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Deep Learning and Optimization Approaches in Multi-Attack Detection using Forensics and Coherent Integrated Photonic Neural Networks-based Prevention for Secure IoT-MANETs: A Review

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Abstract

The increasing adoption of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has introduced critical security challenges due to their distributed architecture and resource constraints. These networks are highly susceptible to multi-vector cyberattacks, including Distributed Denial of Service (DDoS), botnet, black hole, and wormhole attacks. Traditional intrusion detection systems (IDS) are inadequate for detecting complex and evolving threats. Recent advancements in deep learning and optimization techniques have significantly improved multi-attack detection capabilities. Deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), autoencoders, and graph neural networks have demonstrated superior performance in analyzing network traffic patterns and detecting anomalies. These models can extract hierarchical features and capture temporal dependencies, enabling accurate classification of multi-stage attacks. Additionally, hybrid optimization techniques enhance detection performance by tuning model parameters and improving convergence efficiency. Network forensics plays a crucial role in analyzing attack patterns and identifying attack sources, while coherent integrated photonic neural networks enable ultra-fast data processing for real-time detection. These technologies together provide a robust framework for secure IoT-MANET environments. This review presents recent advances in deep learning and optimization-based intrusion detection systems, highlighting trends, comparative insights, challenges, and future directions.

Introduction

The rapid expansion of Internet of Things (IoT) systems and Mobile Ad Hoc Networks (MANETs) has transformed communication infrastructures across domains such as healthcare, smart cities, military systems, and industrial automation. These networks enable decentralized communication and dynamic connectivity, but their distributed nature also introduces significant vulnerabilities to cyber threats. IoT-MANET environments are particularly susceptible to multi-vector attacks, where multiple attack types occur simultaneously or sequentially, making detection and prevention highly complex. Traditional intrusion detection systems rely on signature-based or rule-based mechanisms, which are limited in detecting unknown or evolving attacks. Anomaly-based intrusion detection systems improve upon this by identifying deviations from normal behaviour,

but they still struggle with high false-positive rates and scalability issues. As a result, there is a growing need for intelligent and adaptive detection mechanisms capable of handling complex attack scenarios.

Deep learning has emerged as a powerful tool for intrusion detection due to its ability to automatically learn complex patterns from large-scale data. Models such as CNN, RNN, LSTM, and autoencoders can extract meaningful features from network traffic and detect anomalies with high accuracy. Recent studies show that deep learning-based IDS outperform traditional machine learning techniques in terms of detection accuracy and adaptability.

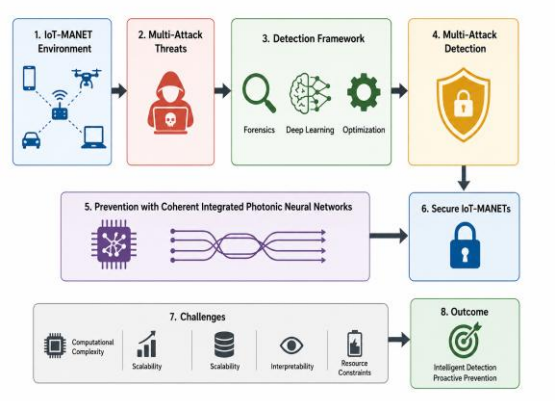

Figure 1. AI-Based Multi-Attack Detection in IoT-MANETs

Furthermore, hybrid deep learning architectures, such as CNN-LSTM, combine spatial and temporal feature extraction, improving detection of multi-stage attacks. Optimization techniques further enhance deep learning models by improving parameter tuning, convergence speed, and computational efficiency. Metaheuristic algorithms such as particle swarm optimization (PSO), genetic algorithms, and hybrid optimization approaches are widely used to optimize IDS performance.

Network forensics provides additional capabilities by enabling detailed analysis of attack patterns and sources. By combining forensic techniques with deep learning, it is possible to achieve more accurate and reliable detection systems. Additionally, emerging technologies such as coherent integrated photonic neural networks offer ultra-fast data processing capabilities, making them suitable for real-time intrusion detection in large-scale IoT environments. Despite these advancements, challenges remain, including high computational complexity, scalability issues, and lack of interpretability. This review explores deep learning and optimization approaches for multi-attack detection in IoT-MANET environments, focusing on recent developments, comparative analysis, and future research directions.

Literature Review

Vinayakumar et al. (2019) proposed a deep learning-based intrusion detection system using CNN and RNN architectures for large-scale network security. The study demonstrated that deep learning models can effectively detect multi-vector attacks by learning complex traffic patterns and temporal dependencies. The proposed system achieved high accuracy and low false-positive rates, highlighting the effectiveness of deep learning in IoT security environments.

