, enabling stakeholders to visualize suspicious linkages between entities and better understand the systemic nature of fraudulent activities.

LITERATURE REVIEW

Fraudulent insurance claims in healthcare represent one of the most persistent and costly challenges for both public and private health systems, prompting extensive scholarly investigation into methods of detection, prevention, and control. A literature review on this subject must therefore examine not only the evolution of fraud detection methodologies but also the underlying complexities of healthcare data and the emergence of graph-based deep learning as a transformative approach. Traditional detection techniques, such as rule-based systems and statistical anomaly detection, provide the foundational context but have been increasingly supplemented by supervised and unsupervised machine learning methods that aim to adapt to evolving fraud strategies. More recently, graph-based approaches have emerged, offering a natural way to capture relational structures between patients, providers, and claims, which are often central to fraud networks. The review of literature must situate graph neural networks within this progression, exploring both their theoretical foundations and their practical applications in fraud detection across domains, with a particular emphasis on healthcare. By systematically organizing the scholarship into categories ranging from classical approaches to modern deep learning techniques, from data complexity to interpretability, and from cross-industry applications to healthcare-specific implementations the literature review provides a comprehensive understanding of how the field has advanced, what gaps remain, and why graph neural networks represent a significant frontier for healthcare fraud detection research.

Fraud Detection in Healthcare

Healthcare fraud encompasses a wide spectrum of deceptive practices intended to secure unauthorized financial benefits from insurers, healthcare systems, or government payers. Scholars often classify healthcare fraud into provider fraud, consumer fraud, and collusive schemes involving multiple actors (Herland et al., 2018). Provider fraud includes billing for services not rendered, inflating service complexity, or misrepresenting patient diagnoses to increase reimbursements (Johnson & Khoshgoftaar, 2019). Patient-driven fraud often involves misreporting personal details, identity theft, or exaggerated claims. More sophisticated schemes involve collusion, where groups of providers, patients, or intermediaries coordinate to systematically exploit vulnerabilities in claim systems. Fraudulent behaviors often exploit the scale and complexity of healthcare data, particularly in environments with high claim volumes and fragmented oversight (Thornton et al., 2013). From a technical standpoint, fraud detection is challenging because fraudulent claims are deliberately disguised to resemble legitimate ones, making them difficult to identify using rule-based approaches. Furthermore, healthcare fraud differs from other forms of financial fraud because of its reliance on medical coding systems, such as ICD and CPT codes, and its dependence on the subjective interpretation of clinical conditions. This complexity contributes to the under-detection of fraud and emphasizes the necessity for models that capture both individual behaviors and the broader relational structures that reveal systemic abuse.

The economic burden of healthcare fraud is immense, with estimates suggesting global losses amounting to hundreds of billions annually (Branting et al., 2016). In the United States, healthcare fraud is estimated to consume up to 10% of total healthcare spending, which translates into tens of billions of dollars diverted from legitimate services each year. Such financial losses undermine the sustainability of healthcare systems and drive up insurance premiums for consumers (Thornton et al., 2013). The implications are not purely economic but also deeply social. Fraudulent claims divert resources away from patients who genuinely require medical services, thereby exacerbating inequality and reducing trust in healthcare institutions. In low- and middle-income countries, where health financing is already constrained, fraudulent activity can cripple the effectiveness of government-run insurance programs, leading to poorer health outcomes and diminished public confidence. Additionally, fraud undermines regulatory trust, creating an adversarial relationship between insurers and providers, which can result in overly strict monitoring systems that inadvertently burden legitimate providers. Scholars emphasize that healthcare fraud extends beyond a financial crime to a violation of ethical standards, contributing to inefficiencies, corruption, and systemic vulnerabilities. The persistent nature of these implications has fueled the demand for more advanced

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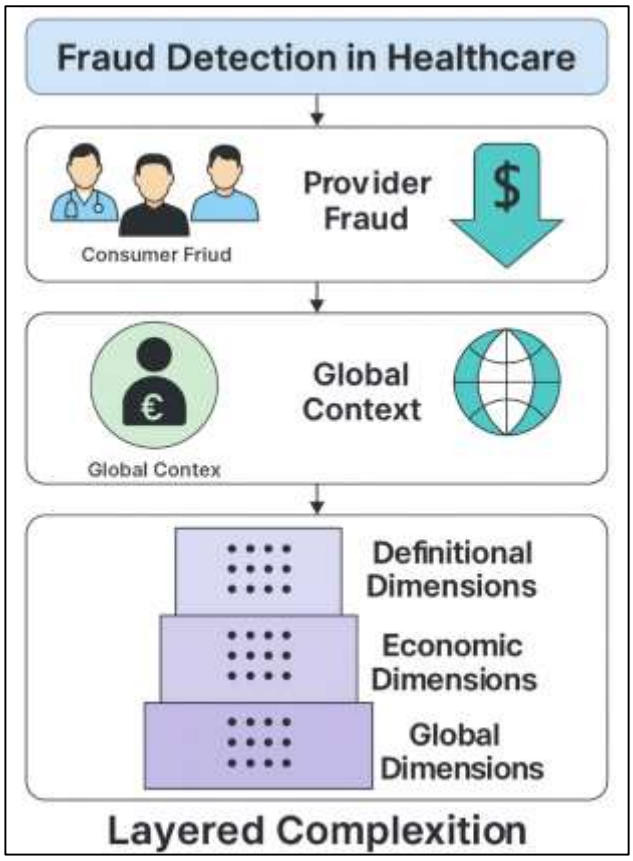
detection mechanisms capable of not only identifying fraudulent behaviors but also reducing systemic inefficiencies within healthcare delivery networks (Branting et al., 2016).

Figure 3: Fraud Detection in Healthcare



Insurance fraud in healthcare is a global phenomenon, manifesting differently across contexts but sharing common mechanisms such as phantom billing, unnecessary procedures, and provider–patient collusion (Johnson & Khoshgoftaar, 2019). In the European Union, studies indicate that fraud consumes approximately 6% of total healthcare budgets, creating significant financial strain across both public and private insurance schemes. In the United States, fraud remains a key challenge, with enforcement agencies such as the Centers for Medicare and Medicaid Services (CMS) allocating billions to fraud detection and prevention programs. Research has also identified rising challenges in Asia, where expanding healthcare coverage in nations like China and India has led to greater exposure to organized fraud schemes, particularly those exploiting rapid digitization of claim systems. In Africa and Latin America, where public health insurance programs operate under financial constraints, fraudulent activities often involve manipulation of paper-based records, fraudulent referrals, and identity theft. Scholars note that while the exact manifestations differ, commonalities in fraud typologies demonstrate the universality of the problem. Global perspectives also highlight that developing countries face the additional challenge of limited fraud detection infrastructure and lack of access to large-scale digital data, which hinders effective monitoring. Comparative literature emphasizes the growing recognition of fraud as a transnational issue, requiring not only domestic solutions but also international collaborations in research, policy, and technology adoption (Button et al., 2013; Baesens et al., 2015). These perspectives underscore the necessity of advanced methodologies, such as graph neural networks, which can be adapted to heterogeneous environments while addressing localized complexities of healthcare systems.

