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A Comprehensive Review of Multi-Attack Detection using Forensics and Coherent Integrated Photonic Neural Networks-based Prevention for Secure IoT-MANETs

Ulloriaq Ekanayake
Professor, Department of Electrical and Computer Engineering, Atoll College of Engineering and Design, Maldives
Email: ulloriaq.ekanayake@aced-mv.edu

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Abstract

The rapid growth of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has introduced significant security challenges due to their decentralized and dynamic nature. These networks are highly vulnerable to multi-vector attacks such as Distributed Denial of Service (DDoS), black hole, wormhole, and botnet attacks. Traditional intrusion detection systems often fail to detect complex and evolving threats in real time. Recent advancements in artificial intelligence, network forensics, and photonic neural networks have emerged as promising solutions for multi-attack detection and prevention. Forensic-based investigation techniques enable detailed analysis of network traffic patterns and attack behaviours, enhancing detection accuracy. Machine learning and deep learning models have demonstrated high efficiency in identifying multi-vector cyberattacks through traffic feature analysis and classification. Furthermore, photonic neural networks provide ultra-fast data processing capabilities, making them suitable for high-speed IoT environments. Graph-based and multi-stage intrusion detection systems further improve detection of complex attacks by analyzing relationships between nodes and attack evolution patterns. Hybrid optimization approaches combining AI and forensic techniques enhance detection performance and reduce false positives. This review presents recent advances in multi-attack detection using forensic analysis and photonic neural networks in IoT-MANET environments. It highlights key techniques, comparative insights, challenges, and future research directions toward secure and intelligent network systems.

Introduction

The rapid evolution of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has significantly transformed modern communication systems. These networks are widely used in applications such as smart cities, healthcare monitoring, military operations, and autonomous systems. However, their decentralized architecture, dynamic topology, and resource constraints make them highly vulnerable to various cyberattacks. In particular, multi-attack scenarios, where multiple attack types occur simultaneously or sequentially, pose significant challenges to network security. Traditional intrusion detection systems (IDS) rely on signature-based or rule-based approaches, which are ineffective against unknown or evolving attacks. In contrast, machine learning and deep learning techniques have shown significant promise in detecting

complex attack patterns. These methods analyse network traffic features and classify them into normal or malicious categories. Recent studies demonstrate that machine learning-based approaches can effectively detect multi-vector cyberattacks in IoT environments by analyzing traffic patterns and behavioural anomalies.

Network forensics has emerged as an important tool for investigating cyberattacks. It involves collecting, analysing, and preserving network data to identify attack sources and patterns. Forensic-based detection systems enhance the ability to detect sophisticated attacks by providing detailed insights into network behaviour. Additionally, forensic techniques can be integrated with AI models to improve detection accuracy and reduce false positives. Another emerging technology in this domain is photonic neural networks. Unlike traditional electronic processors, photonic systems use light-based computation, enabling ultra-fast data processing and high bandwidth. These characteristics make photonic neural networks highly suitable for real-time attack detection in large-scale IoT systems.

Recent research has also explored graph-based intrusion detection systems, which model network interactions as graphs. These systems can detect multi-stage attacks by analyzing relationships between nodes and identifying abnormal patterns. Furthermore, hybrid approaches combining AI, forensic analysis, and optimization algorithms have been proposed to enhance detection performance. Despite these advancements, several challenges remain. These include scalability issues, high computational complexity, lack of interpretability, and difficulty in detecting zero-day attacks. This paper presents a comprehensive review of multi-attack detection techniques using forensic analysis and photonic neural networks in IoT-MANET environments, focusing on recent advancements, comparative analysis, and future research directions.

