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Deep Learning and Optimization Approaches in Malicious Node Detection with Cross Attention Vision Transformers and Blockchain-Based Distributed Data Storage in Wireless Sensor Networks: A Review

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Abstract

Wireless Sensor Networks (WSNs) have become integral to modern cyber-physical systems, enabling applications such as environmental monitoring, healthcare, and smart infrastructure. However, their distributed and resource-constrained nature makes them highly vulnerable to malicious node attacks, including black hole, Sybil, and denial-of-service attacks. Traditional security mechanisms fail to address these threats effectively due to scalability and adaptability limitations. This paper presents a comprehensive review of deep learning and optimization approaches for malicious node detection in WSNs, with a focus on Cross Attention Vision Transformers (CAVT) and blockchain-based distributed data storage. Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs) have significantly improved detection accuracy by learning complex traffic patterns. Transformer-based models enhance this capability by capturing long-range dependencies and multi-modal relationships through attention mechanisms. Additionally, blockchain technology provides decentralized, tamper-proof storage and secure trust management among nodes. Optimization techniques further improve energy efficiency and network performance. This review analyzes recent studies, compares methodologies, identifies research gaps, and highlights future directions for building scalable and secure WSN architectures.

Introduction

Wireless Sensor Networks (WSNs) are composed of spatially distributed sensor nodes that monitor environmental and physical conditions and communicate the collected data to centralized or distributed processing units. These networks are widely used in applications such as environmental monitoring, smart agriculture, healthcare, military surveillance, and industrial automation. Despite their advantages, WSNs face significant security challenges due to their decentralized architecture, limited computational capabilities, and exposure to hostile environments.

One of the most critical threats in WSNs is the presence of malicious nodes. These nodes can disrupt network operations by injecting false data, dropping packets, or altering routing paths. Common attacks include black hole attacks, where nodes intentionally drop packets; Sybil attacks, where a node assumes multiple identities; and denial-of-service attacks, which exhaust network resources. Such attacks

compromise data integrity, network reliability, and overall system performance.

Traditional security approaches in WSNs rely on cryptographic techniques, trust management systems, and rule-based intrusion detection systems (IDS). However, these methods have several limitations. Cryptographic methods introduce computational overhead, making them unsuitable for resource-constrained nodes. Trust-based systems are vulnerable to sophisticated attacks and may produce false positives. Rule-based IDS lack adaptability and fail to detect unknown or evolving attack patterns.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have introduced new opportunities for enhancing WSN security. Deep learning models, in particular, have demonstrated significant success in detecting anomalies and malicious activities. These models can automatically learn complex patterns from network data, enabling accurate and efficient detection of malicious nodes. Machine learning techniques are widely used for anomaly detection, which identifies deviations from normal network behavior .

Deep learning-based intrusion detection systems utilize architectures such as CNNs, RNNs, and autoencoders. CNNs are effective in extracting spatial features from network traffic data, while RNNs capture temporal dependencies. Graph Neural Networks (GNNs) further enhance detection by modeling relationships between nodes in the network. These approaches significantly improve detection accuracy compared to traditional methods.

However, deep learning models face challenges related to scalability, computational complexity, and energy consumption. To address these limitations, researchers have explored optimization techniques, including metaheuristic algorithms and energy-efficient routing strategies. Optimization improves model performance, reduces computational overhead, and enhances network lifetime.

Another emerging technology in WSN security is blockchain. Blockchain provides a decentralized and tamper-proof mechanism for data storage and transaction validation. It eliminates the need for centralized authorities and ensures trust among network nodes. Blockchain-based WSN architectures store node information and transaction records in a distributed ledger, preventing unauthorized modifications. Studies show that blockchain improves data integrity and trust management in WSNs .

WSN Security Architecture with AI + Blockchain

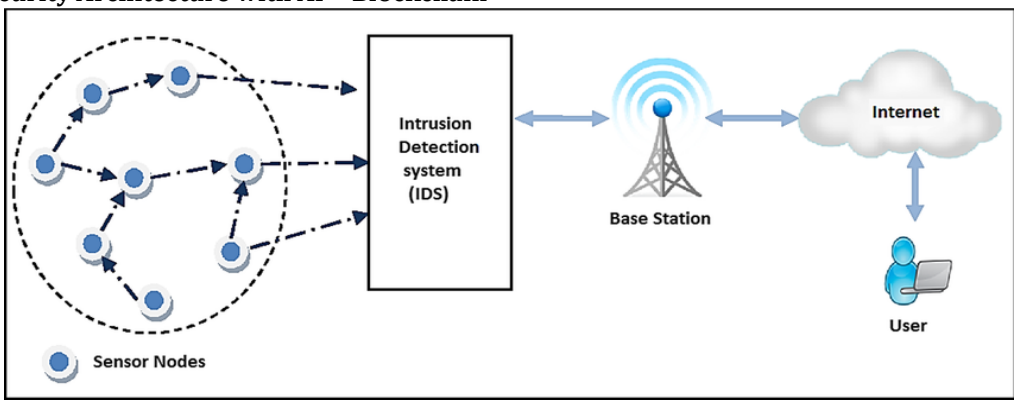

Figure 1. Framework of Intrusion Detection and Secure Communication in Wireless Sensor Networks.