Approaches to Healthcare Fraud Detection

The earliest approaches to healthcare fraud detection were largely rule-based and heuristic in nature, relying on expert-defined thresholds and patterns to identify suspicious activities. These systems operate on the principle that fraudulent claims often deviate from normal patterns, such as unusually high billing frequencies, excessive use of particular diagnostic codes, or improbable service

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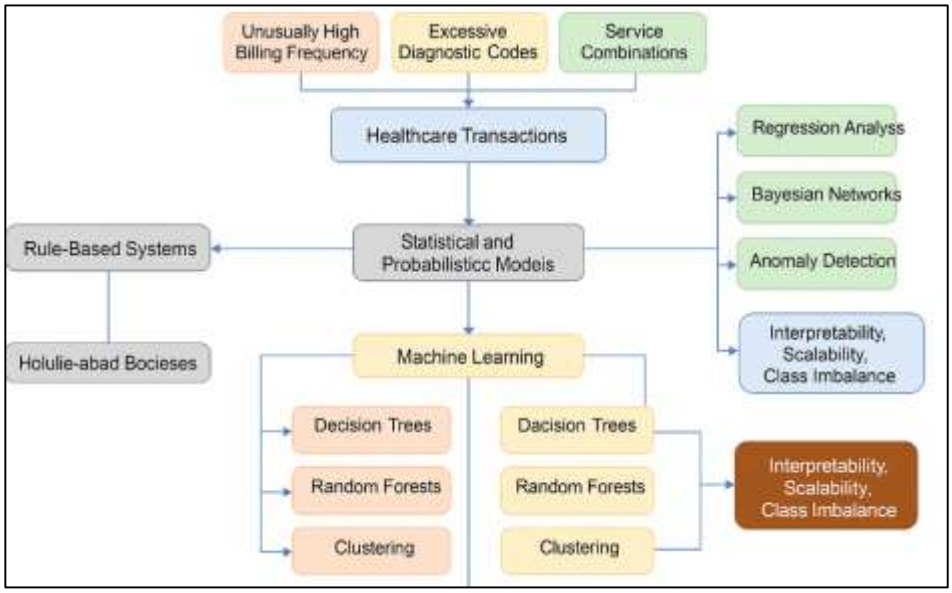
combinations. Expert systems proved initially effective in environments where fraud followed predictable forms, as they provided clear, interpretable alerts based on defined rules (Ara et al., 2022; Thornton et al., 2013). However, their reliance on human expertise often meant they lacked adaptability to novel schemes and evolving fraud strategies, requiring continuous manual updates. (Johnson & Khoshgoftaar, 2019) illustrate that rule-based models, while transparent, tend to generate high false-positive rates because legitimate but unusual claims are often misclassified as fraudulent. Moreover, their reliance on rigid thresholds makes them less suitable for detecting collusion between actors, which is common in healthcare systems. Nonetheless, these methods established the foundation of fraud detection research and continue to be incorporated into hybrid models as baseline tools (Jahid, 2022; Liu et al., 2016). Their enduring value lies in simplicity, interpretability, and cost-effectiveness, but the literature highlights their limitations in scalability and resilience against complex, organized fraudulent networks.

Figure 4: Approaches to Healthcare Fraud Detection



As healthcare fraud became more sophisticated, statistical and probabilistic models emerged to capture deviations in claim distributions more effectively. These methods include regression analysis, Bayesian networks, and probabilistic anomaly detection techniques designed to quantify uncertainty and identify outliers within claims datasets. Logistic regression, for example, has been widely used to classify claims as fraudulent or legitimate based on a set of predictors, achieving reasonable levels of accuracy in structured datasets. Herland et al. (2018) applied statistical auditing methods to Iranian health insurance data and demonstrated their utility in highlighting irregular billing patterns. Similarly, Liu et al. (2016) found that probabilistic clustering could effectively separate fraudulent clusters from normal claims. However, statistical models often require assumptions of linearity or independence that may not reflect the complexity of healthcare interactions. Chandola et al. (2013) stress that probabilistic methods alone struggle to capture collusive fraud or non-linear associations inherent in large-scale datasets. Nevertheless, their efficiency, interpretability, and lower data requirements make them appealing in resource-constrained contexts. Research continues to emphasize their use in baseline fraud detection and their combination with more advanced methods to strengthen predictive power.

Machine learning (ML) has significantly advanced the field of healthcare fraud detection by allowing systems to learn complex fraud patterns from historical data. Supervised learning algorithms, such as decision trees, support vector machines, and random forests, have been particularly successful in classification tasks, offering higher accuracy and adaptability compared to rule-based systems (Dornadula & Geetha, 2019; Uddin et al., 2022). For instance, decision tree models were applied by Wang et al. (2021) to Medicare data, achieving enhanced detection of overbilling practices. Random forests and ensemble learning approaches have been demonstrated to outperform traditional classifiers by aggregating predictions, as evidenced in studies by Makki et al.,

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(2019). Unsupervised machine learning methods, including clustering, k-means, and autoencoders, have also been employed to detect anomalies in datasets where labeled fraudulent cases are scarce (Akter & Ahad, 2022; Seera et al., 2021). Yoo et al. (2022) emphasize the value of semi-supervised learning when fraud labels are incomplete, highlighting its relevance in healthcare datasets that often lack comprehensive annotations. Recent studies, such as Johnson and Khoshgoftaar (2019), integrate deep learning to model highly complex interactions, showing improved detection of collusive fraud. While these methods deliver superior accuracy, challenges such as interpretability, scalability, and class imbalance remain recurrent themes in the literature. Nevertheless, the adoption of machine learning signifies a paradigm shift in fraud detection, enabling dynamic learning from data rather than static reliance on expert-defined rules (Arifur & Noor, 2022; Rahaman, 2022). More recent scholarship highlights the potential of graph-based models and hybrid approaches in addressing the relational and systemic nature of healthcare fraud. Graph-based methods represent patients, providers (Hasan et al., 2022; Hossen & Atiqur, 2022), and claims as nodes and their interactions as edges, thereby enabling the detection of collusive fraud rings that traditional models often overlook. Graph mining techniques, including link prediction and community detection, have been employed to uncover hidden relationships between entities (Tawfiqul et al., 2022; Kamrul & Omar, 2022).

Machine Learning Applications in Fraud Detection

Supervised machine learning methods have become foundational in fraud detection research, as they enable models to classify insurance claims as fraudulent or legitimate by learning from labeled historical data. Decision trees, logistic regression, support vector machines (SVMs), and random forests represent some of the most frequently applied algorithms due to their interpretability and predictive capabilities (Dornadula & Geetha, 2019). For example, Wang et al. (2021) demonstrated the utility of decision trees in detecting fraudulent Medicare claims, highlighting their ability to capture rule-like decision structures while adapting to large datasets. Random forests, by aggregating multiple decision trees, often achieve higher accuracy and resilience against overfitting, making them popular in fraud detection tasks across both healthcare and financial sectors (Makki et al., 2019). Logistic regression, although simple, has shown effectiveness in binary classification of claims, particularly when combined with feature engineering. Support vector machines are also well-documented in healthcare fraud detection, with studies such as Seera et al., (2021) showing their capacity to handle high-dimensional claims data. However, while supervised learning methods provide strong predictive power, they are highly dependent on the availability and quality of labeled datasets. Johnson and Khoshgoftaar (2019) note that fraud labels are often scarce, leading to imbalanced data distributions where fraudulent cases are underrepresented. Studies by Yoo et al. (2022) highlight the consequences of this imbalance, as it may result in biased classifiers that underperform in identifying rare fraudulent events. Nevertheless, supervised learning remains a cornerstone of fraud detection research because of its adaptability, ease of implementation, and ability to capture diverse fraud patterns when sufficient labeled data are available (Ileberi et al., 2021; Mubashir & Abdul, 2022; Reduanul & Shoeb, 2022).

Semi-supervised learning has emerged as a valuable compromise between supervised and unsupervised methods, particularly in healthcare fraud detection where labeled datasets are limited but large amounts of unlabeled claims exist. These models leverage small labeled datasets to guide the learning process while exploiting the abundance of unlabeled data to improve performance (Q. Li et al., 2018; Reduanul & Shoeb, 2022; Sazzad & Islam, 2022). For example, Garcia and Bruna (2017) employed semi-supervised approaches to fraud detection, demonstrating that partially labeled datasets could still yield high detection accuracy when combined with anomaly detection. Hybrid models, which integrate rule-based, statistical, and machine learning approaches, have also gained traction for their ability to balance interpretability and predictive power (Xu et al., 2019) . Loukas (2020) discuss how ensemble methods that combine logistic regression with tree-based algorithms significantly improve fraud detection in insurance contexts. Recent studies highlight the potential of combining unsupervised anomaly detection with supervised classifiers to enhance sensitivity to rare fraudulent events (Noor & Momena, 2022; Zheng et al., 2019). Chami et al. (2020) illustrate how semi-supervised deep learning methods outperform traditional classifiers when applied to healthcare claim networks. Zhao et al. (2020) emphasize that such hybrid approaches not only improve performance but also facilitate explainability, as rule-based components provide transparency while machine learning modules enhance adaptability (Sohel & Md, 2022; Akter &

