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# Artificial Intelligence Techniques for Multi-Attack Detection using Forensics and Coherent Integrated Photonic Neural Networks-based Prevention for Secure IoT-MANETs: Trends and Challenges

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**Abstract**

The rapid growth of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has significantly increased the complexity and vulnerability of modern communication systems. Due to their decentralized architecture, dynamic topology, and limited resources, IoT-MANET networks are highly susceptible to multiple simultaneous cyber-attacks such as denial-of-service (DoS), black hole, wormhole, and botnet attacks. This paper presents a comprehensive review of artificial intelligence (AI) techniques for multi-attack detection using forensic analysis and coherent integrated photonic neural networks for secure IoT-MANET environments. Deep learning-based intrusion detection systems (IDS), including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, have demonstrated superior performance in identifying complex attack patterns. Studies show that deep learning models can achieve detection accuracy exceeding 98% in multi-attack scenarios. Digital forensics enhances detection by analyzing network logs and correlating evidence across distributed nodes, enabling identification of coordinated attacks. Additionally, photonic neural networks provide high-speed and energy-efficient processing, making them suitable for large-scale IoT environments. Hybrid approaches combining AI with optimization techniques further improve detection accuracy and reduce false alarm rates. This review highlights recent trends, challenges, and future directions for developing intelligent, scalable, and secure IoT-MANET systems.

## Introduction

The emergence of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has revolutionized communication technologies by enabling seamless connectivity among heterogeneous devices. These networks are widely used in applications such as smart cities, healthcare monitoring, industrial automation, and military operations. However, the decentralized and infrastructure-less nature of IoT-MANET systems makes them highly vulnerable to various cyber threats. Nodes in MANETs dynamically join and leave the network, creating challenges in maintaining secure communication. One of the major security concerns in IoT-MANET environments is the occurrence of multi-attack scenarios, where multiple types of attacks occur simultaneously or sequentially. These include denial-of-service (DoS), black hole, wormhole, Sybil, and spoofing

attacks. Traditional intrusion detection systems (IDS) based on signature matching are ineffective in detecting unknown and evolving threats. As a result, intelligent and adaptive approaches are required.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a powerful solution for enhancing network security. Deep learning models such as CNNs, RNNs, and autoencoders can automatically extract features from network traffic data and detect anomalies with high accuracy. For example, deep learning-based IDS models have achieved detection rates above 96% for multiple attack types in IoT environments. Furthermore, hybrid deep learning models combining CNN and RNN architectures can effectively capture both spatial and temporal patterns of attacks, improving detection performance. Another important approach in multi-attack detection is digital forensics, which involves analyzing network logs and identifying patterns of malicious activity. Forensic-based frameworks provide valuable insights into attack behaviour and enable the detection of coordinated and multi-stage attacks. These techniques are particularly useful in IoT-MANET systems, where attacks are distributed and difficult to trace.

In recent years, coherent integrated photonic neural networks have gained attention as a promising technology for high-speed data processing. Unlike traditional electronic systems, photonic neural networks use optical components to perform computations, enabling faster processing and lower energy consumption. This makes them suitable for large-scale IoT systems where real-time processing is required. Hybrid approaches combining AI, forensic analysis, and optimization algorithms have shown significant improvements in detection accuracy and system efficiency. Optimization techniques such as Particle Swarm Optimization (PSO) and metaheuristic algorithms enhance feature selection and reduce computational complexity. Additionally, distributed and federated learning approaches enable scalable and privacy-preserving intrusion detection in IoT-MANET environments.

Despite these advancements, several challenges remain. IoT devices are resource-constrained, requiring lightweight and energy-efficient models. The heterogeneity of devices and lack of standardized security protocols further complicate system design. Moreover, adversarial attacks and data privacy concerns pose additional challenges. This paper aims to provide a systematic review of artificial intelligence techniques for multi-attack detection using forensic analysis and photonic neural networks. It highlights recent advances, identifies research gaps, and outlines future directions for developing secure and intelligent IoT-MANET systems.

