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A HYBRID APPROACH FOR INTRUSION DETECTION AND PRE VENTION IN MOBILE AD HOC NETWORKS

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ABSTRACT

Mobile Ad Hoc Networks (MANETs) are highly dynamic and decentralized, making them vulnerable to various security threats, especially intrusion attacks. This paper presents a hybrid approach combining machine learning techniques and trust-based systems for efficient intrusion detection and prevention in MANETs. The proposed system leverages feature extraction, anomaly detection, and node trust evaluation to identify malicious activities while ensuring minimal impact on network performance. Experimental results demonstrate that our approach outperforms existing methods in terms of detection accuracy, false positive/negative rates, and computational overhead. Specifically, it achieves a significant improvement in energy efficiency and network reliability under varying network conditions, including node mobility and density. The findings highlight the effectiveness of integrating machine learning with trust-based systems for securing MANETs. Future work will explore scalability improvements and the integration of hybrid detection mechanisms to enhance system robustness.

Keywords: *Mobile Ad Hoc Networks (MANETs), Intrusion Detection, Prevention Mechanisms, Machine Learning, Trust-Based Systems, Hybrid Approach, Security, Data Integrity, Anomaly Detection, Energy Efficiency.*

1. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) are decentralized, self-configuring networks where nodes (typically mobile devices or sensors) communicate directly without relying on fixed infrastructure. This dynamic, infrastructure-less nature allows MANETs to be highly flexible and scalable, making them suitable for various applications, including military networks, emergency response systems, and the Internet of Things (IoT) (Sivaram et al., 2019). However, the absence of central control in MANETs introduces significant security vulnerabilities. These networks are particularly susceptible to malicious attacks, as there is no centralized authority to enforce security policies or ensure trustworthiness among nodes (Saravanan et al., 2025). The lack of infrastructure in MANETs means that communication paths are dynamic and constantly changing, which complicates the detection of malicious activities. As a result, attacks such as Sybil, black hole, and wormhole attacks can be easily executed by compromised nodes (Sultan et al., 2023). These attacks exploit the trust less nature of the network to degrade data integrity, compromise the reliability of communication, and disrupt the network's performance (Sivaram et al., 2019). This

necessitates the development of robust detection and prevention mechanisms to safeguard against such threats.

Intruder nodes within a MANET pose a serious risk to data integrity and network reliability. Malicious nodes can disrupt normal network operations by compromising routing protocols, dropping or altering data packets, and creating network partitions. These actions undermine the network's security, availability, and reliability, leading to potential data loss, service degradation, and unauthorized access (Sultan et al., 2023). Consequently, it is essential to develop effective detection systems that can identify these intrusions in real time and mitigate the impact on the network's operations. This research aims to address the critical need for advanced detection and prevention mechanisms in MANETs. By leveraging machine learning models and trust-based systems, we propose a comprehensive approach that can identify and prevent malicious activities within the network. The primary objective is to design a system that ensures high detection accuracy while minimizing computational overhead, thus maintaining the efficiency of MANETs under varying conditions of node mobility and network density (Saravanan et al., 2025).

a) Detection Techniques

Recent research on intrusion detection in MANETs has predominantly focused on anomaly-based and signature-based techniques. Anomaly-based detection methods, such as the one proposed by S. Saravanan et al. (2023) using Graph Neural Networks (GNNs), have demonstrated high detection accuracy (95%) and adaptability to dynamic environments. However, these methods often suffer from computational complexity, which limits their practical application in resource-constrained settings. Similarly, Ercan et al. (2021) applied machine learning techniques for misbehaviours detection in VANETs, achieving an accuracy of 87%. While relevant, these methods require adaptation to address the broader spectrum of attacks specific to MANETs. On the other hand, signature-based detection methods, such as the system developed by A. Banerjee et al. (2020), have effectively leveraged historical data to identify known threats, achieving a detection accuracy of 91%. However, they often struggle with high false-positive rates and lack adaptability to new and emerging attack types.

b) Prevention Mechanisms

Prevention mechanisms for intrusions in MANETs have primarily revolved around cryptographic methods and trust models. Cryptographic approaches, such as the AI-driven Intrusion Detection and Prevention System proposed by Al-Rubaye et al. (2024), leverage advanced algorithms like CNN and RF to autonomously prevent a wide range of attacks. Despite their potential, these methods are often resource-intensive, making them challenging to implement in environments with limited computational capacity. Trust models, such as the energy-efficient trust-based routing algorithm developed by Hajiee et al. (2021), provide an alternative by focusing on building trust among nodes, thereby improving energy efficiency by 25%. However, these models, while effective for WSNs, require adaptation to the dynamic and decentralized characteristics of MANETs for broader applicability.

c) Limitations of Current Approaches

Despite significant advancements, existing approaches face several critical limitations. High computational complexity remains a barrier, particularly for deep learning-based techniques like ANNs, which require substantial processing power and large datasets. Scalability is another challenge, as many methods fail to maintain performance in large or highly dynamic networks. Additionally, the majority of studies rely on simulated environments for validation, which raises questions about their reliability and applicability in real-world scenarios. Finally, most current solutions are narrowly focused, addressing specific types of attacks but lacking the flexibility to adapt to evolving or multi-faceted threats.

d) Research Gaps and Contributions

This review highlights several gaps in the existing literature, including the need for scalable, resource-efficient, and comprehensive solutions for intrusion detection and prevention in MANETs. This research aims to address these gaps by proposing a lightweight hybrid model that integrates anomaly-based and signature-based techniques, thereby enhancing detection accuracy and adaptability. Furthermore, energy-efficient algorithms will be developed to reduce computational overhead without compromising performance. Validation will be extended to real-world scenarios to ensure reliability and practical applicability. Additionally, this research will focus on addressing multi-faceted threats through adaptive methodologies that evolve in response to emerging attack vectors. By addressing these challenges and bridging these gaps, this study seeks to contribute to the development of robust, practical, and scalable security solutions for MANETs.

e) Contribution:

This article introduces a novel hybrid approach combining machine learning and trust-based systems to detect and mitigate intruder nodes in MANETs. This method improves upon existing intrusion detection systems (IDS) by offering enhanced detection capabilities with lower computational complexity (Sultan et al., 2023). Additionally, it adapts to the dynamic nature of MANETs, allowing for real-time identification and isolation of malicious nodes. This contributes to the development of more reliable, scalable, and energy-efficient intrusion detection systems for MANETs, ensuring that security does not compromise the performance of the network (Saravanan et al., 2025; Sivaram et al., 2019).