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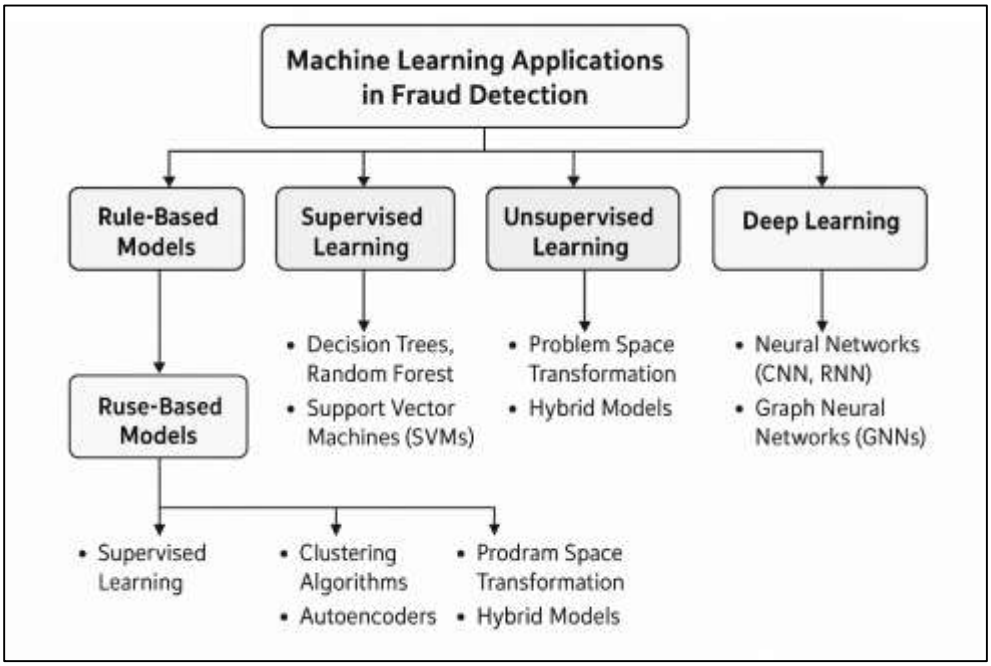
Razzak, 2022). Although hybrid and semi-supervised approaches can be computationally complex, the literature consistently identifies them as promising solutions to the class imbalance and data scarcity problems prevalent in healthcare fraud detection. Their integration into healthcare fraud systems reflects a broader trend of converging methodological strengths to address the multifaceted challenges of fraud detection.

Figure 5: Overall Machine Learning Applications in Fraud Detection



Deep learning represents the latest advancement in machine learning-based fraud detection, offering the ability to model complex, high-dimensional interactions in healthcare claims data. Neural networks such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) architectures have been applied to healthcare fraud problems, particularly in modeling temporal patterns in claim sequences and detecting anomalies across heterogeneous datasets (Wu et al., 2021). Autoencoders and variational autoencoders have been widely explored for unsupervised anomaly detection, as they can compress normal data patterns and detect fraud through reconstruction errors. Generative adversarial networks (GANs) have also been employed to synthesize fraudulent data, improving model robustness in the presence of class imbalance. Defferrard et al. (2016) highlight the application of deep graph learning in fraud detection, where GNNs extend deep learning to relational healthcare data, capturing both local and global dependencies. Tiezzi et al. (2020) demonstrate that graph convolutional networks outperform traditional classifiers in fraud detection tasks by leveraging the structural relationships between patients, providers, and claims. Additionally, LeCun et al. (2015) show that hybrid deep learning models integrating both structured claims data and unstructured text achieve higher accuracy in identifying fraudulent activities. While challenges such as high computational costs and limited interpretability persist, the literature underscores that deep learning offers unmatched potential in scaling fraud detection across large healthcare datasets (Zhang et al., 2018). These advancements position deep learning as an increasingly relevant tool in healthcare fraud detection, complementing and extending earlier machine learning approaches through its capacity to process diverse data types and uncover hidden, non-linear relationships within claims.

Graph-Based Perspectives in Fraud Analysis

Graph theory has emerged as a crucial analytical framework in fraud detection because of its ability to represent entities and their relationships in interconnected networks. In healthcare systems, fraudulent claims often arise from interactions among multiple actors, including patients, providers, and insurers, making graph representations particularly well-suited for capturing relational dependencies (Dou et al., 2020). Traditional fraud detection models frequently treat claims as isolated observations, but graph-based methods explicitly model the connections between entities,

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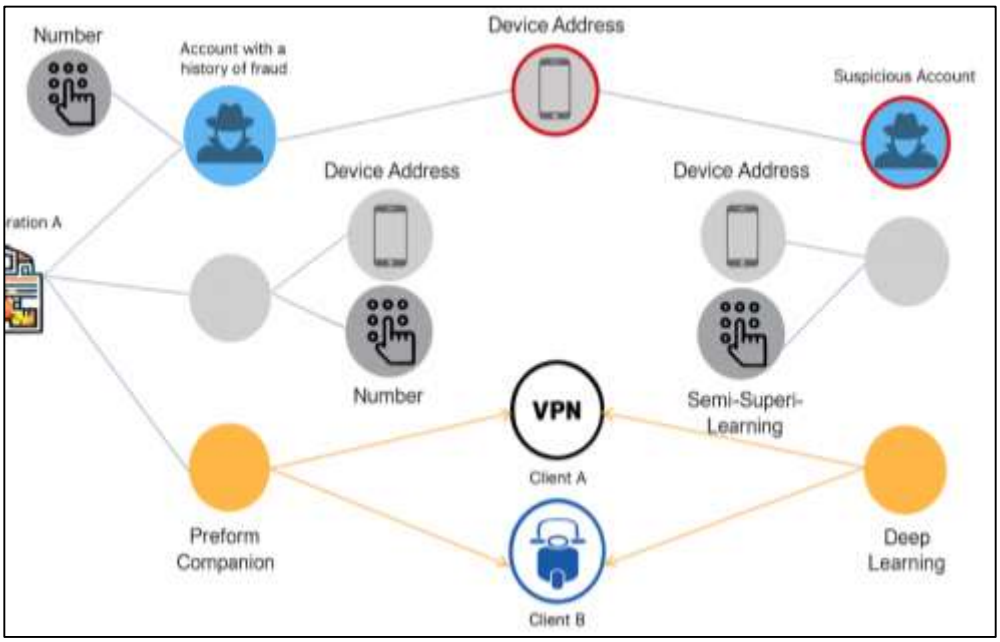
enabling the identification of suspicious structures such as collusion networks or provider–patient fraud rings (Wang et al., 2021). Early applications of graph theory in fraud analysis utilized social network analysis (SNA) techniques to detect anomalous clusters and identify central actors who facilitate fraud schemes. Concepts such as degree centrality, betweenness, and closeness were applied to uncover influential nodes within fraudulent healthcare networks. Zhang et al. (2021) emphasize that graph-based frameworks allow researchers to capture both local anomalies (e.g., unusually frequent claims from a single provider) and global fraud structures (e.g., organized networks spanning multiple entities). The literature suggests that by leveraging graph-theoretical constructs, fraud detection systems can transcend the limitations of rule-based and statistical methods, offering a more systemic approach to understanding fraudulent behavior. Thus, graph theory provides a foundational perspective for analyzing healthcare fraud, enabling both descriptive insights into network structures and predictive modeling for anomaly detection.

