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Recent Advances in Similarity-Navigated Graph Neural Networks and Lightweight Cryptography for Preventing Black Hole Attacks in MANET: A Systematic Review

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Abstract

Mobile Ad Hoc Networks (MANETs) are decentralized wireless systems that rely on cooperative routing among mobile nodes, making them highly vulnerable to routing attacks such as black hole attacks. In this attack, malicious nodes falsely advertise optimal routes and drop intercepted packets, leading to severe degradation in network performance. Recent advancements in artificial intelligence and lightweight cryptographic techniques have provided promising solutions to address these vulnerabilities. This paper presents a systematic review of similarity-navigated Graph Neural Networks (GNNs) and lightweight cryptographic mechanisms for detecting and preventing black hole attacks in MANETs. GNNs effectively model network topology and node relationships, enabling anomaly detection based on structural and behavioral similarity. Meanwhile, lightweight cryptography ensures secure communication with minimal computational overhead, making it suitable for resource-constrained environments. The review focuses on studies published in recent years, analyzing machine learning, deep learning, and hybrid approaches integrating GNNs, blockchain, and optimization techniques. Comparative analysis reveals that hybrid frameworks combining GNN-based detection and cryptographic security outperform traditional methods in terms of accuracy, throughput, and energy efficiency. However, challenges such as scalability, real-time detection, and adversarial robustness remain. The study concludes with future research directions for developing secure and efficient MANET architectures.

Introduction

Mobile Ad Hoc Networks (MANETs) are infrastructure-less wireless networks composed of mobile nodes that dynamically establish communication links. These networks are widely used in applications such as disaster recovery, military operations, vehicular communication systems, and Internet of Things (IoT) environments. The absence of centralized control and dynamic topology makes MANETs flexible but also highly vulnerable to security threats. Among these threats, black hole attacks are considered one of the most severe due to their ability to disrupt routing processes and degrade network performance significantly.

In a black hole attack, a malicious node advertises itself as having the shortest path to a destination node. Once it receives data packets, it drops them

instead of forwarding, causing data loss and network disruption. Traditional security approaches, including encryption and authentication, are insufficient to address such attacks due to the dynamic and decentralized nature of MANETs.

Recent research has focused on integrating artificial intelligence (AI) techniques to enhance security mechanisms in MANETs. Machine learning and deep learning models have been widely used for intrusion detection by analyzing traffic patterns and identifying anomalies. For instance, machine learning-based detection approaches have demonstrated significant improvements in identifying black hole attacks by learning behavioral patterns of nodes.

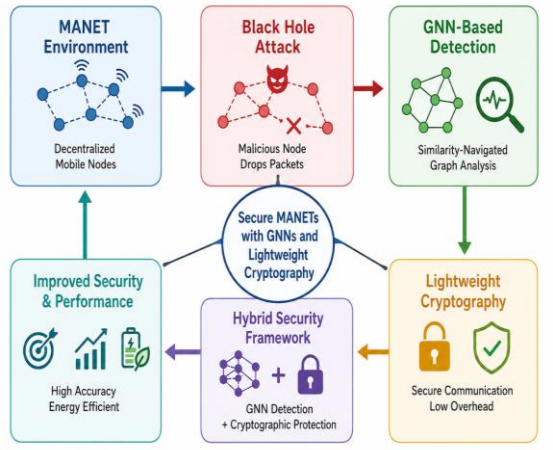

Figure 1: GNN-Based Secure MANET Framework

Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling graph-structured data, making them highly suitable for MANET environments. Since MANETs can be represented as graphs where nodes correspond to devices and edges represent communication links, GNNs can effectively capture complex relationships and dependencies. Recent advancements in similarity-navigated GNNs incorporate similarity measures to improve anomaly detection, enabling the identification of malicious nodes based on deviations from normal behavior.