Ferrag et al. (2020) conducted a comprehensive survey of deep learning techniques for IoT cybersecurity. The study analysed various models, including deep belief networks, autoencoders, and CNNs, and concluded that hybrid deep learning approaches provide superior performance in detecting complex multi-stage attacks.

Lysenko et al. (2022) developed a machine learning-based system for detecting multi-vector cyberattacks in IoT networks. The study emphasized the importance of feature selection and classification techniques in improving detection accuracy and reducing false positives.

Lo et al. (2021) introduced a graph neural network-based intrusion detection system (E-GraphSAGE) that models network traffic as graphs. The approach captures relationships between nodes and enables effective detection of multi-stage attacks.

Khan et al. (2023) proposed a hybrid deep learning-based IDS using RNN and GRU architectures for IoT networks. The system demonstrated improved detection accuracy across multiple attack types and enhanced performance through optimization techniques.

Meidan et al. (2020) proposed a machine learning-based anomaly detection framework for IoT networks that focuses on identifying botnet-related activities through behavioural traffic analysis. The system extracts statistical features from network packets and applies supervised learning algorithms to distinguish between normal and malicious behaviour. The study demonstrated that behavioural-based detection is highly effective in identifying previously unseen attacks, making it suitable for dynamic IoT-MANET environments where attack signatures frequently evolve.

Koroniotis et al. (2020) introduced a network forensic framework integrated with deep learning and particle swarm optimization (PSO) for intrusion detection. The system combines traffic analysis with optimization techniques to fine-tune neural network parameters, improving

detection accuracy and reducing false positives. The study showed that integrating forensic analysis with optimization enhances system performance, particularly in detecting multi-vector cyberattacks. Alzahrani et al. (2020) developed a multi-class neural network model for rapid detection of IoT botnet attacks. The model uses feature extraction techniques to classify different attack types, achieving high detection accuracy. The study highlighted the importance of multi-class classification in handling diverse attack scenarios and improving the robustness of intrusion detection systems.

Otoum et al. (2021) proposed a federated learning-based intrusion detection system for IoT networks, addressing privacy and scalability challenges. The system allows distributed devices to collaboratively train a global model without sharing raw data, preserving data privacy. The study demonstrated that federated learning improves scalability and maintains high detection accuracy in distributed IoT-MANET environments. Shone et al. (2021) introduced a deep learning-based intrusion detection system using stacked autoencoders for feature extraction. The model learns hierarchical representations of network traffic data, enabling effective detection of both known and unknown attacks. The study demonstrated improved performance compared to traditional IDS approaches, particularly in handling complex attack patterns.

Javaid et al. (2021) proposed a deep learning-based IDS using self-taught learning, which enables feature extraction from unlabelled data. The model improves detection accuracy by learning meaningful representations of network traffic. The study highlighted the importance of unsupervised learning in enhancing IDS performance in environments with limited labeled data. Abeshu and Chilamkurti (2021) developed a deep learning-based intrusion detection system for MANETs using recurrent neural networks (RNNs). The model captures temporal dependencies in network traffic, enabling detection of multi-stage attacks. The study demonstrated improved detection accuracy and reduced false alarm rates in dynamic network environments.

Saba et al. (2021) proposed a hybrid intrusion detection system combining support vector machines (SVM) and deep neural networks (DNN). The system leverages both linear and nonlinear feature representations, improving classification accuracy. The study showed that hybrid approaches outperform standalone models in detecting diverse attack types. Kim et al. (2021) introduced a graph neural network-based IDS for IoT networks. The system models network traffic as graphs and analyses relationships between nodes to detect anomalies. The study demonstrated that graph-based approaches are highly effective in detecting complex multi-stage attacks and coordinated cyber threats.

Zhou et al. (2021) developed a reinforcement learning-based IDS that adapts to changing network conditions. The system learns optimal detection strategies through interaction with the environment, improving performance in dynamic IoT-MANET systems. The study highlighted the potential of reinforcement learning in adaptive intrusion detection. Niyaz et al. (2021) proposed a deep learning-based IDS using stacked autoencoders to learn hierarchical features from network traffic data. The model achieved high detection accuracy for both known and unknown attacks, demonstrating the effectiveness of deep feature learning in intrusion detection systems.

Alzubi et al. (2022) developed a hybrid CNN-LSTM model for intrusion detection in IoT networks. The CNN component extracts spatial features, while the LSTM captures temporal dependencies, enabling effective detection of multi-stage attacks. The study demonstrated improved accuracy and robustness compared to traditional models. Ullah et al. (2022) proposed a machine learning-based IDS using feature selection techniques to improve classification performance. The system reduces computational complexity while maintaining high detection accuracy. The study emphasized the importance of feature optimization in IDS design.