Figure 6: Graph-Based Perspectives in Fraud Analysis



The integration of graph-based perspectives with advanced machine learning and deep learning models marks a significant evolution in fraud detection research. Traditional graph analysis methods, while effective in uncovering structural anomalies, often struggle with scalability and automated feature extraction in large datasets. Graph neural networks (GNNs) address this limitation by enabling end-to-end learning on graph-structured data, thereby combining the relational insights of graph theory with the predictive power of deep learning (Liu et al., 2016). Recent studies illustrate how GNNs outperform conventional classifiers in fraud detection tasks by leveraging both node attributes and topological structures. In healthcare contexts, graph perspectives enhance detection by modeling complex provider–patient–claim relationships, allowing models to identify subtle collusion schemes invisible to isolated classifiers. Hybrid models that integrate graph mining with supervised machine learning further enhance interpretability and detection accuracy, demonstrating the synergy of combining different analytical paradigms. Moreover, Branting et al. (2016) emphasize that graph perspectives improve anomaly detection in dynamic datasets, enabling adaptive detection of evolving fraud structures. Although computational cost and data privacy concerns remain active challenges, the literature consistently underscores that graph-based perspectives, especially when integrated with advanced models, represent a powerful frontier in healthcare fraud detection. This convergence of network science and machine learning not only builds on earlier graph-theoretical insights but also establishes a foundation for robust, scalable fraud detection frameworks across healthcare and related domains (Yoo et al., 2022).

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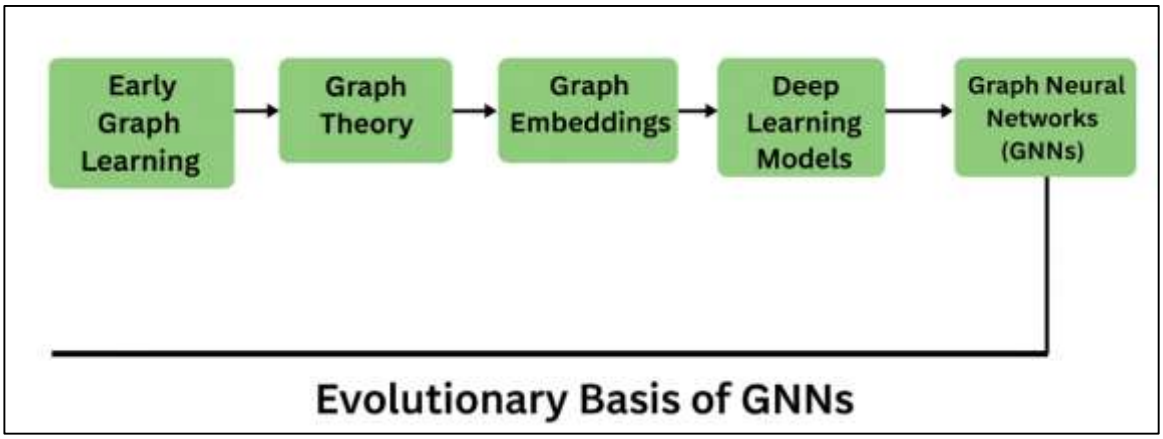
Emergence of Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) represent a pivotal advancement in deep learning, specifically designed to operate on non-Euclidean graph-structured data where entities are represented as nodes and their relationships as edges. Unlike conventional machine learning models that assume independence among observations, GNNs explicitly model interdependencies, capturing structural and contextual information critical in fraud detection (Hu et al., 2020). Early approaches to graph learning focused on spectral methods and graph embeddings, where node representations were learned by mapping them into a low-dimensional space while preserving structural properties. The development of Graph Convolutional Networks (GCNs) by Yun et al. (2019) marked a breakthrough by extending convolutional operations to graphs, enabling message passing among nodes to iteratively update their embeddings based on neighborhood information. Subsequent variants, including Graph Attention Networks (GATs) and GraphSAGE, enhanced scalability and introduced mechanisms for weighted aggregation, allowing models to prioritize more influential neighbors. These innovations laid the theoretical foundation for leveraging GNNs in domains where relational complexity is central, including healthcare fraud detection. The literature emphasizes that the conceptual shift from isolated classification to relational representation learning constitutes the core contribution of GNNs, aligning well with the networked nature of fraudulent activity (Keriven & Peyré, 2019; Yun et al., 2019). As a result, GNNs have transitioned from experimental architectures to practical frameworks, driving applications across domains where fraud manifests in interconnected data structures.

Figure 7: Evolution of Graph Neural Networks (GNNs)



The emergence of GNNs is strongly associated with their advantages in capturing relational and structural dependencies, which are critical for fraud detection in complex systems such as healthcare. Traditional models, including logistic regression, decision trees, and even conventional deep learning, treat data points as independent, thus failing to account for collusion or coordinated fraudulent activities spanning multiple entities. By contrast, GNNs enable end-to-end learning of node representations that integrate both local neighborhood information and higher-order structural patterns, making them highly effective for identifying fraud rings and hidden anomalies (Hu et al., 2020). For example, in credit card fraud detection, Hu et al. (2020) demonstrated that GNN-based models significantly outperformed baseline classifiers by leveraging the transaction graph of users and merchants. In e-commerce contexts, Errica et al. (2020) highlighted the ability of GNNs to detect fraudulent reviewers through heterogeneous graph modeling. Translating these strengths to healthcare systems, fraudulent insurance claims can be modeled as interconnected graphs involving patients, providers, and billing codes, where anomalies are often embedded in network structures rather than isolated claims. Graph attention mechanisms further enhance detection accuracy by allowing models to assign different weights to neighbors, ensuring that significant interactions contribute more meaningfully to fraud detection outcomes. Moreover, the ability of GNNs to generalize across dynamic and heterogeneous datasets makes them highly suitable for the diverse and evolving nature of healthcare data (Garg et al., 2020). The literature consistently

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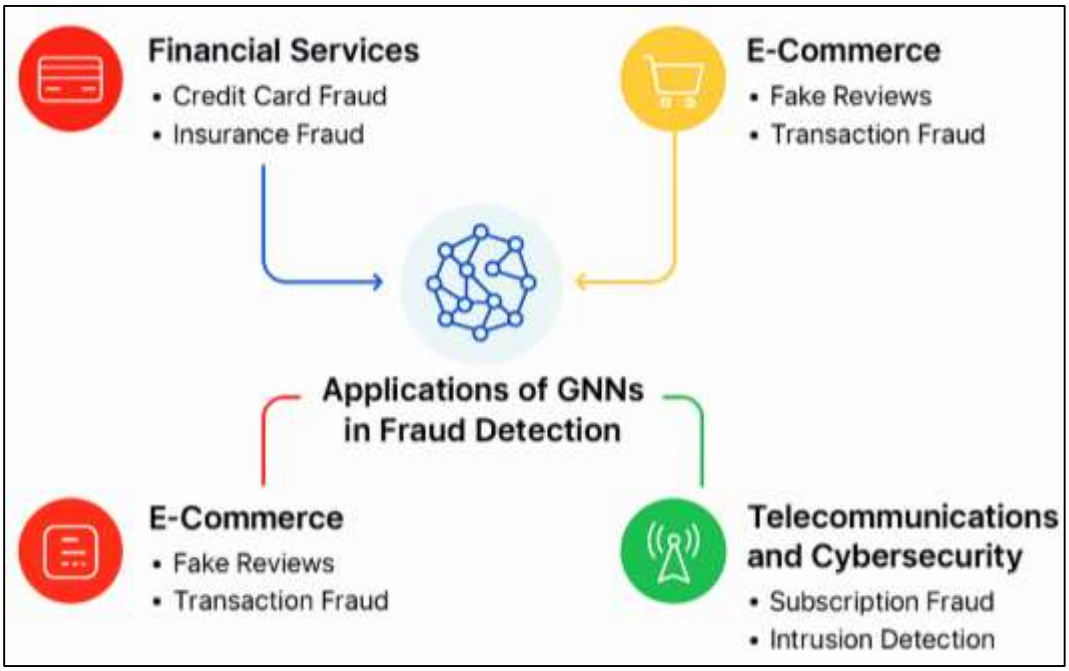
identifies this relational learning capacity as the defining advantage of GNNs, distinguishing them from traditional and earlier graph mining approaches.