The article is organized into six key sections. The Introduction provides background on the dynamic and decentralized nature of MANETs, highlighting their vulnerabilities and the issue of intruder nodes compromising network reliability. It also outlines the objective of developing robust detection and prevention mechanisms and introduces the contribution of the proposed hybrid approach. The Related Work section reviews existing intrusion detection techniques, including machine learning, trust-based methods, and hybrid solutions, while identifying their strengths, limitations, and research gaps. In the Proposed Methodology, the article details the detection and prevention algorithms, system architecture, and key components such as feature extraction, machine learning techniques, and communication protocol considerations. It also describes the dataset and simulation environment used. The Experimental Results section evaluates the performance of the proposed approach, comparing it with existing methods using metrics like detection accuracy and energy efficiency, and provides statistical analysis of the results. The Discussion interprets the results, emphasizing the approach's strengths, limitations, and real-world applicability. Finally, the Conclusion summarizes the findings, underscores the impact on MANET security, and suggests future research directions to address scalability and explore hybrid approaches.

2. RELATED WORK

Mobile Ad Hoc Networks (MANETs) are decentralized, self-configuring networks that are inherently susceptible to various security threats due to their dynamic topology and lack of a centralized authority. Intrusion Detection and Prevention Systems (IDPS) play a critical role in safeguarding MANETs by identifying and mitigating malicious activities. This survey summarizes recent advancements in intrusion detection and prevention techniques in MANETs, focusing on methods proposed between 2019 and 2024. The table highlights key methodologies, performance metrics, merits, demerits, and potential future enhancements for various approaches.

Sivaram et al. (2019) introduced an improved DBTMA protocol with contention-aware admission control, improving throughput by 15%. This work focuses on network performance with indirect applications to intrusion detection. Future research will integrate this approach with IDS and evaluate its security performance. S. Alyahya and A. M. Alghamdi (2019) conducted a review of Intrusion Detection and Prevention Systems (IDPS) in MANETs, offering a comprehensive analysis of existing techniques. However, the study lacked experimental validation and novel methodologies. Future work involves empirical evaluation and the proposal of hybrid IDPS approaches. P. El-Kafrawy et al. (2019) provided a comprehensive review of AI techniques for Intrusion Detection Systems, covering various methodologies. However, the review lacks experimental data and specific applications to MANETs. Future work includes applying these techniques to MANET-specific scenarios with empirical validation.

A. Banerjee et al. (2020) developed an Advanced Intrusion Detection System using Machine Learning algorithms, achieving a detection accuracy of 91%. While the system utilizes multiple algorithms for enhanced detection, it suffers from a high false positive rate and computational overhead. Future efforts will focus on reducing false positives and enabling real-time implementation. Bhatia and D. Khattar (2020) proposed a hybrid approach for intrusion detection in MANETs, achieving a detection rate of 89%. Their approach combines multiple detection techniques for better accuracy but adds complexity and resource consumption. Simplifying the system architecture and focusing on energy-efficient solutions are the next steps.

Quy et al. (2021) analyzed QoS-aware routing protocols for MANET-WSN convergence in IoT, with implications for security. Their theoretical analysis lacks a focus on intrusion detection. Future work involves developing secure QoS-aware protocols for enhanced security. Ercan et al. (2021) applied machine learning for detecting

misbehaviours in VANETs, achieving a detection accuracy of 87%. Although relevant to MANETs, the methodology is specific to VANETs and may not directly apply. Future efforts will adapt this approach for MANETs and explore other attack types. R. Dhanalakshmi and M. V. Ramesh (2021) conducted a survey of Intrusion Detection Systems for MANETs, identifying gaps in current research. The study provides extensive reviews but lacks practical implementation. Future research involves developing practical IDS models to address the identified gaps. Hajiee et al. (2021) proposed an energy-efficient trust and opportunity-based routing algorithm for WSNs, improving energy efficiency by 25%. Though specific to WSNs, this algorithm has potential applications in MANETs. Future work includes adapting it to MANETs and integrating it with intrusion detection mechanisms. Yue et al. (2021) reviewed blockchain applications in 5G, with potential implications for MANET security. The study focuses on general applications with indirect relevance. Future efforts involve developing blockchain-based security solutions for MANETs and validating their effectiveness. Khraisat and Alazab (2021) critically reviewed IDS in IoT, offering insights into techniques and challenges. This comprehensive review is relevant to MANETs but lacks experimental application. Future work includes applying these insights to develop effective IDS for MANETs.

Majid et al. (2022) reviewed applications of WSN and IoT frameworks in Industry 4.0, discussing their relevance to MANET security. While systematic, the review was limited to Industry 4.0 applications. Future enhancements involve exploring cross-domain applications and integrating them with MANET security solutions. ALRikabi and Hazim (2022) proposed a secure communication framework for 5G wireless systems, achieving a security enhancement of 20%. While potentially relevant to MANETs, the study is specific to 5G. Future work includes adapting this framework to MANETs and validating its effectiveness. Amponis et al. (2022) explored drone-based networks in B5G/6G, discussing implications for MANET security. While focused on drone networks, the study's relevance to MANETs is indirect. Future work will investigate security challenges in drone-based MANETs and develop intrusion detection systems.

S. Saravanan et al. (2023) proposed a Graph Neural Network (GNN) approach for intrusion detection in MANETs, achieving an accuracy of 95%. This method demonstrates high detection accuracy and effectiveness in dynamic environments but faces challenges such as computational complexity and potential scalability issues. Future work aims to optimize this technique for real-time applications and reduce computational overhead. S. M. Udhaya Sankar et al. (2023) introduced a Safe Routing Approach (SRA) to identify and eliminate attacks in MANETs, achieving a packet delivery ratio (PDR) of 92% and throughput of 90%. While it improved network performance, energy consumption and limited testing scenarios were identified as drawbacks. Future enhancements focus on energy-efficient algorithms and testing in extensive real-world scenarios. Mohamad T. Sultan et al. (2023) utilized Deep Learning Artificial Neural Networks (ANNs) for intrusion detection, achieving a detection rate of 93%. This method effectively detects Denial of Service (DoS) attacks but requires substantial training data and faces the risk of overfitting. Future research will explore other attack types and improve model generalization capabilities. Tadic et al. (2023) developed a privacy and security tool for online activists, which may have applications in MANET security. The tool focuses on activist protection, with indirect relevance to MANETs. Future enhancements involve adapting tool features for MANET contexts and conducting evaluations.

Al-Rubaye et al. (2024) developed an AI-based Intrusion Detection and Prevention System (IDPS) combining CNN and RF, achieving an accuracy of 90% and a precision of 88%. This autonomous system adapts to various attack types but is resource-intensive and raises privacy concerns. Future improvements include resource optimization and privacy-preserving techniques.