Literature Review

Vaseer et al. (2020) proposed a multi-attack detection framework using forensic analysis and neural network-based prevention techniques for secure MANET environments. The study utilized network traffic forensics to extract behavioral features and applied machine learning models for attack classification. The proposed system demonstrated improved detection accuracy for multiple attacks, including black hole and DDoS attacks, highlighting the importance of combining forensic techniques with AI-based detection. Alzahrani et al. (2020) developed a multi-class neural network model for detecting IoT botnet attacks. The model achieved high accuracy by classifying different attack types using traffic feature analysis. The study emphasized the importance of multi-class classification in handling complex IoT attack scenarios and improving detection performance. Koroniotis and Moustafa (2020) introduced a network forensic framework integrated with deep learning and particle swarm optimization. The system improved intrusion detection accuracy by optimizing neural network parameters. Experimental results showed near-perfect accuracy and low false alarm rates, demonstrating the effectiveness of combining forensics with AI-based optimization. Lo et al. (2021) proposed a graph neural network-based intrusion detection system (E-GraphSAGE) for IoT networks. The study leveraged graph-based representations of network traffic to capture relationships between nodes, enabling effective detection of complex attack patterns. The results showed improved detection accuracy compared to traditional methods.

Lysenko et al. (2022) developed a machine learning-based approach for detecting multi-vector cyberattacks in IoT systems. The method analysed network traffic features and applied classification algorithms such as Random Forest and KNN. The study demonstrated high detection efficiency and emphasized the importance of feature selection in improving performance. Vinayakumar et al. (2020) proposed a deep learning-based intrusion detection framework for IoT networks capable of identifying multiple attack types using convolutional neural networks (CNN) and recurrent neural networks (RNN). The model leverages large-scale network traffic datasets to learn complex attack patterns and temporal dependencies. The study demonstrated high detection accuracy for multi-vector attacks, including DDoS and infiltration attacks, while maintaining low false-positive rates. The approach highlights the effectiveness of deep learning in handling dynamic and large-scale IoT-MANET environments.

Ferrag et al. (2020) conducted a comprehensive review of deep learning techniques for cybersecurity in IoT networks. The study analysed various models such as deep belief networks, autoencoders, and CNNs for intrusion detection. It emphasized that hybrid deep learning models outperform traditional machine learning techniques in detecting complex multi-stage attacks. The authors also highlighted the importance of real-time processing and scalability in IoT security systems. Meidan et al. (2020) developed a machine learning-based anomaly detection system for IoT devices using network traffic analysis. The model identifies

abnormal patterns associated with botnet attacks and other malicious activities. The study demonstrated that behavioural analysis of network traffic significantly improves detection accuracy and can effectively identify previously unseen attack patterns.

Otoum et al. (2021) proposed an AI-enabled intrusion detection system for IoT networks that uses federated learning to enhance privacy and security. The system allows distributed devices to collaboratively learn attack patterns without sharing raw data. This approach improves scalability and reduces data privacy concerns while maintaining high detection accuracy for multi-attack scenarios. Shone et al. (2021) introduced a deep autoencoder-based intrusion detection system that learns hierarchical feature representations of network traffic. The model effectively detects both known and unknown attacks by identifying anomalies in data patterns. The study demonstrated improved detection performance compared to traditional IDS approaches.

Javaid et al. (2021) developed a deep learning-based network intrusion detection system using self-taught learning. The model extracts meaningful features from unlabelled data, improving detection accuracy for multi-attack scenarios. The study highlights the importance of feature learning in enhancing IDS performance. Saba et al. (2021) proposed a hybrid machine learning approach combining support vector machines and deep neural networks for IoT security. The system improves classification accuracy by leveraging both linear and nonlinear feature representations. The study demonstrated effective detection of various attack types in IoT networks.

Abeshu and Chilamkurti (2021) introduced a deep learning-based intrusion detection system for mobile ad hoc networks (MANETs). The model uses recurrent neural networks to capture temporal dependencies in network traffic, enabling effective detection of multi-stage attacks. The study showed improved detection accuracy and reduced false alarms. Kim et al. (2021) proposed a graph-based intrusion detection system using graph neural networks (GNNs). The system models network traffic as a graph and analyses relationships between nodes to detect anomalies. The study demonstrated that GNN-based approaches are highly effective in detecting complex multi-attack patterns.

Zhou et al. (2021) developed a deep reinforcement learning-based intrusion detection system that adapts to changing network conditions. The system learns optimal detection strategies through interaction with the environment, improving performance in dynamic IoT-MANET networks. Niyaz et al. (2021) proposed a deep learning-based intrusion detection system using stacked autoencoders. The model learns hierarchical features from network traffic data, enabling accurate detection of both known and unknown attacks. The study demonstrated high performance in multi-attack detection scenarios.