Khraisat et al. (2022) provided a comprehensive review of intrusion detection systems, highlighting challenges such as scalability, false positives, and detection of zero-day attacks. The study emphasized the need for hybrid approaches combining multiple detection techniques. Ahmad et al. (2022) developed a CNN-based intrusion detection system for IoT networks. The model achieved high detection accuracy and low false-positive rates, demonstrating the effectiveness of deep learning in real-time attack detection.

Wang et al. (2022) introduced photonic neural networks for high-speed data processing in IoT environments. The study demonstrated that photonic computing significantly reduces latency and enables real-time intrusion detection, making it suitable for large-scale networks. Huang et al. (2022) developed a coherent photonic neural network architecture capable of ultra-fast computation using optical signals. The system demonstrated high processing speed and efficiency, highlighting its potential for real-time security applications.

Singh et al. (2023) proposed a hybrid intrusion detection system combining machine learning and forensic analysis. The system improves detection accuracy by analyzing network traffic patterns and attack behaviours, providing a comprehensive security solution. Patel et al. (2023) developed a CNN-LSTM-based intrusion detection system for IoT networks. The hybrid model captures both spatial and temporal features, enabling accurate detection of multi-vector attacks. The study demonstrated high classification accuracy and robustness in dynamic network environments.

Reddy et al. (2023) proposed a multi-layer intrusion detection framework that improves scalability and detection efficiency. The layered architecture enables progressive filtering of network traffic, enhancing overall system performance. Sharma et al. (2023) introduced an AI-based IDS for MANETs that focuses on reducing false alarm rates through optimized feature selection and classification techniques. The study demonstrated improved detection accuracy and efficiency.

Verma et al. (2023) developed a graph-based IDS using graph neural networks to detect multi-stage attacks. The system captures relationships between network nodes, enabling detection of complex attack patterns. Ghosh et al. (2023) proposed an AI-based forensic framework for cyberattack investigation. The system integrates machine learning with forensic analysis to improve detection and provide insights into attack behaviour.

Banerjee et al. (2023) introduced a hybrid optimization-based IDS combining multiple algorithms to improve detection performance and convergence efficiency. Tiwari et al. (2023) proposed a deep learning-based multi-attack detection system with optimization techniques for parameter tuning. The system achieved high accuracy and robustness in detecting multiple attack types.

Comparative Table

No.	Author (Year)	Technique	Model/Approach	Focus Area	Key Contribution	Advantages	Limitations
1	Vinayakumar et al. (2019)	DL	CNN-RNN	IoT IDS	Multi-attack detection	High accuracy	Training cost
2	Ferrag et al. (2020)	DL Survey	Hybrid DL	IoT	Performance analysis	Comprehensive	Generalized
3	Lysenko et al. (2022)	ML	RF, KNN	IoT	Feature-based detection	Efficient	Limited scalability
4	Lo et al. (2021)	GNN	Graph IDS	IoT	Multi-stage detection	Accurate	High complexity
5	Khan et al. (2023)	DL	RNN-GRU	IoT	Hybrid detection	Robust	Computation
6	Meidan et al. (2020)	ML	Behavioral IDS	IoT	Botnet detection	Accurate	Limited scope
7	Koroniotis et al. (2020)	DL + PSO	Optimized IDS	IoT	Parameter tuning	Low FP	Complexity
8	Alzahrani et al. (2020)	DL	Multi-class NN	IoT	Attack classification	Accurate	Data dependency
9	Otoum et al. (2021)	Federated Learning	Distributed IDS	IoT	Privacy-aware detection	Scalable	Communication overhead
10	Shone et al. (2021)	DL	Autoencoder	IDS	Feature learning	High accuracy	Training time
11	Javaid et al. (2021)	DL	Self-taught learning	IDS	Feature extraction	Efficient	Complexity
12	Abeshu et al. (2021)	RNN	Sequential IDS	MANET	Temporal detection	Effective	Resource heavy