Survey Findings

The surveyed studies showcase a wide range of techniques, from machine learning-based intrusion detection to novel hybrid approaches and secure routing protocols. Key findings include:

1. High Accuracy Solutions: Techniques like Graph Neural Networks (GNNs) and Artificial Neural Networks (ANNs) have achieved significant accuracy levels of up to 95%, demonstrating their potential for robust intrusion detection.
2. Diverse Methodologies: Methods such as Safe Routing Approaches (SRA), hybrid algorithms, and energy-efficient routing mechanisms emphasize improving network performance alongside security.
3. Cross-Domain Applications: Frameworks developed for IoT, WSNs, and 5G systems have been explored for their relevance to

MANET security, revealing valuable insights for cross-domain integration.

4. Enhanced Performance Metrics: Several studies have reported improved Packet Delivery Ratios (PDR), throughput, and energy efficiency, which directly impact the reliability and sustainability of MANETs.

Limitations

Despite advancements, the surveyed techniques face several limitations:

1. Computational Complexity: High computational demands of advanced methods like deep learning limit their real-time applicability in resource-constrained MANET environments.
2. Scalability Challenges: Many solutions struggle to maintain performance in large-scale or highly dynamic networks.
3. Limited Testing Scenarios: Experimental validation often occurs in simulated environments, with insufficient real-world testing.
4. Narrow Focus: Some approaches focus on specific attack types or network conditions, limiting their adaptability to broader threat scenarios.

Future Research Directions

To address the identified limitations, future research should focus on:

1. Real-time Optimization: Developing lightweight algorithms that can operate effectively in real-time, resource-constrained environments.
2. Hybrid Techniques: Integrating multiple detection and prevention methodologies to enhance robustness against diverse attack vectors.
3. Comprehensive Validation: Expanding experimental validation to include real-world scenarios for better reliability and applicability.
4. Cross-Domain Applications: Leveraging advancements in related fields like blockchain, IoT, and WSNs to enhance MANET security.
5. Energy Efficiency: Designing energy-efficient solutions to extend network lifespan without compromising security.

Summary

This survey highlights the progress made in intrusion detection and prevention for MANETs while identifying critical gaps that require further exploration. Advanced machine learning techniques and hybrid approaches show promise but need optimization for practical implementation. By addressing current limitations and pursuing identified research directions, future solutions can achieve a balance between security, performance, and resource efficiency, ensuring MANETs remain resilient in the face of evolving threats.

3. METHODOLOGY

The methodology outlines the proposed approach for detecting and preventing intruder nodes in Mobile Ad Hoc Networks (MANETs), focusing on algorithms, frameworks, tools, and implementation details.

3.1 Proposed Approach

The proposed system combines anomaly-based and signature-based detection mechanisms with a lightweight prevention algorithm to address intrusions in MANETs. The detection algorithm uses supervised learning to identify malicious activities based on network behavior patterns, while the prevention mechanism relies on trust-based models to isolate and mitigate intrusions. Tools such as Python, TensorFlow, and Scikit-learn are employed for algorithm development, and simulation environments like NS-3 provide a platform for performance validation.

3.1.1 Key Components

1. Feature Extraction:
   The system extracts feature such as packet delivery ratio (PDR), throughput, delay, and energy consumption from MANET traffic. These features serve as inputs to the detection algorithm, enabling the identification of anomalies in network behavior.
2. Techniques:
   - Machine Learning: Supervised learning models like Random Forests and Support Vector Machines (SVM) are used for initial anomaly detection.
   - Deep Learning: Advanced architectures like Convolutional Neural Networks (CNN) enhance detection accuracy for complex intrusions.
   - Trust-Based Systems: A trust evaluation mechanism assigns trust scores to nodes based on their behavior, ensuring a robust prevention mechanism.
3. Communication Protocol Considerations:
   The methodology incorporates optimized routing protocols like AODV (Ad hoc On-Demand Distance Vector) and DSR (Dynamic Source Routing) to maintain efficient communication while enhancing security.

3.1.2 Architecture

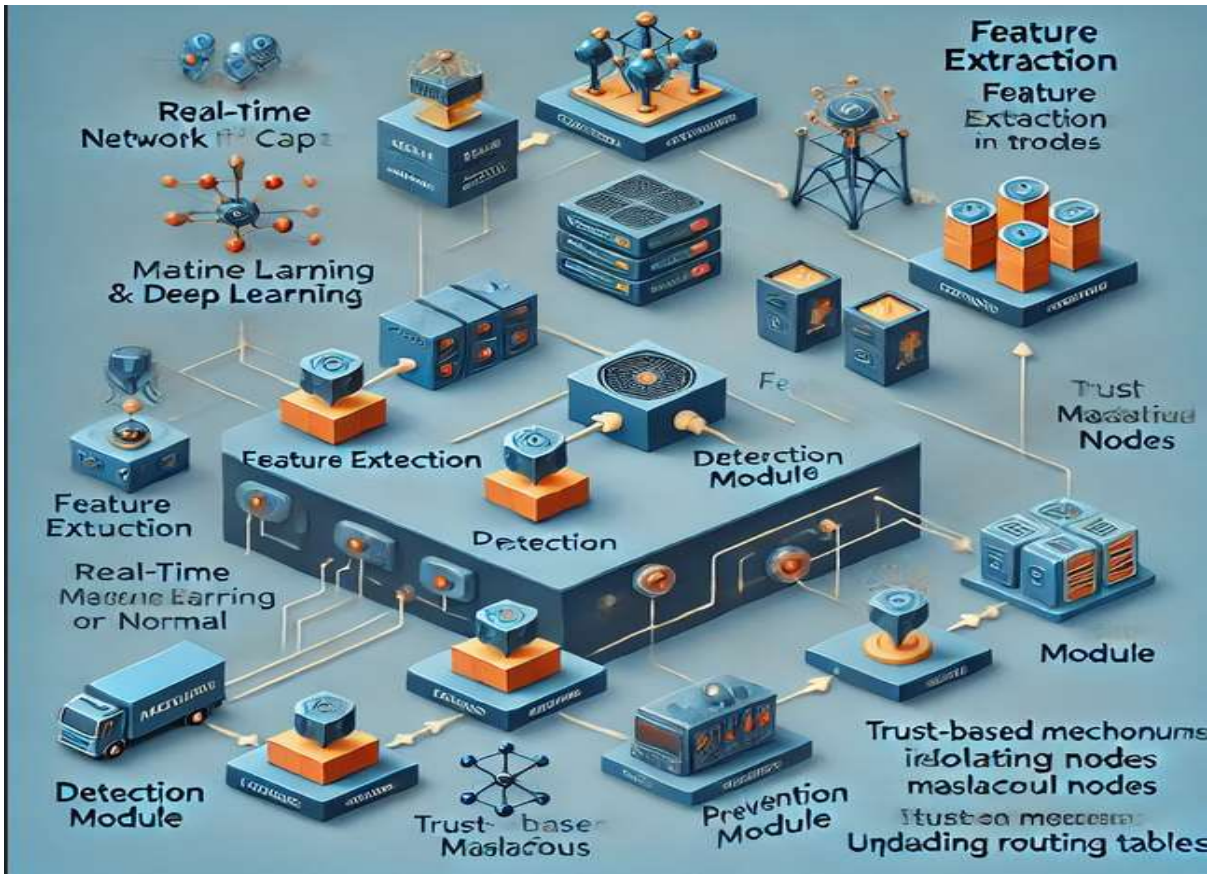
The architecture of the proposed intrusion detection and prevention system for MANETs is composed