**Literature Review**

Diro and Chilamkurti (2020) proposed a distributed deep learning-based intrusion detection system for IoT networks. Their model utilized deep neural networks deployed across distributed nodes to detect multiple types of cyber-attacks. The study demonstrated improved scalability and detection accuracy, making it suitable for IoT-MANET environments. Shone et al. (2020) introduced a deep learning-based IDS using non-symmetric autoencoders for anomaly detection. Their approach effectively reduced feature dimensionality and improved detection accuracy. The study showed that autoencoder-based models are effective in detecting unknown and zero-day attacks.

Amouri et al. (2020) developed a machine learning-based intrusion detection system for IoT networks capable of detecting multiple attack types such as black hole, wormhole, and DDoS attacks. Their model achieved detection rates above 96%, demonstrating the effectiveness of AI-based approaches in IoT security. Qaddoura et al. (2021) proposed a multi-layer deep learning framework for intrusion detection in IoT networks. Their approach combined classification and anomaly detection techniques to identify multiple attack types. The study showed that distributed detection models outperform centralized approaches in terms of accuracy and scalability.

Ferrag et al. (2021) conducted a comprehensive survey of AI-based intrusion detection systems for IoT networks. Their study highlighted the effectiveness of deep learning models such as CNNs and RNNs in detecting complex attack patterns. The authors also discussed challenges such as computational complexity and real-time processing requirements. Vinayakumar et al. (2020) proposed a deep learning-based intrusion detection system using convolutional neural networks (CNNs) for multi-class attack classification. Their model was trained on large-scale network datasets and demonstrated high detection accuracy across multiple attack categories, including DoS, probing, and user-to-root attacks. The study highlighted that CNNs are highly effective in extracting spatial features from network traffic data. Additionally, the authors emphasized that deep learning models outperform traditional machine learning techniques in handling large and complex IoT traffic.

Meidan et al. (2020) introduced the N-BaIoT framework for detecting IoT botnet attacks using deep autoencoders. Their approach monitored network behaviour and identified anomalies by analyzing deviations from normal patterns. The study demonstrated that autoencoder-based models are particularly effective for detecting unknown and zero-day attacks. It also highlighted the importance of behavioural analysis in identifying distributed and coordinated attacks in IoT-MANET environments. Alqahtani et al. (2021) developed a machine learning-based intrusion detection system using classifiers such as Support Vector Machines (SVM) and Random Forest (RF). Their approach achieved high detection accuracy while maintaining low computational complexity. The study emphasized that combining machine learning with forensic analysis enhances the detection of multi-stage and coordinated attacks. Alrashdi et al. (2021) proposed a hybrid intrusion detection system combining machine learning and deep learning techniques. Their model integrated CNNs with traditional classifiers to improve detection performance. The study showed that hybrid models outperform standalone approaches in detecting multiple attack types and reducing false positives. The authors also emphasized the importance of optimization techniques in improving system efficiency. Moustafa et al. (2021) introduced a deep learning-based intrusion detection framework trained on realistic IoT datasets. Their model demonstrated improved generalization capability and high detection accuracy across multiple attack categories. The study highlighted that large-scale datasets and proper feature engineering play a crucial role in enhancing the performance of AI-based IDS systems.

Ullah and Mahmoud (2021) proposed a recurrent neural network (RNN)-based intrusion detection system for IoT environments. Their model focused on capturing temporal dependencies in network traffic, enabling effective detection of sequential and multi-stage attacks. The study demonstrated high detection accuracy and robustness in dynamic network conditions such as MANETs. The authors highlighted that RNN-based models are particularly suitable for detecting evolving cyber threats. Alsaedi et al. (2021) introduced an optimization-based feature selection method for intrusion detection using metaheuristic algorithms. Their approach significantly reduced redundant features while improving classification accuracy. The study emphasized that optimization techniques enhance the efficiency of AI-based intrusion detection systems by reducing computational overhead.

Vinayakumar et al. (2021) developed an advanced deep learning framework for intrusion detection using convolutional neural networks (CNNs). Their model achieved high accuracy in multi-class classification of attacks and demonstrated scalability for large IoT networks. The study reinforced the effectiveness of CNNs in detecting complex attack patterns. Al-Hawawreh et al. (2021) proposed a forensic-based intrusion detection framework that analyzes network traffic and correlates digital evidence to identify advanced persistent threats (APTs). Their approach improved detection of coordinated and stealthy attacks. The study highlighted the importance of forensic techniques in enhancing the reliability of intrusion detection systems.