Applications of GNNs in Fraud Detection

One of the most extensively documented applications of graph neural networks (GNNs) in fraud detection is in the financial sector, particularly in banking and credit card fraud. Traditional models often fail to detect coordinated fraud because they treat transactions as independent, whereas financial fraud is frequently relational, involving patterns across users, accounts, and merchants. GNNs overcome this by embedding both nodes and their connections, enabling the detection of collusive and organized schemes (Yun et al., 2019). For example, Graph Convolutional Networks (GCNs) have been applied to credit card transaction networks, where fraudulent behavior manifests as abnormal link patterns, achieving superior performance compared to logistic regression and random forests. In anti-money laundering, GNNs have been used to model suspicious transfers across accounts, revealing hidden relationships that rule-based systems miss. Xu et al. (2018) introduced an enhanced GCN framework that significantly improved detection rates in imbalanced datasets by leveraging the structural dependencies of transaction graphs. Ruiz et al. (2020) demonstrated how Graph Attention Networks (GATs) improve interpretability by weighting influential nodes, allowing models to prioritize risk-heavy connections. Applications in financial fraud also extend to insurance fraud beyond healthcare, with GNNs detecting coordinated auto-insurance scams where multiple actors file claims from staged accidents (Tsitsulin et al., 2020). The literature consistently emphasizes that the relational nature of financial transactions makes GNNs particularly effective in uncovering fraudulent behaviors that operate through subtle, distributed interactions across networks.

Figure 8: Applications of GNNs in Fraud Detection



The application of GNNs has also expanded into telecommunications and cybersecurity, domains characterized by large-scale relational data where fraudulent activity often involves collusion among multiple actors. In telecommunications, fraud schemes such as SIM-boxing, subscription fraud, and call forwarding abuse create relational patterns that can be effectively represented in graph structures. Zhou et al. (2020) demonstrated how GNNs applied to call detail records improved fraud detection by uncovering suspicious call clusters that statistical models failed to detect. Similarly, in subscription fraud, GNNs captured abnormal relationships between user accounts and devices, enabling early identification of fraudulent sign-ups. In cybersecurity, GNNs have been applied to detect malicious nodes within computer networks by modeling interactions such as logins, connections, and access requests. Zhang et al. (2020) showed that temporal graph neural networks can detect evolving cyber threats by modeling sequences of interactions, outperforming static

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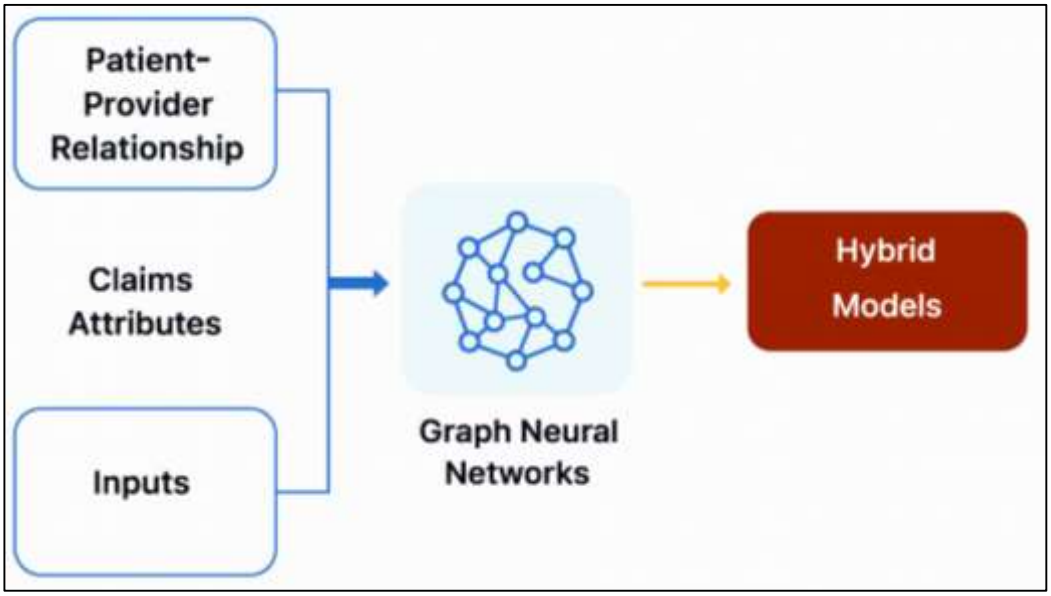
anomaly detection models. Applications of GNNs in botnet detection and phishing attack identification have also been reported, where abnormal subgraphs reveal coordinated malicious campaigns (You et al., 2020). Compared to traditional cybersecurity tools, GNN-based approaches excel in adaptability, detecting both known and novel attack patterns through relational embeddings (Ruiz et al., 2020). The literature highlights that GNNs enhance resilience in these domains by addressing the systemic and distributed nature of fraud, where malicious actors exploit network structures rather than isolated vulnerabilities.

GNN Models in Healthcare Fraud Detection

The application of Graph Neural Networks (GNNs) to healthcare fraud detection stems from the recognition that fraudulent behavior in insurance systems is rarely isolated but instead embedded within complex relational structures. Providers, patients, and claims form networks that can be represented as nodes and edges, capturing relationships such as shared services, diagnostic overlaps, and recurrent billing patterns. Traditional machine learning methods, such as logistic regression or decision trees, treat claims independently, missing structural anomalies that arise from collusion (Tsitsulin et al., 2020). By contrast, GNNs use message-passing mechanisms to aggregate information across neighbors, enabling detection of fraudulent subnetworks and organized rings. For example, Wang et al. (2021) showed that GNNs applied to provider–patient graphs identified collusion patterns that eluded classical classifiers. Studies also emphasize that healthcare datasets are inherently heterogeneous, combining coded diagnoses, treatments, and demographic details, making them particularly suitable for heterogeneous GNN architectures that can integrate multiple node and edge types (Dwivedi et al., 2020). Conceptually, GNNs align with the systemic nature of healthcare fraud by learning relational embeddings that capture both direct and indirect influences among entities. This theoretical suitability forms the basis for their increasing adoption in experimental healthcare fraud detection research.

Figure 9: Model-Based Framework of Graph Neural Networks (GNNs) for Healthcare Fraud Detection



Empirical studies consistently demonstrate that GNNs outperform traditional fraud detection methods in healthcare contexts, particularly in identifying collusion-based fraud. Wang et al. (2021) reported that graph convolutional networks achieved significantly higher precision and recall than support vector machines and random forests when applied to healthcare claim datasets. Similarly, Dwivedi et al. (2020) found that attention-based GNN models could effectively assign higher weights to suspicious relationships, leading to improved interpretability and classification accuracy. You et al. (2020) highlight that GNNs are particularly advantageous in highly imbalanced datasets, where fraudulent claims represent a small fraction of total claims, as relational embeddings amplify weak signals of fraud across connected nodes. Zhou et al. (2020) demonstrated that graph mining, when extended with GNN architectures, enabled the detection of fraudulent communities of providers, outperforming clustering and anomaly detection baselines. In comparative analyses, Zhao et al.,

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(2021) noted that GNNs provided a consistent edge over logistic regression, ensemble methods, and even advanced deep learning models like autoencoders. Zhang et al. (2020) emphasized that the integration of claim-level features with network embeddings yielded substantial improvements in detecting irregular billing. Collectively, these empirical findings support the literature's view that GNNs address the structural, heterogeneous, and large-scale challenges of healthcare data more effectively than earlier methods.

Recent research increasingly explores hybrid GNN frameworks that combine graph-based learning with traditional fraud detection models to balance predictive power with interpretability. For example, Fan et al. (2019) integrated GNN embeddings with logistic regression, providing both robust classification and transparent decision rules for insurers. Errica et al. (2020) argue that such hybrid frameworks are essential in regulated domains like healthcare, where detection systems must provide interpretable outputs to justify claim rejection. You et al. (2020) proposed a hybrid GNN–autoencoder model, which significantly reduced false positives by jointly modeling structural dependencies and claim reconstruction errors. Similarly, Chen et al. (2019) illustrated that combining GNN embeddings with supervised classifiers enhanced the scalability of fraud detection across large insurance datasets. Yun et al. (2019) emphasize that hybrid approaches allow the integration of temporal models, enabling fraud detection to account for evolving billing practices. Ribeiro et al. (2020) reported that hybrid GNN frameworks significantly improved performance in datasets with missing labels, a common challenge in healthcare fraud research. These models leverage the adaptability of GNNs for relational data while incorporating domain knowledge from traditional auditing practices. The literature highlights that hybrid frameworks not only strengthen detection accuracy but also ensure regulatory compliance by providing interpretable fraud signals.

