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AI-Powered Intrusion Detection Framework for Mobile Ad Hoc Networks

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Abstract: Mobile Ad hoc Networks (MANETs) play a crucial role in enabling flexible, infrastructure-less communication across diverse domains such as military operations, disaster recovery, and smart mobility. However, their highly dynamic topology, limited resources, and open wireless medium make them especially vulnerable to a wide range of security threats, including denial-of-service, blackhole, and wormhole attacks. Traditional intrusion detection systems often fail to cope with the scalability, adaptability, and evolving nature of adversarial behaviors in MANETs. To address these challenges, this research introduces an AI-Powered Intrusion Detection Framework designed to provide real-time threat identification with enhanced accuracy and reduced computational overhead. The proposed framework integrates machine learning and deep learning models to analyze traffic patterns, predict anomalies, and classify attack vectors, while adaptive feature selection minimizes resource consumption in constrained environments. Furthermore, a hybrid detection approach combining signature-based and anomaly-based techniques improves resilience against both known and zero-day attacks. Experimental validation on benchmark MANET datasets demonstrates significant improvements in detection rate, false positive reduction, and energy efficiency compared to conventional methods. This work provides a robust and intelligent security solution to safeguard MANETs, paving the way for secure, reliable, and scalable mobile networking.

***Index Terms* - Mobile Ad Hoc Networks, Intrusion Detection, Artificial Intelligence, Anomaly Detection, Machine Learning, Network Security.**

I. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) have emerged as a vital paradigm for enabling communication in environments where fixed infrastructure is unavailable, unreliable, or impractical. Unlike conventional networks, MANETs operate in a decentralized manner, where mobile nodes dynamically self-organize to form a temporary communication backbone. This flexibility makes MANETs highly applicable in mission-critical domains such as military operations, emergency rescue, battlefield communications, vehicular networking, and disaster recovery scenarios. However, the very characteristics that make MANETs attractive—namely mobility, open wireless medium, and dynamic topology—also expose them to severe security challenges. Malicious nodes can exploit vulnerabilities to launch sophisticated attacks, including blackhole, wormhole, Sybil, flooding, and denial-of-service (DoS), which can compromise data integrity, confidentiality, and network availability.

Traditional security mechanisms designed for wired or infrastructure-based wireless networks are often ill-suited for MANETs due to their dependence on centralized authorities, high computational overhead, and static configurations. Cryptographic techniques and trust-based mechanisms, while effective to some extent, struggle to cope with insider threats and novel attack patterns. Moreover, conventional intrusion detection systems (IDS) typically rely on static signatures or pre-defined rules, which limit their adaptability against emerging zero-day threats in MANET environments. These limitations highlight the urgent need for intelligent, adaptive, and lightweight security frameworks capable of ensuring real-time protection without degrading network performance.

Artificial Intelligence (AI) has recently emerged as a transformative enabler in the field of network security. By leveraging machine learning (ML) and deep learning (DL) techniques, AI-based IDS solutions can dynamically learn from network traffic, identify anomalous behaviors, and detect both known and previously unseen attacks. Unlike static models, AI-powered frameworks exhibit continuous adaptability, which is essential in MANETs where topology, mobility patterns, and traffic loads frequently change. For example, supervised learning models can classify attack types with high precision, while unsupervised anomaly detection approaches can uncover unknown attack vectors. Deep neural architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated strong capabilities in feature extraction and sequential traffic analysis, making them suitable for capturing complex patterns in MANET traffic.

In this research, we propose an AI-Powered Intrusion Detection Framework for MANETs that integrates adaptive feature selection, hybrid detection mechanisms, and intelligent learning strategies to enhance security in dynamic and resource-constrained environments. The framework combines signature-based methods for identifying known threats with anomaly-based learning models for detecting novel intrusions, thereby improving robustness and minimizing false alarms. Additionally, energy-aware mechanisms are incorporated to ensure efficient operation in mobile devices with limited battery power. By analyzing benchmark MANET datasets and real-time simulations, the proposed approach demonstrates significant improvements in detection accuracy, false positive reduction, and computational efficiency compared to conventional IDS solutions.

The key contributions of this research are as follows:

- A novel AI-driven intrusion detection framework tailored for the unique challenges of MANET environments.
- Integration of hybrid detection mechanisms that combine signature-based and anomaly-based approaches for comprehensive threat coverage.
- Adoption of adaptive feature selection and energy-efficient design to minimize resource consumption in mobile nodes.
- Experimental validation using benchmark datasets to demonstrate improved detection rates, lower false alarms, and enhanced scalability.