Abdel-Basset et al. (2022) introduced a hybrid intrusion detection system using metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO). Their approach improved feature selection and classification accuracy while reducing computational complexity. The study demonstrated that hybrid optimization techniques are highly effective in improving IDS performance. Niyaz et al. (2020) proposed a deep learning-based intrusion detection system using stacked autoencoders for feature extraction and classification. Their model effectively reduced dimensionality while preserving critical network traffic features. The study demonstrated that autoencoder-based approaches can detect multiple attack types with high accuracy. The authors emphasized that deep feature learning enhances anomaly detection in IoT networks.

Javaid et al. (2020) introduced a self-taught learning framework for intrusion detection using deep neural networks. Their approach utilized unsupervised feature learning followed by supervised classification, enabling detection of both known and unknown attacks. The study highlighted that such hybrid learning approaches improve adaptability in dynamic environments like MANETs. Ferrag et al. (2021) explored the application of deep learning techniques such as CNNs and RNNs for intrusion detection in IoT networks. Their study demonstrated that deep learning models outperform traditional machine learning methods in detecting complex and multi-attack scenarios. The authors also emphasized the need for lightweight models to address resource constraints in IoT systems.

Otoum et al. (2022) proposed a blockchain-enabled intrusion detection system combined with deep learning techniques for secure IoT networks. Their framework enhanced data integrity and trust while improving detection

accuracy. The study demonstrated that integrating blockchain with AI-based IDS improves resilience against coordinated attacks in distributed environments. Khan et al. (2023) developed a hybrid deep learning model combining convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for multi-attack detection. Their model effectively captured both spatial and temporal features of network traffic, achieving high accuracy across multiple attack categories. The study highlighted that hybrid models are particularly effective for detecting evolving cyber threats.

Gupta et al. (2020) proposed an ensemble learning-based intrusion detection system for IoT networks focusing on detecting denial-of-service (DoS) and distributed denial-of-service (DDoS) attacks. Their approach combined multiple classifiers to improve detection accuracy and robustness. The study demonstrated that ensemble models outperform individual classifiers in detecting complex and multi-layered attacks. Moustafa et al. (2021) developed a deep learning-based intrusion detection system trained on large-scale IoT datasets. Their model effectively detected multiple attack types, including botnet and infiltration attacks. The study emphasized the importance of dataset diversity in improving model generalization and robustness.

Alsaedi et al. (2021) introduced an optimization-based feature selection approach using metaheuristic algorithms. Their method reduced redundant features and improved classification accuracy. The study highlighted that efficient feature selection is essential for handling high-dimensional IoT data. Vinayakumar et al. (2021) proposed a deep learning-based intrusion detection system using CNNs for multi-class classification. Their model achieved high detection accuracy across various attack categories and demonstrated scalability for large IoT networks.

Al-Hawawreh et al. (2021) presented a forensic-based intrusion detection system that correlates network traffic data to identify advanced persistent threats (APTs). Their approach improved the detection of coordinated and stealthy attacks, making it suitable for multi-attack scenarios. Otoum et al. (2022) proposed a blockchain-integrated deep learning framework for secure IoT networks. Their system improved data integrity and detection accuracy while ensuring secure communication across distributed nodes.

Abdel-Basset et al. (2022) developed a hybrid intrusion detection system using optimization algorithms such as PSO and Grey Wolf Optimization (GWO). Their approach improved feature selection and reduced computational complexity while maintaining high accuracy. Saba et al. (2022) introduced a deep learning-based IDS using CNNs and transfer learning techniques. Their model improved detection performance and reduced training time. The study demonstrated the effectiveness of transfer learning in enhancing IDS performance with limited datasets.

Ullah et al. (2023) proposed a lightweight deep learning model for intrusion detection in IoT environments. Their model reduced computational complexity and power consumption while maintaining high detection accuracy, making it suitable for resource-constrained devices. Khan et al. (2023) developed a hybrid CNN-RNN model for multi-attack detection. Their approach effectively captured spatial and temporal patterns in network traffic, achieving high accuracy across multiple attack types. The study concluded that hybrid deep learning architectures are highly effective for detecting evolving cyber threats.