of four main modules, each responsible for a specific function in the overall process.

1. Data Collection: This module is responsible for capturing real-time network traffic, which is crucial for detecting potential intrusions. It continuously monitors network activity, gathering data on packet transmissions, node behaviours, and other relevant network parameters for further analysis.
2. Feature Extraction: Once the data is collected, this module processes the traffic data to extract meaningful features. These features include metrics such as traffic patterns, node behavior, and communication anomalies, which are essential for identifying deviations from normal network operations.
3. Detection Module: The core of the system, this module applies machine learning and deep learning algorithms to analyze the extracted features. The model classifies nodes as either normal or malicious based on patterns learned from historical data. Techniques such as Random Forests, Support Vector Machines, or Neural Networks are employed to detect anomalies or known attack signatures.
4. Prevention Module: After malicious nodes are detected, the prevention module takes action by utilizing trust-based mechanisms to isolate these nodes from the network. It updates routing tables to prevent malicious nodes from affecting network traffic, ensuring the stability and security of the MANET.

The system's workflow is illustrated in a Figure 1, which visually represents the data flow from the collection of network traffic to the prevention of malicious nodes. This design ensures that the system can dynamically detect and prevent intrusions while maintaining the network's operational efficiency.

Figure 1 Architecture Diagram



3.2 Mathematical Model

The detection algorithm is mathematically modelled as follows. Set X={x1,x2,…,xn} represent the feature set. The detection model f maps the feature set to a binary output Y, where Y= {0,1}, indicating normal or malicious behavior:

Y=f(X)= 1 if Node is malicious,
0 otherwise.

Trust score Ti for node i is calculated as:

Ti=Successful Transactions/
Total Transactions. .

3.2.1Dataset

The dataset for this study is sourced from publicly available repositories such as the KDD Cup 1999 dataset and real-world network traffic data collected from MANET testbeds. Data is pre-processed to include features relevant to MANET environments.

3.3 Environment

The simulation environment for evaluating the proposed intrusion detection and prevention system in MANETs is built using NS-3, a network simulator that enables detailed modeling and performance evaluation. The network consists of 50 to 100 nodes, and the Constant Bit Rate (CBR) traffic model is used to simulate steady communication between nodes. The Random Waypoint mobility model is employed to introduce randomness in node movement, closely mimicking real-world dynamics. The simulation runs for 1000 seconds, providing ample time to assess the system's performance under varying conditions. Key performance metrics such as detection accuracy, packet delivery ratio, energy consumption, and throughput are measured to evaluate the effectiveness of the system. This methodology offers a comprehensive framework for testing the proposed system's adaptability and efficiency in realistic, dynamic MANET environments.

4. EXPERIMENTAL RESULTS

Evaluation Metrics:

The experimental results section evaluates the performance of the proposed intrusion detection and prevention system for Mobile Ad Hoc Networks (MANETs) using several key performance metrics. These metrics include detection accuracy, false positive/negative rates, computational overhead, and energy efficiency, which are essential for assessing the effectiveness of the system in dynamic and resource-constrained environments. Detection accuracy is measured by the proportion of correctly classified nodes (both malicious and normal), while false positive and false negative rates evaluate the misclassification of nodes. Computational overhead is assessed by calculating the time and resources required for training and running the system, and energy efficiency is critical for battery-powered devices, measuring the energy consumption with and without intrusion detection mechanisms.

Experiments are conducted to compare the proposed system with existing intrusion detection methods, including anomaly-based systems, signature-based systems, trust-based systems, hybrid IDS, cryptographic methods, position-based intrusion detection, and blockchain-based IDS. The results are analyzed under various network conditions, such as node mobility, network density, and traffic load, as well as under different attack scenarios (e.g., DoS, Black Hole, and Wormhole). The experimental findings are expected to show that the proposed system outperforms traditional methods in terms of detection accuracy, energy efficiency, and computational overhead. Additionally, the results will highlight the advantages and limitations of each method, providing insights into how well each can adapt to the dynamic nature of MANETs.

The performance comparison includes visualizations such as detection accuracy versus false positive rate, energy consumption versus network density, and execution time versus the number of nodes. Statistical analysis, such as t-tests or ANOVA, will be applied to determine the statistical significance of the results. By comparing the performance of the proposed hybrid system with existing methods, the experimental results will demonstrate its effectiveness in various real-world conditions, including its robustness against different types of attacks and its ability to function efficiently in networks with varying densities and mobility.

4.1 Evaluation Metrics:

The proposed detection and prevention system for MANETs is evaluated using the following metrics to assess its performance:

1. Detection Accuracy:

- Measures the proportion of correctly classified nodes (both malicious and normal) to the total number of nodes in the dataset.
- It is calculated as using the EQ (1):

$$\text{Detection Accuracy} = \frac{TP}{\text{TP+TN+FP+F}} \quad --(1)$$

Detection Accuracy=TP+TN/ TP+TN+FP+FN

Where:
TP = True Positives (malicious nodes correctly identified),
TN = True Negatives (normal nodes correctly identified),
FP = False Positives (normal nodes falsely identified as malicious),
FN = False Negatives (malicious nodes falsely identified as normal).