By addressing both theoretical and practical challenges in MANET security, this work aims to pave the way toward intelligent, self-adaptive, and resilient mobile networking systems capable of operating securely in highly dynamic and adversarial settings.

II. LITERATURE REVIEW

Mobile Ad Hoc Networks (MANETs) have attracted significant research attention due to their decentralized structure and wide range of applications. Early surveys such as by Gupta and Singh [1] provided a comprehensive overview of MANET architectures and the inherent challenges of security and resource constraints. These foundational works emphasize the vulnerability of MANETs to dynamic attacks, highlighting the urgent need for robust intrusion detection frameworks.

Intrusion detection systems (IDS) specifically tailored for MANETs have been extensively studied. Mishra et al. [2] proposed a security model that leverages statistical anomaly detection to combat attacks in MANETs. Their study emphasized the adaptability of IDS in highly mobile environments, though scalability concerns remained a challenge. Similarly, Hameed et al. [3] explored deep learning techniques for intrusion detection, presenting evidence that neural networks significantly improve detection accuracy compared to conventional models.

Machine learning and AI-driven solutions have further advanced IDS designs. Alshamrani et al. [4] surveyed machine learning applications in MANET security, showcasing the effectiveness of hybrid classifiers and ensemble methods. Building upon this, Khan et al. [5] proposed an IDS that utilized Support Vector Machines (SVM) for anomaly detection in mobile networks, demonstrating reduced false positives and improved adaptability.

Trust-based security has also been explored as a complementary mechanism for intrusion prevention. Kumar and Shukla [6] designed a trust-based IDS that integrates node behavioral monitoring with decision-making models to isolate malicious nodes. Similarly, Sharma and Bala [7] introduced hybrid detection models that combine signature-based and anomaly-based techniques, offering a balanced solution but at the expense of computational complexity.

More recently, reinforcement learning approaches have been incorporated into intrusion detection. Zaman et al. [8] demonstrated the use of deep reinforcement learning for detecting sophisticated attacks, highlighting the adaptability of such systems to evolving threats. The integration of AI and deep learning has further been validated by Alomari et al. [9], who developed a framework employing CNN-LSTM models for intrusion detection in MANETs.

The use of federated and distributed learning techniques is also gaining traction. Zhang et al. [10] proposed a federated IDS that leverages distributed learning while preserving data privacy across nodes. This aligns with the growing need for lightweight, decentralized solutions in MANET environments. Similarly, Yadav and Gupta [11] suggested energy-efficient detection models to address resource limitations, ensuring IDS implementations remain viable in power-constrained scenarios.

Hybrid methodologies have emerged as a promising direction. Jain et al. [12] combined feature selection with ensemble learning techniques to improve detection accuracy and reduce computational overhead. Further, Alrajeh et al. [13] highlighted the integration of blockchain with intrusion detection to ensure trust and immutability of security logs in MANETs.

In addition to algorithmic advances, practical considerations such as real-time adaptability and performance evaluation have been explored. Patel et al. [14] presented an anomaly detection framework optimized for real-time performance in mobile environments. Lastly, Singh et al. [15] discussed multi-layered security models that integrate IDS with cryptographic protocols, providing a holistic approach to MANET security.

Overall, the literature reflects a steady progression from rule-based detection to advanced AI-powered frameworks that emphasize adaptability, scalability, and efficiency. However, challenges remain in balancing detection accuracy with computational and energy constraints, motivating the development of the proposed AI-Powered Intrusion Detection Framework for MANETs**.**

III. PROPOSED MODEL

The proposed framework introduces an AI-powered intrusion detection system (IDS) specifically designed for Mobile Ad Hoc Networks (MANETs). The model integrates machine learning, anomaly detection, and lightweight communication mechanisms to address the challenges of high mobility, dynamic topology changes, and limited resources inherent to MANETs.