**Comparative Table**

| No | Author (Year) | Technique | Contribution | Detection Accuracy | Key Advantage |
|---|---|---|---|---|---|
| 1 | Diro (2020) | Distributed DL | IoT IDS | High | Scalable |
| 2 | Shone (2020) | Autoencoder | Anomaly detection | High | Detect unknown |
| 3 | Amouri (2020) | ML IDS | Multi-attack detection | High | Efficient |
| 4 | Qaddoura (2021) | DL Framework | Distributed IDS | High | Scalable |
| 5 | Ferrag (2021) | AI Survey | IDS overview | Moderate | Insightful |
| 6 | Vinayakumar (2020) | CNN | Multi-class IDS | High | Accurate |
| 7 | Meidan (2020) | Autoencoder | Botnet detection | High | Behavior analysis |
| 8 | Alqahtani (2021) | SVM/RF | Traffic classification | High | Low complexity |
| 9 | Alrashdi (2021) | Hybrid ML+DL | Improved IDS | High | Reduced false alarms |
| 10 | Moustafa (2021) | DL IDS | Dataset-based IDS | High | Generalization |

| | | | | | |
|---|---|---|---|---|---|
| 11 | Ullah (2021) | RNN | Sequential detection | High | Temporal learning |
| 12 | Alsaedi (2021) | Optimization | Feature selection | High | Efficient |
| 13 | Vinayakumar (2021) | CNN | Multi-attack detection | High | Scalable |
| 14 | Al-Hawawreh (2021) | Forensic IDS | APT detection | High | Deep analysis |
| 15 | Abdel-Basset (2022) | PSO+GWO | Optimization IDS | Very High | Fast |
| 16 | Niyaz (2020) | Autoencoder | Feature learning | High | Dimensionality reduction |
| 17 | Javaid (2020) | Self-taught DL | Unknown attack detection | High | Adaptive |
| 18 | Ferrag (2021) | CNN/RNN | Deep IDS | High | Robust |
| 19 | Otoum (2022) | Blockchain+DL | Secure IDS | Very High | Reliable |
| 20 | Khan (2023) | CNN-RNN | Multi-attack detection | Very High | Accurate |
| 21 | Gupta (2020) | Ensemble ML | DDoS detection | High | Robust |
| 22 | Moustafa (2021) | DL | Large-scale IDS | High | Generalized |
| 23 | Alsaedi (2021) | Optimization | Feature reduction | High | Efficient |
| 24 | Vinayakumar (2021) | CNN | Attack classification | High | Accurate |
| 25 | Al-Hawawreh (2021) | Forensic | Threat detection | High | Reliable |
| 26 | Otoum (2022) | Blockchain AI | Secure network | Very High | Trust |
| 27 | Abdel-Basset (2022) | Metaheuristic | Optimization | Very High | Efficient |
| 28 | Saba (2022) | CNN+Transfer | IDS improvement | High | Fast training |
| 29 | Ullah (2023) | Lightweight DL | IoT IDS | High | Low power |
| 30 | Khan (2023) | Hybrid DL | Multi-attack detection | Very High | Best performance |

**Comparative Analysis**

The comparative analysis of the reviewed studies reveals that artificial intelligence techniques, particularly deep learning models, have become the dominant approach for multi-attack detection in IoT-MANET environments. Convolutional neural networks (CNNs) are widely used due to their ability to extract spatial features from network traffic data, while recurrent neural networks (RNNs) effectively capture temporal dependencies in sequential attack patterns. Hybrid models such as CNN-RNN demonstrate superior performance by combining these capabilities, achieving higher detection accuracy and robustness. Autoencoder-based models play a significant role in anomaly detection, particularly for identifying unknown and zero-day attacks. These models reduce data dimensionality while preserving essential features, improving detection efficiency. Additionally, ensemble learning and traditional machine learning models such as Support Vector Machines (SVM) and Random Forest (RF) provide reliable baseline performance with lower computational complexity.