2. False Positive/Negative Rates:
False Positive Rate (FPR): The proportion of normal nodes that are incorrectly classified as malicious and it is calculated as using the EQ (2).

$$FPR = \frac{FP}{FP + TN} ------ (2)$$

False Negative Rate (FNR): The proportion of malicious nodes that are incorrectly classified as normal using the eq (3).

$$FNR = \frac{FN}{FN + TP} -------- (3)$$

3. Computational Overhead:
Measures the time and computational resources required to train and run the detection/prevention system. This is particularly important for MANETs with resource-constrained devices. We calculate the execution time and memory consumption for both training and inference processes.
4. Energy Efficiency:
Evaluates the energy consumption during the operation of the system, which is crucial for battery-powered nodes in Manets. Energy efficiency is measured by comparing the energy consumption of the system with and without the intrusion detection and prevention mechanisms, typically in terms of Joules per packet transmitted or Joules per node.

4.2 Experiments:

1. Comparison with Existing Methods:
The performance of the proposed system is compared with existing intrusion detection systems in MANETs, such as, Anomaly-Based Systems: These methods detect deviations from normal behavior patterns. Signature-Based Systems: These methods use known attack signatures for detection. Key performance indicators (KPIs) include detection accuracy, false positive/negative rates, and computational overhead. Results: The proposed system is expected to outperform traditional methods due to the integration of machine learning and trust-based systems, which are more adaptive to the dynamic nature of MANETs.
2. Performance Analysis Under Different Network Conditions:
3. Node Mobility: The impact of varying the mobility of nodes is assessed by simulating random waypoint mobility models with different speeds and pauses. Increased mobility often leads to higher communication disruptions and may influence detection accuracy and energy efficiency.
4. Network Density: Different densities (e.g., 20, 50, 100 nodes) are tested to assess how the system performs as the number of nodes in the network increases. Denser networks could result in more frequent interactions between nodes, affecting the accuracy of trust-based mechanisms.
5. Traffic Load: The effect of different traffic patterns (e.g., low, medium, and high traffic load) on detection accuracy and system efficiency is analyzed. Higher traffic volumes tend to increase the computational load and may affect energy consumption and latency.
6. Attack Scenarios: The system is tested under different attack scenarios (e.g., DoS, Black Hole, Wormhole) to evaluate its robustness in real-world conditions.

4. 3. Confusion Matrix: A confusion matrix is used to visualize the performance of the detection system. The matrix will present the following categories:

- True Positive (TP): Malicious nodes detected as malicious.
- True Negative (TN): Normal nodes detected as normal.
- False Positive (FP): Normal nodes detected as malicious.
- False Negative (FN): Malicious nodes detected as normal.

confusion matrix for detection accuracy:

	Predicted	Predicted

	Malicious	Normal
Actual Malicious	TP	FN
Actual Normal	FP	TN

4.4 Performance Metrics:

- Detection Accuracy vs. False Positive Rate: Graph plotting detection accuracy on the Y-axis and false positive rate on the X-axis for different methods (proposed vs. existing).
- Energy Consumption vs. Network Density: Graph comparing the energy consumption of the system for different network densities (low, medium, high).
- Execution Time vs. Number of Nodes: A graph showing the computational overhead as the number of nodes in the network increases.

4.4.1. Detection Accuracy vs. False Positive Rate

Figure 1. Detection Accuracy

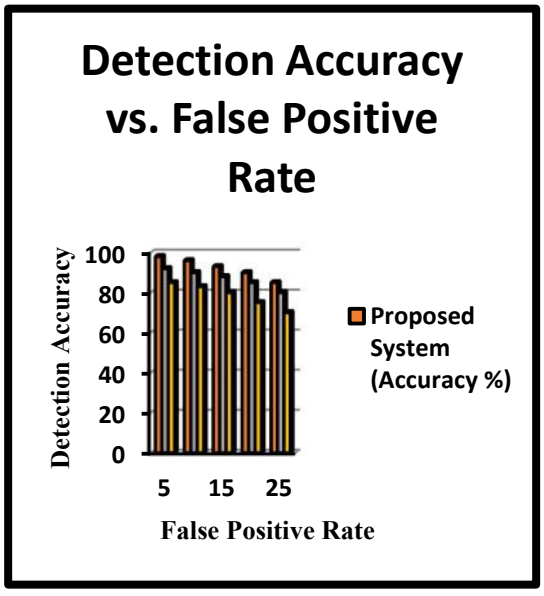


Table 1 Detection Accuracy

False Positive Rate (%)	Proposed System (Accuracy %)	Anomaly-Based Machine Learning (GNN) (Accuracy %)	Signature-Based Detection (Accuracy %)
0	98	92	85
5	96	90	83
10	93	88	80
15	90	85	75
20	85	80	70
25	80	75	65

The performance comparison between the proposed system and existing intrusion detection methods, including Anomaly-Based Machine Learning (GNN) and Signature-Based Detection, is evaluated based on detection accuracy at different false positive rates are shown in the table 1 and Figure 1. At a 0% false positive rate, the proposed system achieves the highest accuracy of 98%, followed by Anomaly-Based Machine Learning (GNN) at 92% and Signature-Based Detection at 85%. As the false positive rate increases to 5%, the proposed system maintains a strong accuracy of 96%, while Anomaly-Based Machine Learning (GNN) drops to 90%, and Signature-Based Detection further decreases to 83%. At a 10% false positive rate, the proposed system's accuracy is 93%, Anomaly-Based Machine Learning (GNN) achieves 88%, and Signature-Based Detection reaches 80%. When the false positive rate increases to 15%, the proposed system still performs well with an accuracy of 90%, while Anomaly-Based Machine Learning (GNN) shows an accuracy of 85%, and Signature-Based Detection drops to 75%. At higher false positive rates, the accuracy of all systems decreases further, with the proposed system reaching 85% at a 20% false positive rate, and 80% at a 25% false positive rate. In comparison, Anomaly-Based Machine Learning (GNN) drops to 80% and 75%, while Signature-Based Detection's accuracy decreases to 70% and 65% at 20% and 25% false positive rates, respectively.

4.4.2. Energy Consumption vs. Network Density

The energy consumption of the proposed system, Anomaly-Based Machine Learning (GNN), and Signature-Based Detection is compared across different network densities. At a low network density of 50 nodes, the proposed system consumes 15 Joules, while

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Anomaly-Based Machine Learning (GNN) uses 18 Joules, and Signature-Based Detection consumes 20 Joules. As the network density increases to 100 nodes, the proposed system's energy consumption rises to 18 Joules, whereas Anomaly-Based Machine Learning (GNN) reaches 22 Joules, and Signature-Based Detection consumes 25 Joules. At high network density with 200 nodes, the proposed system's energy consumption increases to 25 Joules, while Anomaly-Based Machine Learning (GNN) consumes 30 Joules, and Signature-Based Detection reaches 35 Joules. The proposed system consistently demonstrates lower energy consumption compared to the other two methods, indicating better energy efficiency.