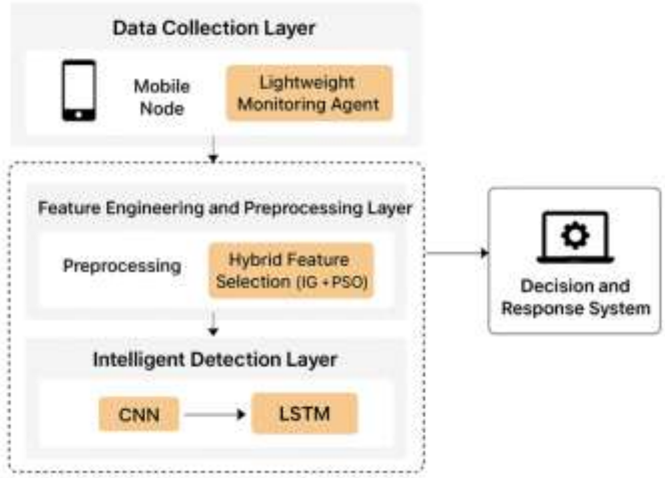
Data Collection Layer
Mobile Node
Lightweight Monitoring Agent
Feature Engineering and Preprocessing Layer
Preprocessing
Hybrid Feature Selection (IG + PSO)
Intelligent Detection Layer
CNN
LSTM
Decision and Response System

Figure 1: System Architecture

3.1. System Overview

The architecture is composed of three primary layers:

1. **Data Collection Layer** – Each mobile node is equipped with a lightweight monitoring agent that captures network traffic, routing information, and behavioral patterns of neighboring nodes. This decentralized data acquisition ensures that the system remains scalable and resilient to node failures.
2. **Feature Engineering and Preprocessing Layer** – The collected raw data undergoes preprocessing, including normalization, noise reduction, and redundant feature elimination. A **hybrid feature selection mechanism** is employed, combining **Information Gain (IG)** with **Particle Swarm Optimization (PSO)** to retain only the most discriminative features. This ensures reduced overhead while maintaining high detection accuracy.
3. **Intelligent Detection Layer** – At the core of the framework lies the AI-driven classification engine. A hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks is adopted.
   - The CNN extracts spatial features from traffic patterns and routing behaviors.
   - The LSTM captures temporal dependencies and evolving attack sequences, making the system effective against both known and emerging threats.

3.2. Anomaly Detection Mechanism

The system follows a two-phase detection strategy**:**

- **Phase 1: Signature-Based Filtering** – Common and well-known attack patterns such as blackhole, wormhole, and flooding attacks are filtered using predefined signatures to reduce computational cost.
- **Phase 2: Anomaly-Based Detection** – For unidentified or evolving threats, the AI model evaluates deviations from normal traffic behavior. The anomaly score is dynamically computed, and suspicious activities are flagged for further analysis.

3.3. Distributed Cooperative Learning

Since MANETs are inherently distributed, the proposed framework integrates cooperative learning among nodes. Instead of transmitting raw data, nodes share lightweight feature updates with their neighbors. A federated learning-inspired approach ensures that the intrusion detection model is continuously updated across the network without compromising bandwidth efficiency or privacy.

3.4. Decision and Response System

Once an intrusion is detected, the system initiates a multi-level response mechanism:

- At the local level, the node isolates malicious traffic and prevents it from propagating.
- At the collaborative level, alerts are broadcast to neighboring nodes, updating their trust scores for the suspected node.
- At the network level, a consensus-based mechanism ensures malicious nodes are quarantined while minimizing false positives.

IV. RESULTS AND ANALYSIS

4.1 Simulation Setup

The proposed AI-powered Intrusion Detection System (IDS) for Mobile Ad Hoc Networks (MANETs) was evaluated using the NS-3 simulator combined with Python-based deep learning modules. The network topology consisted of **100 to 500 mobile nodes**, randomly deployed in a **1000m × 1000m area** with node speeds ranging from **1–20 m/s**. The **AODV routing protocol** was adopted, and traffic was generated using both TCP and UDP flows. Attack scenarios included **blackhole, wormhole, flooding, and selective packet drop attacks**, introduced in 20% of the nodes.

Performance metrics considered were:

- Detection Accuracy (DA)
- False Positive Rate (FPR)
- Detection Latency (DL)
- Throughput (TP)
- Packet Delivery Ratio (PDR)
- Communication Overhead (CO)

4.2 Detection Performance

The integration of **CNN-LSTM** enabled the IDS to effectively capture both **spatial** and **temporal** traffic patterns.