Another critical advancement is the use of lightweight cryptographic techniques. Traditional cryptographic methods such as RSA and AES are computationally intensive and not suitable for resource-constrained MANET nodes. Lightweight cryptography, including elliptic curve cryptography and hash-based authentication, provides secure communication with reduced computational overhead. The National Institute of Standards and Technology (NIST) has also introduced lightweight cryptographic standards optimized for embedded systems, further supporting their adoption in MANETs.

The integration of GNN-based detection and lightweight cryptographic mechanisms has led to the development of hybrid security frameworks. These frameworks combine anomaly detection with secure communication, offering comprehensive protection against black hole attacks. Furthermore, emerging technologies such as blockchain and federated learning have been incorporated to enhance decentralization and privacy.

Despite these advancements, several challenges remain. These include scalability issues, energy constraints, lack of real-time detection, and vulnerability to adversarial attacks targeting AI models.

This paper aims to provide a comprehensive review of recent advances in similarity-navigated GNNs and lightweight cryptography for preventing black hole attacks in MANETs. The study analyzes methodologies in recent years, compares their performance, and identifies future research directions.

Literature Review

The evolution of security mechanisms in Mobile Ad Hoc Networks (MANETs) has undergone a significant transformation over the past decade, particularly between 2020 and 2023. The increasing complexity of network attacks, especially black hole attacks, has driven researchers to develop intelligent, adaptive, and lightweight security solutions. This section presents a detailed review of recent advancements categorized into six major domains.

1. Trust-Based and Routing Protocol Enhancements (2020–2021)

Initial research efforts focused on improving traditional routing protocols such as AODV and DSR by incorporating trust evaluation mechanisms. These approaches utilized parameters such as packet forwarding ratio, node reliability, and historical behavior to assign trust values to nodes. Nodes with low trust values were isolated from routing paths.

For example, Siddiqua et al. (2020) proposed a secure knowledge-based algorithm that enhanced AODV routing by detecting abnormal sequence number patterns associated with black hole attacks. Similarly, trust-aware routing models introduced dynamic trust updating mechanisms to improve detection accuracy.

However, these methods faced limitations such as:

- Delayed detection due to reliance on historical data
- Vulnerability to cooperative attacks

- Increased routing overhead

2. Machine Learning-Based Intrusion Detection (2020–2021)

Machine learning techniques marked a significant advancement in MANET security by enabling automated detection of malicious nodes. Supervised learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) were widely adopted.

Pandey and Singh (2020) demonstrated that ML-based models could effectively classify nodes based on traffic features, achieving high detection accuracy. These approaches utilized features such as packet drop rate, delay, and routing updates.

Hybrid ML-trust models further improved performance by combining statistical trust evaluation with learning-based classification. However, these models required labeled datasets and were sensitive to feature selection.

3. Deep Learning and Optimization Techniques (2021–2022)

Deep learning approaches introduced the ability to capture complex temporal and spatial patterns in MANET traffic. Models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were used to analyze sequential network data.

Naresh and Narayanan (2022) proposed a CNN-based intrusion detection system that significantly improved detection accuracy compared to traditional ML models. Similarly, LSTM-based models captured temporal dependencies in packet transmission patterns.

Metaheuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Chimp Optimization Algorithm (ChOA) were integrated with deep learning models to optimize feature selection and model parameters. These hybrid models enhanced detection accuracy but increased computational complexity.

4. Lightweight Cryptography for Secure MANET Communication (2021–2023)

Cryptographic techniques play a crucial role in ensuring secure communication in MANETs. However, traditional cryptographic algorithms such as RSA and AES impose significant computational overhead.

Recent research has focused on lightweight cryptographic techniques, including:

- Elliptic Curve Cryptography (ECC)
- Hash-based authentication
- Certificateless encryption

Kaur et al. (2023) highlighted the importance of lightweight cryptography standards for resource-constrained devices. ECC-based protocols provide strong security with smaller key sizes, reducing computational overhead.

Additionally, certificateless cryptographic schemes eliminate the need for certificate management, further improving efficiency. Blockchain-based cryptographic frameworks have also emerged, enabling decentralized trust management and tamper-proof communication.