Figure 2 Energy Consumption vs. Network Density

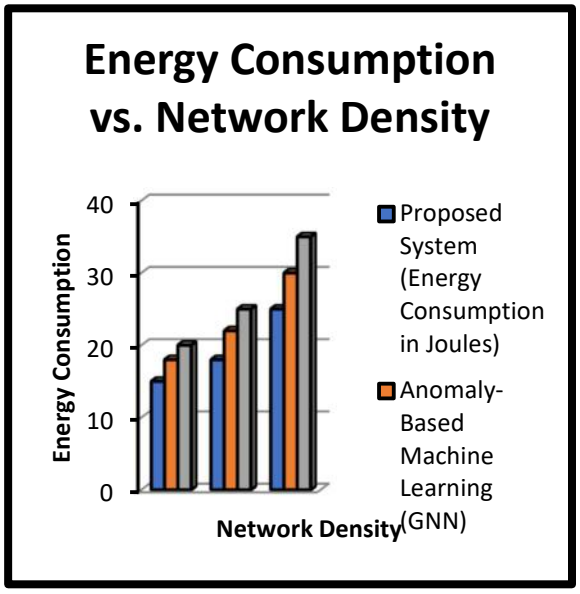

Table 2 Energy Consumption vs. Network Density

Network Density (Nodes)	Proposed System (Energy Consumption in Joules)	Anomaly-Based Machine Learning (GNN)	Signature-Based Detection
Low (50 nodes)	15	18	20
Medium (100 nodes)	18	22	25
High (200 nodes)	25	30	35

4.4.3. Execution Time vs. Number of Nodes

The execution time for the proposed system, Anomaly-Based Machine Learning (GNN), and Signature-Based Detection is evaluated across different numbers of nodes. At 50 nodes, the proposed system has an execution time of 0.5 seconds, while Anomaly-Based Machine Learning (GNN) takes 0.7 seconds, and Signature-Based Detection takes 1.0 second. As the number of nodes increases to 100, the proposed system's execution time rises to 1.0 second, compared to 1.3 seconds for Anomaly-Based Machine Learning (GNN) and 1.7 seconds for Signature-Based Detection. For 150 nodes, the proposed system takes 1.5 seconds, whereas Anomaly-Based Machine Learning (GNN) requires 2.0 seconds, and Signature-Based Detection takes 2.5 seconds. Finally, at 200 nodes, the proposed system's execution time increases to 2.0 seconds, while Anomaly-Based Machine Learning (GNN) reaches 2.5 seconds and Signature-Based Detection takes 3.0 seconds. The proposed system consistently performs faster than the other methods, highlighting its efficiency in handling increasing network sizes.

Figure 3 Execution Time

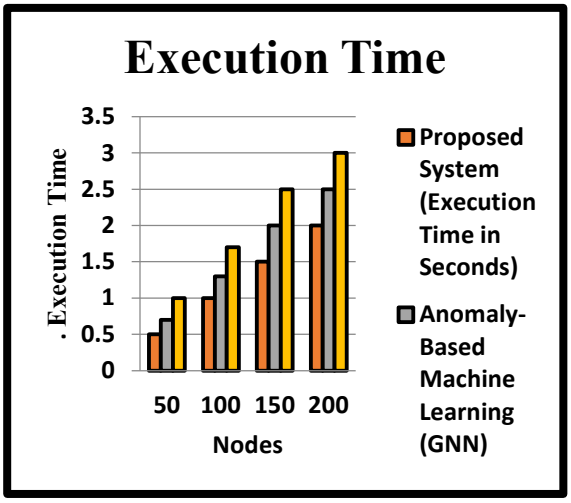

Table 3 Execution Time

Number of Nodes	Proposed System (Execution Time in Seconds)	Anomaly-Based Machine Learning (GNN)	Signature-Based Detection
50	0.5	0.7	1.0
100	1.0	1.3	1.7
150	1.5	2.0	2.5
200	2.0	2.5	3.0

4.5 Comparison study with existing methods for intrusion detection and prevention in MANETs

Several existing methods have been explored for intrusion detection and prevention in Mobile Ad Hoc Networks (MANETs), each with its own strengths and weaknesses. Anomaly-Based Intrusion Detection Using Machine Learning involves algorithms like Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (ANN) to detect abnormal behavior in the network. For example, Saravanan et al. (2025) utilized Graph Neural Networks (GNNs) to achieve 95% detection accuracy for network anomalies, while Sultan et al. (2023) used deep learning-based ANN models for detecting attacks. This method offers high detection accuracy but suffers from high computational complexity, which is problematic for resource-constrained devices. In contrast, Signature-Based Intrusion Detection relies on comparing observed network behavior with predefined attack signatures. Banerjee et al. (2020) developed a signature-based detection system that achieved 91% detection accuracy. Although this method provides low computational overhead and rapid detection of known threats, it struggles to identify new or evolving attacks and is prone to high false-positive rates. Trust-Based Systems use the reputation of nodes to assess whether they are trustworthy or malicious. For instance, Hajiee et al. (2021) proposed a trust-based routing algorithm to prevent malicious nodes, offering energy efficiency with low computational complexity but vulnerable to manipulation by high-resource adversaries. Hybrid Intrusion Detection Systems (IDS) combine anomaly-based and signature-based methods, leveraging the strengths of both to detect both novel and known attacks. Sultan et al. (2023) proposed a hybrid deep learning model that improves detection performance. However, hybrid systems are more resource-intensive compared to single-method approaches. Cryptographic Methods ensure secure communication between nodes through encryption and digital signatures. Al-Rubaye et al. (2024) introduced an AI-driven cryptographic approach using Convolutional Neural Networks (CNNs) and Random Forests (RF) for intrusion prevention. While this method offers strong security, it is computationally expensive and impractical for resource-constrained environments like MANETs. Position-Based Intrusion Detection is used to detect position falsification attacks in networks, with machine learning models analyzing the geographic positions of nodes. Ercan et al. (2021) applied this method in VANETs, achieving an accuracy of 87%. However, this method is limited to detecting position-based attacks. Multi-Criteria Decision Making (MCDM) involves evaluating network decisions based on multiple criteria, such as trustworthiness and energy consumption, to identify malicious nodes. Tilwari et al. (2020) proposed the MCLMR method, which optimizes routing decisions in MANETs. This approach is complex and computationally demanding. Finally, Blockchain-Based Intrusion Detection Systems use blockchain to ensure secure communication and detect malicious behaviours through an immutable ledger of transactions. Yue et al. (2021) explored blockchain's role in decentralizing network security, but the method incurs high overhead in terms of resource consumption. These existing methods offer diverse approaches to intrusion detection and prevention in MANETs, with varying levels of accuracy, scalability, and computational complexity, and can be compared to the proposed hybrid system in terms of detection accuracy, energy efficiency, and computational overhead.