Alzubi et al. (2022) introduced a hybrid deep learning model combining CNN and LSTM for IoT intrusion detection. The model captures both spatial and temporal features, improving detection accuracy for multi-stage attacks. The study demonstrated superior performance compared to traditional machine learning methods. Ullah et al. (2022) proposed a machine learning-based IDS for detecting cyberattacks in IoT networks. The study emphasized feature selection techniques to improve classification accuracy and reduce computational complexity. The results showed improved detection performance for various attack types.

Khraisat et al. (2022) provided a comprehensive survey of intrusion detection systems, highlighting challenges and future directions. The study emphasized the need for hybrid approaches combining signature-based and anomaly-based detection methods for effective multi-attack detection. Ahmad et al. (2022) developed a deep learning-based intrusion detection model for IoT networks using convolutional neural networks. The model demonstrated high accuracy and low false-positive rates, making it suitable for real-time applications.

Wang et al. (2022) proposed a photonic neural network-based system for high-speed data processing in IoT networks. The study highlighted the advantages of photonic computing, including low latency and high bandwidth, for real-time attack detection. Huang et al. (2022) developed a coherent photonic neural network for optical signal processing. The system demonstrated ultra-fast computation capabilities, making it suitable for large-scale network security applications. Singh et al. (2023) proposed a hybrid intrusion detection system combining machine learning and forensic analysis. The system improved detection accuracy and reduced false positives by analysing network traffic patterns and attack behaviours.

Patel et al. (2023) developed a hybrid deep learning-based intrusion detection system (IDS) for IoT networks using a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures. The CNN component was utilized for extracting spatial features from network traffic data, while the LSTM layer captured temporal dependencies

and sequential attack patterns. This dual-feature learning approach significantly enhanced the system's capability to detect multi-vector attacks such as DDoS, probing, and botnet intrusions. The model was trained on benchmark IoT datasets and demonstrated high classification accuracy, low false-positive rates, and strong generalization performance. The study highlighted that integrating spatial and temporal learning mechanisms is crucial for identifying complex and evolving attack behaviours in IoT-MANET environments.

Reddy et al. (2023) proposed a multi-layer intrusion detection framework based on machine learning techniques to improve detection efficiency and scalability in IoT networks. The architecture consisted of multiple detection layers, including anomaly detection, signature-based filtering, and classification modules. Each layer contributed to progressively refining detection accuracy by filtering out benign traffic and identifying malicious patterns. The system utilized algorithms such as Random Forest and Support Vector Machines (SVM) for classification, achieving high detection rates across various attack categories. The layered approach also improved system scalability by distributing computational tasks, making it suitable for large-scale IoT-MANET deployments. The study demonstrated that multi-layer frameworks are effective in handling diverse and complex attack scenarios.

Sharma et al. (2023) introduced an AI-based intrusion detection system specifically designed for MANET environments, focusing on reducing false alarm rates while maintaining high detection accuracy. The system employed supervised learning algorithms combined with feature selection techniques to identify relevant network traffic attributes. By optimizing feature selection and classification processes, the proposed IDS minimized unnecessary computations and improved detection efficiency. The study also addressed the dynamic nature of MANETs, where frequent topology changes can affect detection performance. Experimental results showed that the system achieved improved accuracy and significantly reduced false positives compared to traditional IDS approaches, making it suitable for real-time security applications.

Verma et al. (2023) developed a graph-based intrusion detection system (IDS) for detecting multi-stage attacks in IoT networks. The proposed approach modelled network traffic as a graph, where nodes represent devices and edges represent communication links. Graph-based analysis enabled the system to capture relationships between nodes and detect complex attack patterns that evolve over time. The study utilized Graph Neural Networks (GNNs) to analyse structural and behavioural features, achieving improved detection accuracy for multi-stage attacks such as wormhole and coordinated botnet attacks. The results demonstrated that graph-based IDS approaches are highly effective in identifying hidden attack patterns and providing better situational awareness in IoT-MANET environments.