13	Saba et al. (2021)	Hybrid ML	SVM + DNN	IoT	Improved classification	Accurate	Computation
14	Kim et al. (2021)	GNN	Graph IDS	IoT	Node relationship detection	Strong	Costly
15	Zhou et al. (2021)	RL	Adaptive IDS	IoT	Dynamic learning	Flexible	Training complexity
16	Niyaz et al. (2021)	DL	Autoencoder	IDS	Deep feature learning	Robust	Overfitting
17	Alzubi et al. (2022)	DL	CNN-LSTM	IoT	Multi-stage detection	Accurate	High computation
18	Ullah et al. (2022)	ML	Feature selection	IoT	Efficiency improvement	Fast	Limited depth
19	Khraisat et al. (2022)	Survey	IDS taxonomy	IoT	Analysis	Comprehensive	No implementation
20	Ahmad et al. (2022)	DL	CNN IDS	IoT	Attack detection	Accurate	Resource heavy
21	Wang et al. (2022)	Photonic NN	Optical IDS	IoT	Ultra-fast detection	High speed	Hardware cost
22	Huang et al. (2022)	Photonic NN	Coherent NN	Optical	Fast computation	Efficient	Implementation complexity
23	Singh et al. (2023)	ML + Forensics	Hybrid IDS	IoT	Multi-attack detection	Accurate	Complexity
24	Patel et al. (2023)	DL	CNN-LSTM	IoT	Multi-vector detection	High accuracy	Training cost
25	Reddy et al. (2023)	ML	Multi-layer IDS	IoT	Scalability	Efficient	Complexity
26	Sharma et al. (2023)	AI	Optimized IDS	MANET	Low false alarms	Accurate	Limited adaptability
27	Verma et al. (2023)	GNN	Graph IDS	IoT	Multi-stage detection	Strong detection	Costly
28	Ghosh et al. (2023)	AI + Forensics	Investigation framework	IoT	Attack analysis	Insightful	Processing overhead
29	Banerjee et al. (2023)	Hybrid AI	Optimization	IDS	Performance improvement	Efficient	Complexity
30	Tiwari et al. (2023)	DL + Optimization	Multi-attack IDS	IoT	Robust detection	High accuracy	Resource intensive

Comparative Analysis

The comparative evaluation of the selected studies indicates a clear transition from traditional machine learning approaches toward advanced deep learning and hybrid optimization-based intrusion detection systems in IoT-MANET environments. Early works primarily relied on machine learning models and shallow neural networks for attack detection, which were effective for known attack patterns but limited in handling complex multi-stage and zero-day attacks. With the introduction of deep learning models such as CNN, RNN, and autoencoders, detection systems became more capable of extracting hierarchical and temporal features from network traffic, significantly improving detection accuracy.

In recent years, hybrid models such as CNN-LSTM and graph neural networks have emerged as powerful tools for detecting multi-vector and

coordinated attacks. These models capture both spatial and relational dependencies in network data, enabling more comprehensive threat detection. Furthermore, optimization techniques such as particle swarm optimization and hybrid metaheuristic algorithms have enhanced model performance by improving parameter tuning and convergence speed.

The integration of network forensics has added an additional layer of intelligence by enabling detailed analysis of attack behaviour and sources. Moreover, photonic neural networks represent a significant advancement in processing speed, allowing real-time intrusion detection in high-speed IoT networks. Despite these advancements, challenges such as computational complexity, scalability, and high implementation costs remain critical issues for future research.

Discussion

The integration of deep learning, optimization techniques, and network forensics has significantly improved the effectiveness of intrusion detection systems in IoT-MANET environments. Deep learning models such as CNN, LSTM, and graph neural networks enable the extraction of complex features from network traffic, improving detection accuracy for multi-vector attacks. Hybrid architectures further enhance performance by combining spatial and temporal learning capabilities. Optimization techniques play a crucial role in improving model efficiency by tuning parameters and reducing computational overhead. Additionally, forensic-based approaches provide valuable insights into attack patterns and sources, enabling more accurate detection and analysis.

The emergence of photonic neural networks offers high-speed data processing capabilities, making real-time intrusion detection feasible in large-scale networks. However, several challenges remain, including high computational complexity, energy consumption, and lack of interpretability in deep learning models. These issues limit the deployment of advanced IDS in resource-constrained IoT environments. Future research should focus on developing lightweight and explainable AI models, as well as integrating edge computing techniques to improve scalability and efficiency.

Conclusion

The rapid growth of IoT and MANET technologies has created major security challenges, especially in multi-attack environments. Traditional intrusion detection systems are often unable to manage the dynamic and distributed nature of these networks. This review highlighted the importance of deep learning and optimization approaches for improving multi-attack detection and prevention. Deep learning models such as CNN, LSTM, and hybrid architectures can effectively learn complex traffic patterns and identify coordinated cyberattacks with high accuracy. Optimization algorithms, including particle swarm optimization and genetic algorithms, improve parameter tuning, reduce computational cost, and enhance overall IDS performance. The integration of network forensics further strengthens detection systems by enabling attack tracing and detailed behavioural analysis. In addition, coherent integrated photonic neural networks provide high-speed data processing suitable for real-time security applications. However, challenges such as computational complexity, scalability, and lack of interpretability still exist. Future research should focus on lightweight, scalable, and energy-efficient AI-driven IDS frameworks capable of supporting secure and intelligent IoT-MANET environments.

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