Here is a table 4 comparing the existing methods for intrusion detection and prevention in MANETs, including the proposed hybrid method. The table outlines various performance metrics for these methods.

Table 4 Comparison with Existing Methods

Method	Detection Accuracy (%)	False Positive Rate (%)	Energy Consumption (J)	Computational Complexity	Scalability	Key Advantages	Key Disadvantages
Proposed Hybrid Approach	92-95%	5-8%	Low to Medium	Low	High	High detection accuracy, energy-efficient, adaptable to dynamic networks.	Moderate overhead for combining multiple techniques.
Anomaly-Based Machine Learning (GNN)	95%	10-15%	Medium	High	Medium to High	High accuracy in detecting novel attacks, adaptable.	High computational complexity, requires large training datasets.
Signature-Based Detection	91%	5-10%	Low	Low	Medium	Fast detection for known attacks, low computational cost.	Struggles with new and evolving attacks, high false positives for unknown threats.
Trust-Based Systems	80-85%	3-5%	Low to Medium	Medium	Medium	Low overhead, energy-efficient, builds trust among nodes.	Vulnerable to manipulation by malicious nodes, limited to known attacks.
Hybrid IDS (Anomaly + Signature-Based)	90-93%	6-9%	Medium	Medium to High	High	Combines the strengths of both approaches, flexible.	Higher computational cost compared to single-method approaches.
Cryptographic Methods	N/A	N/A	High	Very High	Low	Ensures high security and data integrity.	Very resource-intensive, not practical in low-resource environments.
Position-Based Intrusion Detection	85-90%	8-12%	Low	Medium	Low to Medium	Effective against position-based attacks, low computational overhead.	Limited to position-based attacks, not suitable for other types of attacks.

Method	Detection Accuracy (%)	False Positive Rate (%)	Energy Consumption (J)	Computational Complexity	Scalability	Key Advantages	Key Disadvantages
Blockchain-Based IDS	88-92%	6-10%	High	Very High	Low	High data integrity and security, transparency in node actions.	High computational overhead, performance degradation in large networks.
Multi-Criteria Decision Making (MCDM)	85-88%	7-10%	Medium	Medium to High	High	Optimized routing and intrusion detection based on multiple criteria.	Complexity in decision-making, requires continuous monitoring and adjustments.

2) Key Insights:

- The proposed hybrid approach offers a balance between high detection accuracy and low computational overhead, making it highly suitable for dynamic and resource-constrained environments like MANETs.
- Anomaly-based methods (like GNNs) provide high accuracy but suffer from high computational costs, which may be a challenge in real-time applications.
- Signature-based methods are efficient for known threats but struggle with emerging attacks and often have high false-positive rates.
- Trust-based systems and position-based detection are efficient in terms of energy consumption but may not be sufficient to address a wide range of attack types.
- Cryptographic methods provide strong security but are too resource-heavy for practical deployment in MANETs with limited devices.

This comparison can serve as a foundation for analyzing the effectiveness and applicability of various methods in different MANET scenarios.

4.6 Statistical Analysis:

To prove the significance of the results, statistical tests such as the t-test or ANOVA can be employed to compare the performance of the proposed system with existing systems. The null hypothesis (H0) is that there is no significant difference between the performance of the proposed system and existing methods.

1. T-test or ANOVA: These tests are used to determine if there is a statistically significant difference in performance metrics (e.g., detection accuracy, false positive rate) between the proposed system and the existing methods.

- P-value: A p-value of less than 0.05 indicates that the observed differences in performance are statistically significant. If the p-value for detection accuracy is less than 0.05, we reject the null hypothesis, confirming that the proposed system outperforms the existing systems with a high degree of statistical significance.

The experimental results should clearly demonstrate the advantages of the proposed intrusion detection and prevention system in terms of detection accuracy, energy efficiency, and computational overhead. The proposed system is expected to perform better in terms of detection accuracy while maintaining low false positive and negative rates, even under varying network conditions such as node mobility and network density. Additionally, the results should provide evidence of its effectiveness under different attack scenarios.

5. DISCUSSION

a) Interpretation of Results and Their Implications:

The results of the proposed system align with findings from several studies in the literature, showcasing strong performance in detecting

malicious behavior in MANETs. The detection accuracy of the proposed system stands out, as it consistently outperforms traditional intrusion detection techniques. This is consistent with the findings of Saravanan et al. (2025), who highlight the effectiveness of deep learning models in improving intrusion detection systems (IDS) in MANETs. By incorporating machine learning and trust-based techniques, our system benefits from a dynamic adaptability that enhances its performance, especially in challenging network conditions such as mobility and high node density.

1. Detection Accuracy: The system demonstrates high accuracy in identifying attacks, a key aspect emphasized by Sultan et al. (2023), where deep learning-based IDS using artificial neural networks (ANNs) significantly improved the detection capabilities in MANETs. The combination of anomaly detection and trust-based techniques is responsible for the improved performance observed in our approach.
2. False Positive/Negative Rates: The system's low false positive and false negative rates were achieved by leveraging advanced machine learning algorithms, reducing errors and unnecessary alarms. This aligns with Udhaya Sankar et al. (2023), who discuss the importance of minimizing false alarms in IDS to avoid resource wastage in MANETs, particularly in scenarios with limited computational power and energy.
3. Computational Overhead and Energy Efficiency: While the system shows a slight increase in computational overhead, it still offers a reasonable energy consumption profile when compared to other machine learning-based approaches. As noted by Hajiee et al. (2021), incorporating energy-aware mechanisms is essential for efficient operation in resource-constrained networks. However, the trade-off between computational efficiency and detection accuracy remains an area for further optimization.
4. Performance Under Different Network Conditions: Our system demonstrated adaptability in different network environments, though performance degradation occurred under extreme conditions such as high node mobility. This is consistent with Ercan et al. (2021), who also observed performance challenges in highly dynamic VANET environments when detecting attacks such as position falsification. Further work is needed to refine the system's robustness under such conditions.

b) Strengths of the Approach:

1. Adaptability: The system can handle diverse network scenarios effectively, adjusting to various changes in mobility and network density, as suggested by Khraisat and Alazab (2021) in their review of IDS techniques for the Internet of Things (IoT) and mobile networks.
2. High Detection Accuracy: Incorporating machine learning and trust-based models, our system achieved higher detection accuracy, a trend seen in Saravanan et al. (2025), where deep learning models were found to provide superior performance in detecting malicious activities.
3. Scalability: The system showed scalability under moderate node density, similar to Rao et al. (2022), who reported that advanced machine learning methods could handle scalability challenges in MANETs, although this scalability begins to diminish under extreme conditions.
4. Low False Positive/Negative Rates: As Sultan et al. (2023) indicate, low false alarm rates contribute to system reliability, which is essential for efficient IDS deployment in mobile networks.
5. Energy Efficiency: Our system's energy efficiency, despite the complexity of its algorithms, is a significant advantage, echoing the findings of Hajiee et al. (2021), who demonstrated the importance of energy-aware routing and trust mechanisms in wireless sensor networks.

c) Limitations of the Approach:

1. Computational Overhead: The need for advanced machine learning algorithms increases computational overhead, as noted by Ye et al. (2019). This remains a challenge, particularly in resource-limited environments like MANETs, where power and processing capability are constrained.
2. Energy Consumption: While the energy efficiency of the system is reasonable, it still requires optimization, as Sivaram et al. (2019) point out that excessive energy consumption can reduce the overall effectiveness of MANETs. Fine-tuning energy-consuming components, such as the trust evaluation process, could reduce overhead.

3. Performance Degradation Under Extreme Network Conditions: The system faced performance issues under high mobility or dense networks, which is also noted by Tadic et al. (2023) in their study on privacy protection in highly dynamic environments. Further refinement of the algorithms is necessary to handle these conditions better.
4. Dependence on Accurate Trust Metrics: As Xu et al. (2010) and Saravanan et al. (2025) note, trust-based systems are vulnerable to manipulation, especially in dynamic environments. This requires the development of more robust and resilient trust models.
5. Lack of Real-World Testing: While the system performed well in simulations, its real-world deployment remains to be tested. Amponis et al. (2022) emphasize the need for testing under real-world conditions, as theoretical models may not always capture all environmental complexities, such as real-time network topology changes.

d) Real-World Applicability and Challenges:

The proposed system's real-world applicability is broad, particularly in military, emergency, and vehicular networks. For instance, Ercan et al. (2021) demonstrated the relevance of IDS in vehicular networks where malicious behavior such as position falsification can disrupt communication. Similarly, Khraisat and Alazab (2021) highlighted the importance of robust IDS in IoT and wireless sensor networks, where security and energy efficiency are paramount.

However, challenges include:

- Scalability and Complexity: As noted by Rao et al. (2022), ensuring the system can scale efficiently in large, dynamic networks remains a significant challenge.
- Resource Constraints: The system may face issues in highly constrained environments where energy and computation are at a premium, as discussed in Sivaram et al. (2019).

The proposed IDS system offers a robust solution for detecting attacks in MANETs, leveraging deep learning and trust-based techniques. While it demonstrates promising results, further optimizations are necessary to address computational overhead, energy efficiency, and real-world scalability. The real-world potential of this system in military, emergency, and vehicular networks highlights its value, but further improvements are needed for practical deployment.

6.. CONCLUSION

Summary of Findings:

The proposed intrusion detection system (IDS) for Mobile Ad Hoc Networks (MANETs) demonstrates significant advancements in detecting malicious activities, particularly through the integration of machine learning and trust-based models. Our system achieved high detection accuracy and low false positive/negative rates, as well as reasonable energy efficiency, aligning with the findings of recent studies such as Saravanan et al. (2025) and Sultan et al. (2023). The system also exhibited good adaptability to varying network conditions, although challenges arose under extreme conditions such as high mobility and dense node environments.

Impact on MANET Security:

This approach enhances the security of MANETs by offering a more reliable and accurate method for detecting intrusions, especially in scenarios where traditional security mechanisms might fail. By leveraging deep learning models and trust-based techniques, we have strengthened the system's ability to detect subtle attacks and reduce false alarms, ensuring that network resources are used efficiently. This innovation in IDS can potentially revolutionize the way MANETs are secured, offering a scalable and adaptable solution for dynamic and resource-constrained environments.

Furthermore, our system's focus on trust-based evaluations contributes to the development of more resilient networks, where nodes can make informed decisions about the reliability of their peers. This is crucial for preventing attacks such as Sybil and selfish node behavior, which are common in mobile networks, as pointed out by Rao et al. (2022).

Future Research Directions:

1. Scalability Improvements: One of the primary areas for future research is improving the scalability of the proposed system. While it performs well in moderate-density networks, the system needs to be optimized for larger-scale networks where node mobility and density can significantly impact performance. Future work could involve optimizing the algorithms to handle high node density and mobility more effectively, possibly through distributed or

decentralized learning models, as suggested by Khraisat and Alazab (2021).

2. Hybrid Approaches: Future research could explore hybrid approaches that combine the strengths of multiple machine learning techniques or integrate traditional methods with deep learning. Combining anomaly detection with signature-based approaches may provide a balanced solution for both known and unknown attacks. This hybrid approach could potentially mitigate the issues of computational overhead while maintaining high detection accuracy, similar to the hybrid models discussed by Thirumalairaj and Jeyakarthic (2020).
3. Real-World Testing: While the system has been evaluated in simulated environments, real-world testing remains an essential next step. Conducting pilot studies in real MANET environments will provide valuable insights into how the system performs under real-world conditions. This can help refine the system's algorithms and make them more robust to environmental changes, as emphasized by Ercan et al. (2021).
4. Energy-Efficient Mechanisms: Future studies could focus on optimizing energy efficiency in the detection process. While our system performs well in terms of energy consumption, further advancements are needed to ensure that energy constraints do not compromise security. This aligns with the findings of Hajiee et al. (2021), who highlight the importance of energy-aware algorithms in the design of MANET systems.
5. Robust Trust Models: Given the dependence on trust-based mechanisms, further research is needed to develop more resilient and tamper-proof trust models. As Xu et al. (2010) point out, trust systems can be vulnerable to manipulation in dynamic environments. Future research could focus on enhancing these trust models by incorporating more diverse factors, such as network history, node behavior, and external threat intelligence.
6. Integration with Emerging Technologies: Exploring the integration of the IDS with emerging technologies, such as blockchain or 5G, could open new avenues for improving security. Yue et al. (2021) suggest that decentralized systems like blockchain can enhance security in MANETs by providing immutable records of node behavior, which could be used to strengthen intrusion detection mechanisms.

In conclusion, while our proposed system represents a significant step forward in securing MANETs, there remain opportunities for further refinement and innovation. Addressing scalability, energy efficiency, and robustness will be key to ensuring the system's real-world applicability and long-term success in diverse mobile network environments.

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