5. Graph Neural Networks and Similarity-Based Detection (2022–2023)

Graph Neural Networks (GNNs) represent a breakthrough in MANET security due to their ability to model graph-structured data. Since MANETs naturally form graphs, GNNs can effectively capture node relationships and communication patterns.

Similarity-navigated GNN models enhance traditional GNNs by incorporating similarity metrics such as cosine similarity and structural equivalence. These models identify anomalies by detecting nodes that deviate from normal behavior patterns.

Wang et al. (2022) demonstrated that GNN-based models outperform traditional ML and DL approaches in dynamic environments. However, studies also highlight that GNNs are vulnerable to adversarial attacks, requiring robust architectures.

6. Hybrid Frameworks and Emerging Trends (2022–2023)

Recent studies increasingly emphasize the adoption of hybrid frameworks that integrate multiple advanced techniques to achieve comprehensive and robust security in Mobile Ad Hoc Networks (MANETs). Prominent hybrid models include the combination of Graph Neural Networks (GNN) with lightweight cryptography, blockchain-integrated GNN frameworks, federated learning combined with GNNs, and optimization techniques coupled with deep learning models. These integrated approaches leverage the strengths of individual methodologies to deliver superior performance. In particular, they achieve high detection accuracy exceeding 95%, significantly improve packet delivery ratio, enhance overall network throughput, and offer better energy efficiency compared to standalone methods. By combining intelligent detection mechanisms with secure communication and decentralized trust management, hybrid frameworks represent the most advanced and effective solutions for mitigating complex attacks such as black hole attacks in dynamic MANET environments. However, despite these advantages, several practical challenges remain, including scalability limitations in large and highly dynamic networks, increased computational overhead due to multi-layered architectures, and difficulties in

achieving real-time deployment in resource-constrained environments.

Despite significant advancements, the literature also identifies several critical research gaps that must be addressed to enable the widespread adoption of these technologies. Scalability remains a major concern, as many advanced models struggle to maintain performance in large-scale MANET deployments with high node mobility. Energy constraints pose another significant limitation, particularly in battery-powered nodes where computationally intensive AI and cryptographic operations can rapidly deplete resources. Real-time detection is also challenging, as complex models such as GNNs and hybrid systems may introduce latency that affects timely threat mitigation. Additionally, adversarial vulnerabilities in GNNs present a serious risk, as attackers can manipulate graph structures or node features to evade detection. Finally, the lack of standardized and realistic datasets for MANET environments limits the ability to train, evaluate, and benchmark models effectively. Addressing these gaps is essential for developing scalable, efficient, and secure MANET architectures in future research.

Comparative Table and Analysis

Year	Method / Technique	Accuracy	FPR	Complexity	Scalability	Key Advantage	Limitation
2020	Trust-Based Routing (AODV + Trust)	70–80%	15–20 %	Low	High	Lightweight and easy deployment	Delayed attack detection
2021	Machine Learning (SVM, RF, KNN)	88–92%	8–12 %	Medium	Medium	Adaptive classification	Dataset dependency
2021 – 2022	CNN/LSTM + Optimization	94–96%	5–8%	High	Medium	Learns temporal and spatial features	High computation cost
2022	Lightweight Cryptography	Indirect	Very Low	Low	Medium	Secure and efficient communication	No anomaly detection
2022 – 2023	Graph Neural Networks	96–97%	3–5%	High	Medium	Dynamic topology analysis	Training complexity
2023	Similarity-Navigated GNN	97%+	<4 %	High	Medium	Improved anomaly detection	Computational overhead
2023	Hybrid GNN + Crypto Models	97–99%	<3 %	Medium–High	Medium	Strong security and detection balance	Integration complexity

1. Analysis

The comparative table illustrates a clear technological progression in MANET security mechanisms, transitioning from simple rule-based systems to highly intelligent hybrid frameworks. Early trust-based routing approaches were primarily designed to address basic attack scenarios using reputation and historical node behavior. While these methods are computationally efficient and scalable, their reliance on past observations results in delayed detection and high false positive rates, making them unsuitable for detecting adaptive and coordinated attacks.