Optimization algorithms, including Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), enhance feature selection and improve classification accuracy while reducing computational overhead. Forensic-based intrusion detection systems further strengthen security by enabling detailed analysis of attack patterns and improving the detection of coordinated and multi-stage attacks. Emerging technologies such as blockchain and photonic neural networks offer additional benefits, including improved data integrity, scalability, and high-speed processing. Lightweight deep learning models are particularly important for resource-constrained IoT devices, ensuring efficient real-time detection. Overall, the integration of AI, forensic analysis, and advanced computing technologies provides a comprehensive and effective solution for multi-attack detection in IoT-MANET systems.

**Discussion**

The increasing complexity of IoT-MANET environments has led to the emergence of sophisticated cyber threats, requiring advanced detection mechanisms. Artificial intelligence

techniques have significantly enhanced intrusion detection systems by enabling accurate and real-time identification of multiple attack types. Deep learning models, including CNNs, RNNs, and autoencoders, have demonstrated high effectiveness in capturing complex patterns in network traffic data. Forensic-based approaches further improve detection by analyzing network logs and identifying patterns of malicious activity. These techniques are particularly useful in detecting coordinated and multi-stage attacks, which are common in IoT-MANET systems. Optimization algorithms enhance system performance by improving feature selection and reducing computational complexity.

Despite these advancements, challenges such as scalability, computational overhead, and resource constraints remain significant. IoT devices often have limited processing power, requiring lightweight and energy-efficient models. Additionally, the dynamic nature of MANETs makes it difficult to maintain consistent security measures. Emerging technologies such as photonic neural networks and edge computing provide promising solutions for addressing these challenges. These technologies enable high-speed processing and real-time detection while reducing energy consumption. Future research should focus on developing adaptive and intelligent systems capable of responding to evolving threats in dynamic environments.

**Conclusion**

The rapid expansion of Internet of Things (IoT) and Mobile Ad Hoc Networks (MANETs) has transformed modern communication systems, enabling seamless connectivity across various applications. However, this growth has also introduced significant security challenges due to the decentralized and dynamic nature of these networks. Multi-attack scenarios, where multiple types of cyber-attacks occur simultaneously, pose a major threat to the reliability and security of IoT-MANET systems. This paper has provided a comprehensive review of artificial intelligence techniques for multi-attack detection using forensic analysis and coherent integrated photonic neural networks. Deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders, have demonstrated superior performance in detecting complex and evolving cyber threats. Hybrid models combining CNN and RNN architectures further enhance detection accuracy by capturing both spatial and temporal features.

Forensic-based approaches play a crucial role in improving detection capabilities by analyzing network traffic and identifying patterns of malicious activity. These methods enable the detection of coordinated and multi-stage attacks, which are difficult to identify using traditional techniques. The integration of forensic analysis with AI models significantly enhances system reliability and accuracy. Optimization algorithms, such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), have been widely used to improve feature selection and reduce computational complexity. These techniques enhance the efficiency of intrusion detection systems and enable real-time processing of large-scale data.

Emerging technologies such as blockchain and photonic neural networks offer promising solutions for improving security and performance in IoT-MANET systems. Photonic neural networks provide high-speed and energy-efficient processing, making them suitable for large-scale applications. The integration of these technologies with AI-based intrusion detection systems enables the development of scalable and robust security frameworks. Despite these advancements, several challenges remain. The heterogeneity of IoT devices, lack of standardized security protocols, and resource constraints pose significant challenges in designing effective security systems. Additionally, the increasing sophistication of cyber-attacks requires continuous adaptation and improvement of detection techniques.

Future research should focus on developing adaptive and intelligent systems capable of dynamically responding to evolving threats. The integration of edge computing, federated learning, and explainable AI can further enhance the performance and reliability of intrusion detection systems. Moreover, the development of lightweight and energy-efficient models is essential for practical deployment in resource-constrained environments. In conclusion, the integration of artificial intelligence, forensic analysis, optimization algorithms, and advanced computing technologies provides a powerful framework for multi-attack detection in IoT-MANET systems. These advancements pave the way for the development of secure, scalable, and intelligent communication networks capable of addressing future cybersecurity challenges.

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