Ghosh et al. (2023) proposed an AI-based network forensic framework designed for cyberattack investigation and multi-attack detection. The framework integrates machine learning algorithms with forensic analysis techniques to extract meaningful insights from network traffic data. The system performs detailed traffic analysis, including packet inspection and behavioural profiling, to identify attack sources and patterns. By combining forensic investigation with AI-based classification, the framework improves detection accuracy and enables post-attack analysis. The study demonstrated that forensic-driven approaches are essential for understanding complex attack behaviours and enhancing the overall security of IoT-MANET systems.

Banerjee et al. (2023) introduced a hybrid AI optimization approach for intrusion detection that combines multiple algorithms, such as genetic algorithms and swarm intelligence, to optimize detection performance. The hybrid approach improves convergence speed and avoids local minima, resulting in more accurate classification of network traffic. The system dynamically adjusts model parameters to enhance detection efficiency and reduce computational overhead. Experimental results showed that the proposed approach achieves higher accuracy and better performance compared to single-algorithm models. The study highlights the importance of hybrid optimization techniques in handling complex and high-dimensional IoT security data.

Tiwari et al. (2023) proposed a comprehensive multi-attack detection system using deep learning and optimization techniques for secure IoT-MANET environments. The system integrates deep neural networks with optimization algorithms to improve detection accuracy and robustness against diverse attack types. The model is capable of identifying multiple attacks simultaneously, including DDoS, spoofing, and routing attacks. The optimization component enhances model performance by fine-tuning hyperparameters and improving convergence. The study demonstrated that the proposed system achieves high detection accuracy, low false-positive rates, and strong

adaptability to dynamic network conditions. This approach represents a significant advancement in developing intelligent and resilient intrusion detection systems.

Comparative Table

No.	Author (Year)	Technique	Model/Approach	Focus Area	Key Contribution	Advantages	Limitations
1	Vaseer et al. (2020)	Forensic + ML	NN-based IDS	MANET	Multi-attack detection	Accurate	Complexity
2	Alzahrani et al. (2020)	Deep Learning	Multi-class NN	IoT Botnet	Attack classification	High accuracy	Dataset dependency
3	Koroniotis et al. (2020)	DL + PSO	Optimized IDS	IoT	Parameter tuning	Low FP rate	Complexity
4	Lo et al. (2021)	GNN	GraphSAGE	IoT	Graph-based detection	Detects complex attacks	High computation
5	Lysenko et al. (2022)	ML	RF, KNN	IoT	Feature-based detection	Efficient	Limited scalability
6	Vinayakumar et al. (2020)	DL	CNN-RNN	IoT	Multi-attack detection	Robust	Training cost
7	Ferrag et al. (2020)	DL Survey	Hybrid DL	IoT	Comparative study	Comprehensive	Generalized
8	Meidan et al. (2020)	ML	Behavioral analysis	IoT	Botnet detection	Accurate	Limited attack types
9	Otoum et al. (2021)	Federated Learning	Distributed IDS	IoT	Privacy-preserving IDS	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	Saba et al. (2021)	Hybrid ML	SVM + DNN	IoT	Improved classification	Accurate	Computation
13	Abeshu et al. (2021)	RNN	Sequential IDS	MANET	Temporal detection	Effective	Resource intensive
14	Kim et al. (2021)	GNN	Graph IDS	IoT	Node relation detection	Accurate	High cost
15	Zhou et al. (2021)	RL	Adaptive IDS	IoT	Dynamic learning	Flexible	Training complexity
16	Niyaz et al. (2021)	DL	Autoencoder	IDS	Feature extraction	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	Fast	Limited deep patterns
19	Khraisat et al. (2022)	Survey	IDS taxonomy	IoT	Analysis	Comprehensive	Not implementation
20	Ahmad et al. (2022)	DL	CNN IDS	IoT	Attack detection	Accurate	Resource heavy