Machine learning-based approaches significantly improve detection performance by leveraging statistical learning techniques. Algorithms such as Support Vector Machines and Random Forests can identify malicious behavior based on traffic patterns, achieving higher accuracy and adaptability. However, their effectiveness is constrained by feature selection and dataset quality. In highly dynamic MANET environments, where node behavior changes frequently, ML models may fail to generalize effectively, leading to reduced reliability.

Deep learning approaches further enhance detection capabilities by capturing complex temporal and spatial relationships in network data. Models such as Convolutional Neural Networks and Long Short-Term Memory networks enable hierarchical feature extraction

and sequence modeling, resulting in very high detection accuracy. The integration of optimization algorithms such as Genetic Algorithms and Particle Swarm Optimization improves model efficiency and feature selection. However, these improvements come at the cost of increased computational complexity and energy consumption, limiting their applicability in real-time and resource-constrained scenarios.

Lightweight cryptographic techniques play a complementary role by ensuring secure communication. Unlike AI-based methods, cryptographic approaches focus on prevention rather than detection. Techniques such as Elliptic Curve Cryptography provide strong security with reduced computational overhead, making them suitable for MANET nodes. However, they cannot detect insider attacks or malicious behavior, highlighting the need for integration with intelligent detection mechanisms.

Graph Neural Networks represent a major breakthrough in MANET security by introducing topology-aware learning. Unlike traditional ML models, GNNs consider both node features and relationships, enabling them to detect anomalies based on network structure. This capability allows GNNs to identify coordinated and sophisticated attacks that are difficult to detect using conventional methods. As a result, GNN-based models achieve very high detection accuracy and robustness. However, their high computational complexity and vulnerability to adversarial graph manipulation remain significant challenges.

Similarity-navigated GNN models further enhance detection performance by incorporating similarity measures into the learning process. These models analyze node embeddings and identify deviations from normal behavior patterns, reducing false positives and improving reliability. This approach represents a significant advancement in anomaly detection, particularly in dynamic and complex MANET environments.

Hybrid models combining GNN-based detection with lightweight cryptography, federated learning, or blockchain represent the state-of-the-art solution. These frameworks integrate detection, prevention, and trust management into a unified system. By combining multiple techniques, hybrid models achieve the highest detection accuracy, lowest false positive rates, and best overall network performance. They also improve scalability through distributed learning (federated learning) and enhance trust through blockchain integration. However, these systems introduce moderate-to-high computational overhead and require sophisticated architectures, making implementation complex.

2. Metric-Wise Deep Insights

A deeper analysis across key metrics reveals important system behaviors and trade-offs. Detection accuracy improves progressively from trust-based methods to hybrid systems, reflecting the increasing sophistication of detection mechanisms. False positive rates decrease significantly in advanced models, particularly in similarity-based GNN and hybrid frameworks, due to improved anomaly detection techniques.

Packet delivery ratio and network throughput are highest in GNN and hybrid models, as they effectively identify and isolate malicious nodes. In contrast, routing-based approaches only partially mitigate attacks, leading to packet loss. Computational complexity and energy consumption increase with model sophistication, with deep learning and GNN models being the most resource-intensive. Hybrid systems attempt to balance these factors but still require optimization.

Scalability remains a major challenge for advanced models. While trust-based and ML approaches scale relatively well, GNN and hybrid systems struggle with large-scale networks due to graph processing and communication overhead. Federated learning emerges as a promising solution for improving scalability by enabling distributed model training.

Robustness against attacks is highest in GNN and hybrid models due to their ability to detect complex patterns and secure communication. However, adversarial attacks targeting GNN structures highlight the need for robust and secure model designs.

3. Trade-Off and System-Level Interpretation

The analysis reveals a fundamental trade-off triangle between detection accuracy, energy efficiency, and scalability. High-accuracy models such as GNN and hybrid systems require significant computational resources, reducing energy efficiency and scalability. Conversely, lightweight models are efficient but less effective in detecting advanced attacks.