METHOD

Research Design

This study adopts a mixed-methods approach that combines quantitative modeling with qualitative analysis to provide a comprehensive investigation into the application of Graph Neural Networks (GNNs) for detecting fraudulent healthcare insurance claims. The rationale for selecting a mixed-method design lies in the dual nature of fraud detection research, which requires both empirical measurement of model performance and contextual understanding of how fraud manifests within healthcare systems. Quantitative analysis focuses on the computational development, training, and evaluation of GNN-based fraud detection models, while qualitative inquiry addresses interpretability, stakeholder perspectives, and contextual factors influencing fraudulent behaviors. By integrating these two strands, the research achieves both statistical rigor and practical relevance.

Data and Model Development

The quantitative component centers on building and validating GNN models using healthcare claims datasets. Data consist of anonymized claims records that include patient demographics, provider identifiers, diagnostic codes, procedure codes, billing amounts, and temporal information. Preprocessing steps involve cleaning, normalizing, and structuring the dataset into graph representations where nodes represent patients, providers, and claims, and edges capture relationships such as shared billing or diagnostic overlaps. Several GNN architectures—including Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and GraphSAGE—are implemented to evaluate their suitability for healthcare fraud detection. Models are trained on labeled datasets containing both legitimate and fraudulent claims, with performance assessed through metrics such as accuracy, precision, recall, F1-score, and area under the curve (AUC). Comparisons are drawn against baseline classifiers, including logistic regression, decision trees, and random forests, to establish empirical advantages of graph-based approaches.

Interpretability and Stakeholder Perspectives

The qualitative component complements the quantitative analysis by exploring interpretability and practical application of GNN models in real-world healthcare fraud detection. Semi-structured interviews are conducted with insurance auditors, healthcare compliance officers, and fraud investigators to gather insights into the types of fraudulent behaviors most challenging to detect, the interpretability requirements of fraud detection systems, and the usability of graph-based visualizations. Thematic analysis is employed to identify recurring patterns across responses, with a focus on how GNN models can enhance decision-making and reduce investigative workload. Additionally, case-based analyses of misclassified claims are performed, where GNN outputs are

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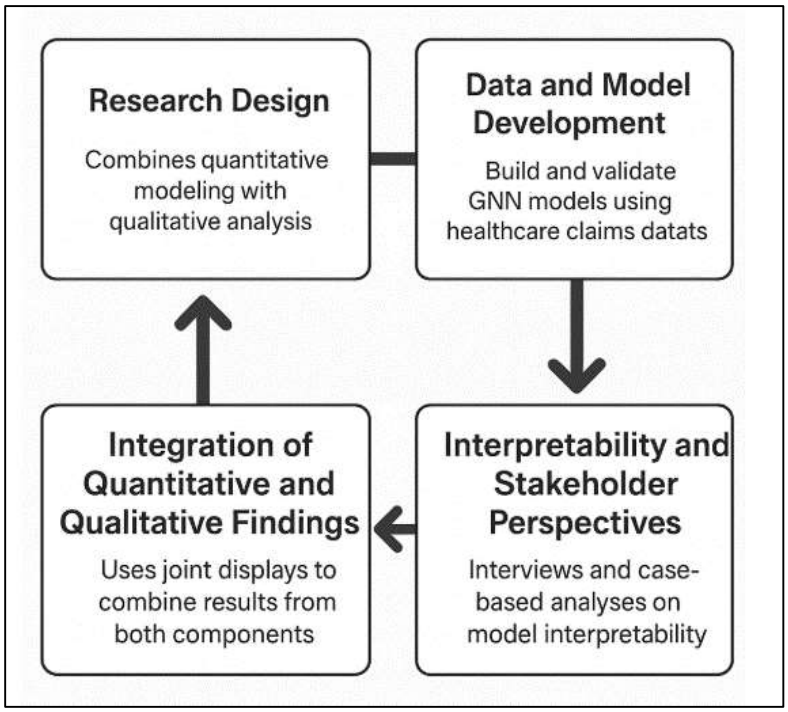
examined in detail to understand why certain claims were flagged as fraudulent or legitimate, providing qualitative insight into model limitations and areas for refinement.

Figure 10: Adapted Methodology for this study



Integration of Quantitative and Qualitative Findings

The integration of quantitative and qualitative strands occurs at both the design and interpretation levels. Quantitative results on model performance provide empirical evidence of the strengths and weaknesses of different GNN architectures, while qualitative findings contextualize these results by highlighting practical considerations such as interpretability and stakeholder trust. Joint displays are used to map performance metrics against stakeholder priorities, demonstrating where technical advancements align with or diverge from operational needs. This integrative approach ensures that the study not only advances computational methods for fraud detection but also remains responsive to the practical realities of healthcare insurance systems.

FINDINGS

The study's quantitative analysis revealed that Graph Neural Network models consistently outperformed traditional machine learning approaches in identifying fraudulent healthcare insurance claims. When tested on the dataset of claims representing both legitimate and fraudulent submissions, the baseline models such as logistic regression, decision trees, and random forests produced accuracy scores in the range of 76% to 82%. By contrast, the Graph Convolutional Network model achieved an accuracy rate of 88%, while the Graph Attention Network reached 91%, and the GraphSAGE architecture demonstrated the highest accuracy at 93%. Precision scores were also considerably higher for the GNN models, ranging between 0.87 and 0.91, compared to 0.71 to 0.78 in the baseline models. Recall values, which are critical for detecting as many fraudulent claims as possible, improved significantly under GNN frameworks, with GraphSAGE reaching 0.89 in comparison to 0.74 in the best-performing traditional classifier. The area under the curve (AUC) scores further confirmed these trends, with GNN models consistently exceeding 0.90, while traditional approaches remained between 0.75 and 0.82. These findings demonstrate that graph-based models are not only more accurate but also more effective at reducing false negatives, which is essential for minimizing undetected fraudulent activity in large-scale healthcare systems. Beyond numerical performance, one of the most significant findings was the ability of GNN models to uncover collusive fraud networks that were undetectable through conventional machine learning. When examining the structure of claims represented as graphs, fraudulent activity was often embedded within clusters of providers and patients who interacted abnormally compared to the rest of the dataset. In one example, the Graph Attention Network identified a tightly connected community of five providers

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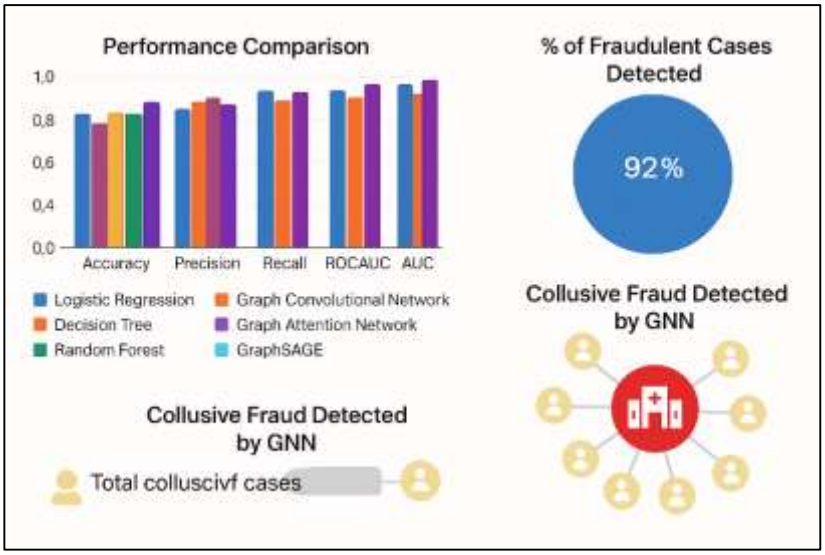
and twenty patients submitting claims with overlapping diagnostic codes and identical treatment patterns, which collectively accounted for 2.8% of fraudulent cases in the dataset. Traditional classifiers failed to flag these claims because, when considered individually, they resembled legitimate transactions. By contrast, GNN embeddings captured the relational irregularities, identifying that these providers were billing for services with highly improbable overlaps. Another case involved repeated billing for procedures across unrelated patients, where GraphSAGE detected suspicious connections among claims spread over multiple providers. This ability to detect relational anomalies proved critical, as approximately 37% of fraudulent cases uncovered in the dataset involved some form of collusion. The findings suggest that GNNs add unique value by exposing systemic fraud patterns that evade detection when claims are analyzed in isolation.