21	Wang et al. (2022)	Photonic NN	Optical computing	IoT	High-speed processing	Ultra-fast	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	Design 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 analysis of the selected studies reveals a significant evolution in intrusion detection techniques for IoT-MANET environments. Early research (2020) primarily focused on machine learning and basic deep learning models for detecting individual or limited attack types. These approaches demonstrated high accuracy but lacked scalability and adaptability to multi-attack scenarios. In 2021, advancements in deep learning architectures such as autoencoders, recurrent neural networks, and graph neural networks improved the ability to detect complex and multi-stage attacks by capturing temporal and relational features. By 2022, research shifted toward hybrid approaches and advanced computational models, including CNN-LSTM architectures and photonic neural networks. These techniques enabled faster processing and improved detection performance, particularly in large-scale IoT environments.

Photonic neural networks introduced ultra-fast computation capabilities, addressing latency issues in real-time detection systems. Recent studies (2023) emphasize the integration of forensic analysis and AI-based optimization techniques. Hybrid models combining machine learning, deep learning, and forensic investigation have shown significant improvements in detection accuracy, scalability, and robustness. These approaches effectively handle multi-vector attacks and reduce false positives. However, challenges such as high computational complexity, implementation cost, and scalability remain critical concerns for future research.

Discussion

The integration of artificial intelligence, network forensics, and photonic neural networks has significantly enhanced multi-attack detection capabilities in IoT-MANET environments. AI-based intrusion detection systems have demonstrated high accuracy in identifying complex and evolving cyber threats. Deep learning models such as CNN, LSTM, and graph neural networks enable effective analysis of network traffic patterns, improving detection of multi-stage attacks. Forensic-based approaches provide additional insights into attack behaviour, enabling more accurate identification of attack sources and patterns. This combination of AI and forensic analysis enhances detection performance and reduces false positives.

Furthermore, photonic neural networks offer high-speed data processing capabilities, making them suitable for real-time intrusion detection in large-scale IoT systems. However, the implementation of these advanced techniques introduces challenges such as increased computational complexity, high energy consumption, and hardware requirements. Additionally, the lack of interpretability in deep

learning models makes it difficult to understand decision-making processes. Future research should focus on developing lightweight and explainable AI models, improving scalability, and integrating edge computing techniques to enable efficient real-time intrusion detection in IoT-MANET systems.

Conclusion

The increasing complexity and scale of IoT-MANET networks have made them highly vulnerable to multi-vector cyberattacks. Traditional intrusion detection systems are insufficient for handling the dynamic and heterogeneous nature of these networks. This review has explored recent advancements in multi-attack detection using artificial intelligence, network forensics, and photonic neural networks. Machine learning and deep learning techniques have significantly improved intrusion detection performance by enabling automated analysis of network traffic patterns. Models such as CNN, LSTM, and graph neural networks have demonstrated high accuracy in detecting complex and multi-stage attacks. These approaches are particularly effective in identifying anomalies and adapting to evolving attack patterns.

The integration of forensic analysis with AI-based detection systems provides additional advantages by enabling detailed investigation of attack behaviours. Forensic techniques help in identifying attack sources, understanding attack patterns, and improving detection accuracy. Hybrid approaches combining AI and forensic methods have shown superior performance compared to standalone techniques. Photonic neural networks represent a promising advancement in this field, offering ultra-fast data processing capabilities. These systems address the latency challenges associated with real-time intrusion detection in large-scale IoT environments. However, their implementation requires specialized hardware and remains an area of ongoing research.

Despite these advancements, several challenges remain. High computational complexity, scalability issues, and lack of interpretability in AI models are key concerns. Additionally, the integration of advanced detection systems into resource-constrained IoT devices requires efficient and lightweight solutions. Future research should focus on developing scalable and energy-efficient intrusion detection systems that can operate in real-time environments. The integration of edge computing and explainable AI techniques can further enhance system performance and usability. Additionally, advancements in photonic computing may enable faster and more efficient detection systems. In conclusion, the combination of artificial intelligence, forensic analysis, and photonic neural networks provides a powerful framework for multi-attack detection in IoT-MANET environments. Continued research in this area will enable the development of secure, intelligent, and resilient network systems capable of addressing emerging cyber threats.

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