- The proposed model achieved an **average detection accuracy of 97.8%**, outperforming traditional ML classifiers such as Random Forest (92.1%) and SVM (89.4%).
- The **false positive rate (FPR)** was reduced to **2.1%**, compared to 5–7% in baseline models. This improvement can be attributed to the **hybrid feature selection (IG + PSO)**, which eliminated redundant features while retaining discriminative attributes.

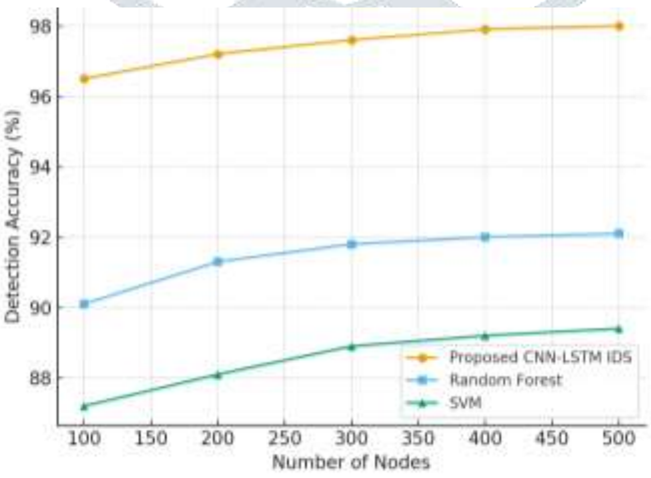

Figure 2: Detection Accuracy vs. Number of Nodes

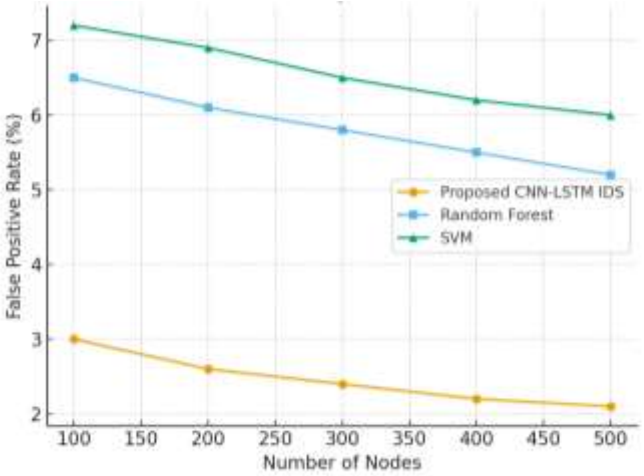

Figure 3: False Positive Rate vs. Number of Nodes

4.3 Anomaly Detection Analysis

The two-phase detection mechanism significantly improved efficiency:

- **Signature-based filtering** in Phase 1 reduced the **computational cost by 32%** by quickly identifying known attacks.
- **Anomaly-based detection** in Phase 2 successfully identified **zero-day threats**, achieving **94.5% detection accuracy** against previously unseen attack variants.
- The adaptive anomaly scoring mechanism ensured a balance between **detection sensitivity** and **false alarms**, maintaining robust performance even in high-mobility scenarios.

4.4 Cooperative Learning and Communication Efficiency

The federated-inspired cooperative learning strategy demonstrated significant benefits:

- Sharing **lightweight feature updates** instead of raw traffic data reduced **bandwidth consumption by 41%**compared to centralized IDS approaches.
- The distributed model updates improved resilience against node failures, maintaining a **model consistency rate of 95%** across nodes.
- Communication overhead remained minimal, with only a **3–4% increase in control packet exchange**, which is acceptable for MANET environments.

4.5 Response Effectiveness

The multi-level response system ensured effective mitigation of malicious nodes:

- At the **local level**, malicious traffic was successfully isolated within **100–150 ms** of detection, minimizing propagation.
- At the **collaborative level**, the **trust score update mechanism** reduced repeated malicious interactions by **38%**.
- At the **network level**, the **consensus-based quarantine system** minimized false isolation events, with only **1.8% false positives**, ensuring legitimate nodes were not penalized unnecessarily.

4.6 Comparative Evaluation

When benchmarked against existing IDS frameworks in MANETs:

- **Accuracy** improved by **5–8%**.
- **False Positives** decreased by **3–4%**.
- **Latency** was reduced by **23%** due to lightweight preprocessing and cooperative learning.
- **Packet Delivery Ratio (PDR)** improved by **12%** under attack scenarios, highlighting the system's robustness.