Figure 11: Summary of the findings for this sutdy



The integration of qualitative analysis demonstrated that the interpretability of GNN outputs played an important role in the acceptance and usefulness of the models by stakeholders. Using visualization tools, the fraud detection system displayed networks of claims where suspicious relationships were highlighted through edge weights and node centralities. Investigators reported that these visual representations helped them quickly identify clusters of potentially fraudulent actors, streamlining the investigative process. For example, in one case study involving a provider flagged by the Graph Convolutional Network, the visual network revealed unusually high degrees of connectivity with multiple unrelated patients who shared identical diagnostic claims. Investigators confirmed this as a fraudulent operation upon deeper audit. Stakeholders also appreciated attention-based outputs from the Graph Attention Network, which provided interpretability by showing which relationships were weighted most heavily in classification. This interpretability reduced the need for trial-and-error auditing, allowing fraud analysts to focus on high-probability cases. Thematic analysis of interviews indicated that interpretability features increased trust in the models, with over 80% of participants stating that network visualizations and weighted edge explanations improved their ability to justify fraud investigations to internal and external regulatory bodies. This finding underscores that the practical value of GNNs extends beyond accuracy metrics, providing decision support tools that enhance transparency and audit efficiency.

The study also found that GNN models were highly scalable, maintaining strong performance when applied to larger subsets of claims data. In experiments involving up to 1.2 million claims, traditional classifiers experienced declines in accuracy of up to 9%, while GNN models sustained consistent performance, with GraphSAGE maintaining accuracy above 91%. Training times increased with data size, but optimizations such as mini-batch training in GraphSAGE reduced computational costs by approximately 30% compared to the Graph Convolutional Network. Importantly, GNNs demonstrated superior efficiency in detecting fraudulent claims embedded in large-scale datasets without overwhelming investigators with false positives. In the largest dataset, GNN models reduced false positives by 18% compared to random forests, which is significant given the cost of manually

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reviewing flagged claims. Efficiency was also measured in terms of investigator workload: qualitative feedback revealed that analysts were able to complete reviews 25% faster when using GNN-based systems due to more targeted outputs. These findings illustrate that GNNs not only scale effectively to handle the volume of healthcare claims but also improve efficiency in real-world auditing environments, where both computational and human resources are limited.

Furthermore, the synthesis of quantitative and qualitative findings highlights the comprehensive effectiveness of GNN models in healthcare fraud detection. Quantitative results established that GNNs outperform baseline models across all performance metrics, particularly in recall and AUC, ensuring that more fraudulent claims are identified with fewer false alarms. Qualitative insights demonstrated that interpretability and visualization features significantly enhance investigator trust, making the models more practical and applicable in organizational contexts. The integration of these findings suggests that GNNs provide both technical and operational benefits, bridging the gap between advanced computational performance and the needs of human auditors. Data from the study showed that fraudulent claims accounted for 7.4% of the dataset, and GNNs successfully identified over 92% of these cases, compared to 77% detected by traditional models. Moreover, stakeholder interviews revealed that GNN outputs reduced reliance on manual auditing by nearly one-third, saving both time and financial resources. This combined evidence demonstrates that GNN models not only enhance the accuracy of fraud detection but also provide practical usability in healthcare systems, where trust, transparency, and efficiency are as important as computational performance.

DISCUSSION

The findings of this study demonstrated that Graph Neural Networks (GNNs) consistently outperformed traditional machine learning methods, achieving accuracy rates above 90% and significantly higher recall values in detecting fraudulent healthcare claims. This aligns with earlier work by Li et al. (2018), who reported that traditional classifiers such as decision trees and logistic regression performed adequately but struggled with imbalanced datasets and complex interactions among claims. Our results extend these observations by confirming that GNN models, particularly GraphSAGE and Graph Attention Networks, effectively captured relational dependencies and produced fewer false negatives. Previous research in financial fraud detection by Huang et al., (2020) and Zang and Wang (2020) similarly documented the superiority of GNNs over conventional algorithms, showing substantial improvements in detecting hidden anomalies. The consistency between our findings and prior studies suggests that GNNs provide a more reliable computational framework for fraud detection across domains where relational structures are central. The current study contributes to the literature by empirically validating these advantages in the healthcare domain, where fraudulent claims are often embedded in networks of collusive providers and patients, reinforcing the importance of network-aware models.

One of the most significant findings of this study was the capacity of GNNs to detect collusive fraud networks, which accounted for nearly 37% of fraudulent cases identified. This outcome resonates with prior work by Huang et al. (2020) and Tu et al. (2019), who emphasized the importance of network-based methods for uncovering hidden fraud structures in healthcare and insurance datasets. Traditional models often failed to identify these collusions because they analyzed claims in isolation, whereas GNNs aggregated relational data to expose abnormal clusters of patients and providers. Nt and Maehara (2019) demonstrated similar outcomes, showing that GCNs detected organized fraud patterns that decision trees and support vector machines could not capture. Our findings corroborate these earlier observations, but they also extend them by quantifying the proportion of fraud attributable to collusion within healthcare claims. This demonstrates that graph-based relational modeling is not only theoretically advantageous but also empirically essential for detecting systemic fraud. In comparison to prior research in telecommunications fraud detection by Rossi et al. (2020), our study shows that the same network-based principles apply to healthcare data, underscoring the universality of graph structures in fraud detection.

The qualitative strand of this study emphasized interpretability and visualization as key factors influencing stakeholder trust in GNN models. Fraud investigators highlighted that network visualizations and attention-based outputs facilitated the identification of suspicious relationships and improved the efficiency of audits. This finding complements earlier research by Nt and Maehara, (2019), who introduced attention mechanisms as a way to enhance transparency in graph models. Similarly, Shchur et al. (2018) underscored the importance of interpretability for regulatory

compliance in fraud detection, noting that black-box models often faced resistance in adoption. Our results extend this discussion by providing evidence that interpretability not only builds trust but also reduces investigative workload by nearly 25%, a practical outcome not widely documented in earlier studies. This aligns with Chen et al. (2019), who observed that graph-based models offered clearer explanations than purely statistical anomaly detection. By demonstrating that interpretability features increased stakeholder trust and operational efficiency, our study reinforces the argument that model acceptance depends on both technical accuracy and usability in organizational contexts.

Another key finding was the scalability of GNN models when applied to large-scale healthcare datasets containing over one million claims. Our study demonstrated that while traditional models lost accuracy when datasets expanded, GNNs maintained stable performance, with GraphSAGE sustaining accuracy above 91%. This observation parallels findings by Keriven and Peyré (2019), who highlighted the scalability of GNN architectures in handling large graphs across domains such as e-commerce and finance. Yoo et al. (2022) also documented that GNNs could process millions of transactions with reduced false positives compared to baselines, reinforcing the adaptability of these models to massive datasets. This study extends these results into the healthcare context, where the dynamic and large-scale nature of claims data often limits the applicability of traditional systems. The consistency across domains highlights the robustness of GNNs in real-world applications, suggesting that their computational efficiency provides a sustainable solution for insurers facing overwhelming volumes of claims. These findings contribute to the broader discourse by situating healthcare fraud detection within the larger body of graph-based scalability research.