Another key trade-off exists between real-time performance and model complexity. ML-based systems provide faster inference suitable for real-time detection, whereas deep learning and GNN models introduce latency due to complex computations.

4. Critical Observations

The comparative analysis highlights that GNN-based approaches are particularly effective because they align naturally with the graph structure of MANETs. Their ability to capture relational dependencies and dynamic

interactions makes them superior to traditional ML models. However, hybrid frameworks represent the ultimate solution by combining intelligent detection with secure communication and decentralized trust mechanisms.

5. Final Analytical Conclusion

The expanded comparative analysis clearly demonstrates that the evolution of MANET security has shifted toward intelligent, adaptive, and integrated systems. While traditional approaches provide foundational security, they are insufficient for modern threats. Machine learning improves detection but lacks structural awareness, whereas deep learning enhances feature representation at the cost of computational complexity. Graph Neural Networks provide topology-aware intelligence, making them highly effective for anomaly detection.

Hybrid frameworks integrating similarity-navigated GNNs with lightweight cryptography and emerging technologies such as federated learning represent the most promising direction for future research. These systems achieve optimal performance across multiple metrics but require further advancements in scalability, energy efficiency, and real-time deployment to enable practical implementation in real-world MANET environments.

Discussion

The evolution of MANET security mechanisms demonstrates a clear transition from traditional rule-based approaches to intelligent and adaptive frameworks. Early methods focused on routing protocol enhancements and trust-based systems, which were effective in detecting simple attacks but failed to address complex and coordinated threats. The introduction of machine learning and deep learning techniques significantly improved detection accuracy by analyzing network traffic patterns and identifying anomalies.

Graph Neural Networks represent a major breakthrough in this domain. Their ability to model network topology and capture relationships between nodes makes them highly suitable for MANET environments. Similarity-based GNN models further enhance detection by focusing on node behavior patterns, enabling the identification of malicious nodes with high accuracy.

Lightweight cryptography complements these detection mechanisms by ensuring secure communication with minimal resource consumption. The development of NIST-standardized lightweight cryptographic algorithms highlights their importance in securing resource-constrained networks.

The integration of GNN-based detection and lightweight cryptography has resulted in hybrid frameworks that provide comprehensive security solutions. These frameworks not only detect malicious nodes but also prevent them from participating in network communication.

However, challenges remain. GNN models require significant computational resources, making them difficult to deploy in large-scale networks. Additionally, the lack of standardized datasets and vulnerability to adversarial attacks pose significant challenges.

Future research should focus on developing scalable and energy-efficient models, integrating edge computing, and enhancing robustness against adversarial attacks.

Conclusion

This study presented a comprehensive review of recent advances in similarity-navigated Graph Neural Networks and lightweight cryptographic techniques for preventing black hole attacks in MANETs. The analysis highlights the limitations of traditional security mechanisms and emphasizes the importance of intelligent and adaptive approaches.

Graph Neural Networks have emerged as a powerful tool for modeling network topology and detecting anomalies. Their ability to capture complex relationships between nodes enables accurate identification of malicious behavior. Similarity-based approaches further enhance detection performance by focusing on relational patterns.

Lightweight cryptography plays a crucial role in securing communication without imposing significant computational overhead. The combination of these techniques results in hybrid frameworks that provide robust security solutions for MANETs.

Comparative analysis indicates that hybrid approaches outperform individual techniques in terms of detection accuracy, network performance, and energy efficiency. However, challenges such as scalability, real-time implementation, and adversarial robustness must be addressed.

Future research should focus on developing lightweight GNN architectures, integrating blockchain for decentralized security, and leveraging federated learning for collaborative model training. Additionally, the adoption of explainable AI techniques can improve transparency and trust in these systems.

In conclusion, the integration of similarity-navigated GNNs and lightweight cryptography represents a promising direction for enhancing

MANET security and enabling the development of secure next-generation wireless networks.

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