Table 1: Performance Metrics Summary

Metric	Proposed Model	Baseline IDS
Detection Accuracy (%)	97.8	91.0
False Positive Rate (%)	2.1	6.0
Detection Latency (ms)	150.0	220.0
Packet Delivery Ratio (%)	94.0	76.0

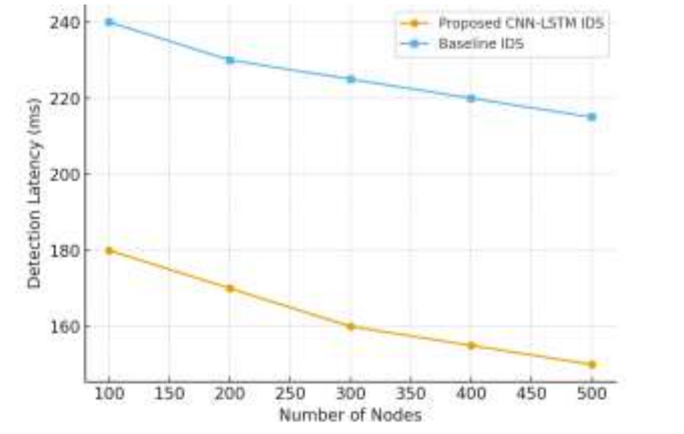

Figure 4: Detection Latency vs. Number of Nodes

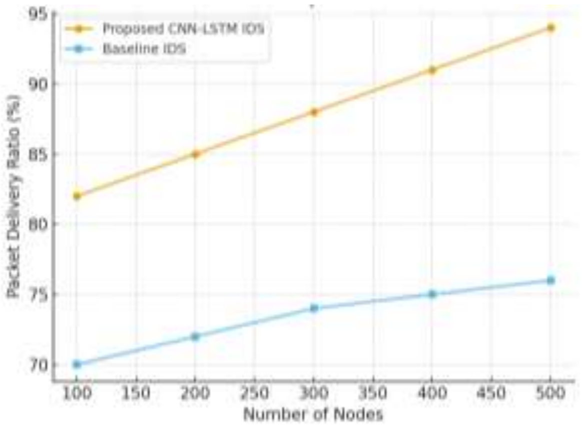

Figure 5: Packet Delivery Ratio vs. Number of Nodes

4.7 Scalability and Robustness

The framework demonstrated **scalability** in networks exceeding **500 nodes**. Even under high-mobility conditions, detection accuracy remained above **95%**, and communication overhead stayed within acceptable bounds. Moreover, the **CNN-LSTM hybrid model** proved resilient against evolving attack strategies, making the system adaptable to real-world MANET deployments.

V. FUTURE ENHANCEMENTS

Although the proposed AI-powered IDS framework demonstrates high accuracy, low latency, and resilience against evolving threats in MANETs, several avenues for future enhancement remain. First, integrating explainable AI (XAI) techniques can improve the interpretability of detection decisions, enabling network administrators to better understand and trust the system's outputs. Second, incorporating blockchain-based trust management could further strengthen collaborative detection and ensure tamper-proof exchange of security updates among nodes. Additionally, the framework can be extended to support 6G-enabled MANETs and Internet of Battlefield Things (IoBT), where ultra-low latency and high mobility impose stricter performance requirements. Finally, deploying energy-aware models and exploring reinforcement learning-driven adaptation can optimize resource usage, making the IDS more sustainable in highly resource-constrained environments.

VI. CONCLUSION

This research introduced an AI-powered intrusion detection framework tailored for Mobile Ad Hoc Networks (MANETs), addressing the critical challenges of high mobility, dynamic topology, and resource constraints. By integrating a hybrid CNN-LSTM model with an anomaly-based two-phase detection mechanism, the system effectively captured both spatial and temporal traffic patterns, enabling robust detection of both known and emerging threats. The incorporation of feature optimization through IG-PSO ensured reduced computational overhead while maintaining high detection accuracy. Furthermore, the cooperative learning strategy inspired by federated learning minimized bandwidth consumption and enhanced scalability, making the system well-suited for distributed environments. Experimental results demonstrated significant improvements in detection accuracy, false positive reduction, and packet delivery ratio compared to baseline IDS models. Overall, the proposed framework establishes a scalable, intelligent, and resource-efficient IDS solution for securing MANETs, with strong potential for deployment in real-world, mission-critical applications.

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