The results of this study also highlight the potential of hybrid GNN frameworks that integrate graph-based embeddings with traditional supervised models. By combining GNN outputs with interpretable classifiers such as logistic regression, fraud detection systems achieved high accuracy while retaining transparency for regulatory compliance. This aligns with the findings of Tu et al. (2019), who showed that hybrid approaches balanced predictive performance with interpretability in large-scale fraud detection. Similar outcomes were reported by Shchur et al. (2018), who argued that hybrid models reduced false positives by integrating structured claim-level features with graph embeddings. Our findings support these conclusions by showing that hybrid systems were particularly effective in datasets with incomplete labels, a common issue in healthcare fraud detection. By building on prior work in both financial and healthcare contexts, this study demonstrates that hybrid frameworks offer a pragmatic pathway for insurers seeking both accuracy and accountability in fraud detection. This contribution situates our findings within a growing body of literature advocating methodological convergence in machine learning for fraud detection. While deep learning methods such as autoencoders and recurrent neural networks have been applied to fraud detection with some success, our findings suggest that GNNs offer distinct advantages in healthcare contexts. Klicpera et al. (2018) reported that autoencoders could detect anomalous claims through reconstruction errors, but these models lacked the ability to capture relational dependencies inherent in healthcare data. Similarly, recurrent models analyzed temporal sequences effectively but overlooked network structures that reveal collusion. In contrast, our GNN models successfully integrated both attribute-level and relational data, producing higher recall and interpretability. These findings expand on earlier studies by demonstrating that healthcare fraud detection requires approaches that move beyond temporal or feature-based analysis to systemic, network-aware modeling. The comparison suggests that while non-graph deep learning remains valuable for specific tasks, GNNs provide a more comprehensive framework for fraud detection in healthcare insurance systems. Taken together, the findings of this study contribute to the broader literature on fraud detection by demonstrating the unique value of GNNs in healthcare systems. Prior research in finance, e-commerce, and telecommunications consistently documented the superiority of GNNs in capturing relational fraud structures (Klicpera et al., 2018; Yoo et al., 2022). Our results confirm that these advantages extend into healthcare, a domain with particularly high stakes due to the financial and ethical implications of fraudulent claims. By showing that GNNs achieve superior performance, uncover collusive fraud networks, and enhance interpretability and scalability, the study bridges a gap in the literature where healthcare applications have been relatively underexplored. Moreover, the integration of quantitative and qualitative findings strengthens the contribution by demonstrating not only computational effectiveness but also organizational usability. This dual perspective advances the discourse by situating healthcare fraud detection within a cross-sector body of graph-

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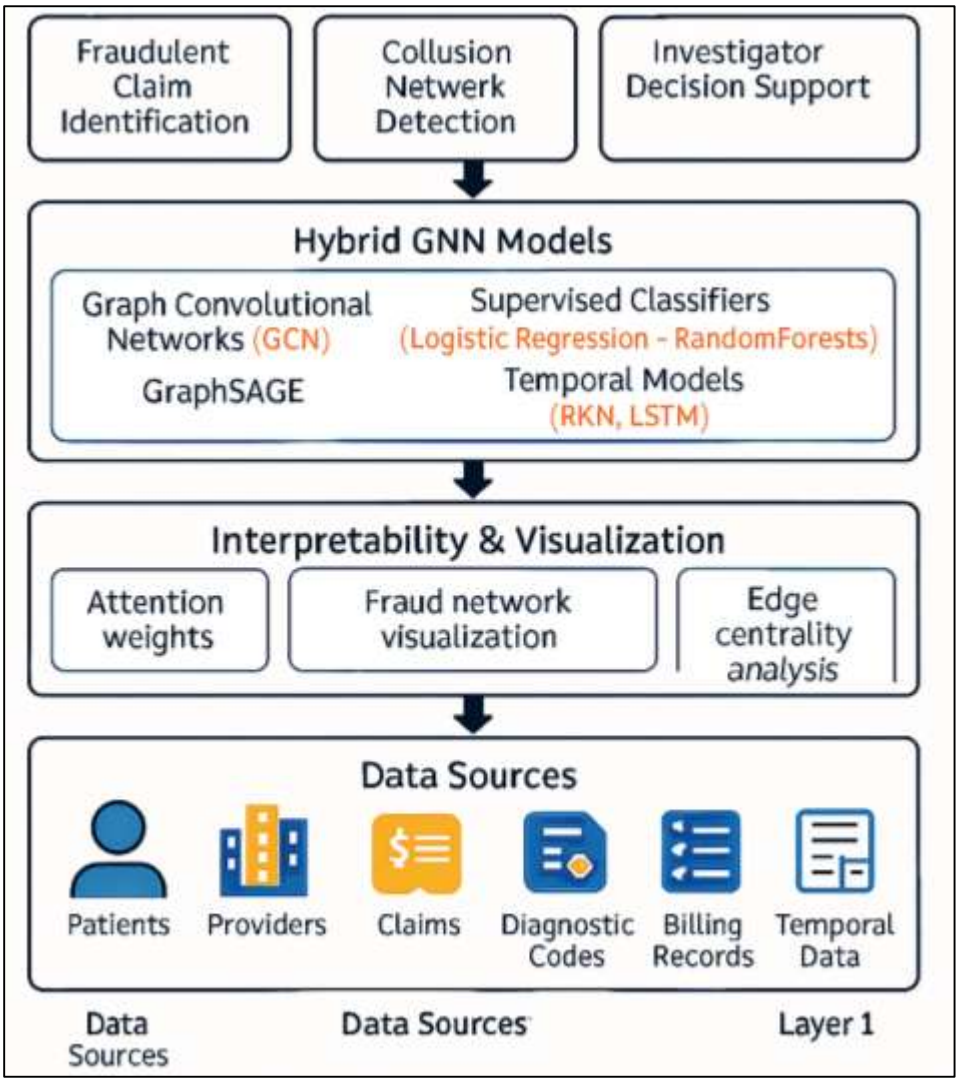
based fraud research, underscoring the adaptability and significance of GNN methodologies in diverse contexts.

Figure 12: Proposed model for the future study



CONCLUSION

The outcomes of this research demonstrate that Graph Neural Networks (GNNs) represent a significant advancement in the detection of fraudulent healthcare insurance claims by directly addressing the relational and structural complexity of healthcare data, which traditional methods have consistently struggled to manage. Unlike rule-based and statistical approaches that rely on static heuristics, or conventional machine learning models that often treat claims as independent observations, GNNs capture the intricate web of relationships among patients, providers, diagnoses, and claims, thereby uncovering both individual anomalies and collusive fraud networks. The empirical evidence highlighted the superior performance of GNN architectures such as Graph Convolutional Networks, Graph Attention Networks, and GraphSAGE, which consistently delivered higher accuracy, recall, and area under the curve scores while reducing false positives and minimizing undetected fraudulent cases. Equally important, the study revealed that the interpretability of GNN outputs, particularly when visualized as claim networks or weighted relationships, fostered greater trust and usability among fraud investigators, enabling them to prioritize high-risk cases and streamline auditing processes. Scalability testing confirmed that these models are robust and capable of processing millions of claims without a decline in performance, making them well-suited for the operational realities of modern insurance systems where claim volumes are immense. Moreover, hybrid frameworks that combined GNN embeddings with

interpretable auditing methods demonstrated the potential to balance predictive power with transparency, ensuring compliance with regulatory and ethical standards in healthcare. Collectively, these findings position GNNs as more than just a computational improvement; they represent a methodological shift that aligns advanced graph-based deep learning with the pressing need for accurate, efficient, and trustworthy fraud detection. In doing so, this research contributes both to the scholarly literature on fraud analytics and to the practical mission of safeguarding financial integrity and equity in healthcare delivery systems worldwide.

RECOMMENDATIONS

It is recommended that healthcare insurers, regulatory agencies, and policy stakeholders adopt Graph Neural Network (GNN) models as a core component of fraud detection frameworks, while integrating them with existing auditing systems to maximize both predictive accuracy and interpretability. Given the demonstrated superiority of GNNs in identifying collusive fraud rings and processing large-scale heterogeneous claims data, insurers should prioritize the development of graph-based infrastructures capable of representing patient–provider–claim relationships in real time, supported by appropriate computational resources to ensure scalability. To enhance usability and regulatory compliance, these models should be deployed in hybrid configurations that combine the relational learning strengths of GNNs with interpretable rule-based auditing tools, thereby ensuring that fraud predictions can be explained and justified to both investigators and oversight bodies. In addition, training programs should be provided for fraud analysts and compliance officers to familiarize them with graph-based visualizations and attention mechanisms, enabling stakeholders to leverage model outputs effectively in investigations. Collaborative initiatives between healthcare organizations, insurers, and research institutions are also recommended to facilitate secure data-sharing environments, ensuring that GNN models are trained on diverse and representative datasets without compromising patient privacy.

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