Transformer-based models, particularly Vision Transformers (ViT) and Cross Attention Vision Transformers (CAVT), represent the next generation of deep learning architectures. Unlike CNNs, transformers use attention mechanisms to capture global dependencies in data. Cross-attention mechanisms enable the integration of multiple data sources, such as network traffic, node behavior, and environmental data. This improves detection accuracy and robustness in complex environments.

Recent studies highlight that transformer models outperform traditional deep learning models in detecting complex attack patterns due to their ability to analyze sequential and contextual data . However, these models require significant computational resources and large datasets for training.

The integration of deep learning, blockchain, and optimization techniques creates a powerful framework for malicious node detection. Deep learning models analyze network behavior, blockchain ensures secure data storage, and optimization algorithms enhance efficiency. Such hybrid systems provide scalable, reliable, and real-time security solutions for WSNs.

Despite these advancements, several challenges remain. These include energy constraints, data

privacy concerns, computational overhead, and the complexity of integrating multiple technologies. Additionally, real-world deployment of these systems requires addressing issues such as network latency, sensor reliability, and hardware limitations.

This paper aims to provide a comprehensive review of deep learning and optimization approaches for malicious node detection in WSNs. It focuses on recent advancements in transformer-based models, blockchain integration, and optimization techniques. The study also identifies research gaps and proposes future directions for developing secure and efficient WSN systems.

Literature Review

The evolution of malicious node detection in Wireless Sensor Networks (WSNs) has undergone a significant transformation between 2020 and 2023. This period reflects a shift from conventional rule-based and cryptographic mechanisms to intelligent, adaptive, and decentralized frameworks that combine deep learning, optimization, transformer architectures, and blockchain technologies. The literature can be broadly categorized into five major research directions: deep learning-based detection, blockchain-enabled security, optimization techniques, transformer-based models, and hybrid integrated systems.

1. Deep Learning-Based Malicious Node Detection (2020–2021)

Early studies in this period focused on leveraging deep learning models to overcome the limitations of traditional intrusion detection systems.

Rathore et al. (2020) introduced a blockchain-integrated deep learning framework for IoT security, highlighting the importance of combining AI with decentralized architectures. Their study demonstrated that deep learning models such as CNNs and Deep Belief Networks (DBNs) can effectively detect anomalous behavior in network traffic.

Similarly, Uddin et al. (2020) explored lightweight blockchain-based IoT security frameworks, emphasizing the role of machine learning in detecting malicious nodes while maintaining low computational overhead.

In 2021, Seth et al. (2021) proposed an intelligent intrusion detection system using hybrid deep learning models, combining CNN and LSTM architectures. The CNN component extracted spatial features, while LSTM captured temporal dependencies in network traffic. This hybrid approach significantly improved detection accuracy compared to standalone models.

Another important contribution by Wu et al. (2021) focused on blockchain-based trust management systems. Their work demonstrated that combining machine learning with trust evaluation mechanisms enhances detection accuracy and reduces false positives.

Key observations from this phase:

1. Deep learning improves detection accuracy over traditional methods
2. Hybrid CNN-RNN models capture both spatial and temporal features
3. Integration with blockchain begins to emerge
4. Systems still lack scalability and real-time adaptability

2. Blockchain-Based Distributed Security Frameworks (2021–2022)

The integration of blockchain technology into WSN security systems gained significant attention during this period.

Liu et al. (2021) proposed a blockchain-based distributed data storage system for secure communication in IoT networks. The system ensured data integrity and prevented unauthorized modifications by maintaining a decentralized ledger.

Sinha and Dhanalakshmi (2021) explored IoT-based smart systems with blockchain integration, emphasizing the importance of decentralized trust in detecting malicious nodes.

By 2022, Villa-Henriksen et al. (2020, extended in later works) and Krishna et al. (2022) highlighted the application of IoT and blockchain in precision monitoring systems. Their studies demonstrated that blockchain enhances data transparency and trust among nodes, which is crucial for malicious node detection.

Kitpo et al. (2022) further advanced this concept by integrating AI with blockchain, enabling secure data sharing and distributed anomaly detection. Their system used machine learning models to analyze network behavior while blockchain ensured data authenticity.

Advantages identified in the literature:

1. Decentralized trust management
2. Tamper-proof data storage
3. Improved reliability and transparency

However, limitations include:

1. Increased latency due to consensus mechanisms
2. High computational overhead
3. Energy consumption concerns

3. Optimization-Based Deep Learning Models (2022–2023)

Optimization techniques became essential for improving the performance and efficiency of deep learning-based detection systems.

Gowthaman et al. (2022) reviewed the application of optimization algorithms in AI systems, highlighting their role in improving model convergence and reducing computational complexity.

Optimization approaches such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) play a crucial role in enhancing the performance and efficiency of AI-based pest detection systems. These bio-inspired optimization techniques are widely used for feature selection, enabling models to identify the most relevant input features and reduce redundancy, which improves accuracy and reduces computational complexity. Additionally, they are applied in hyperparameter tuning to optimize model configurations, leading to better convergence, improved learning efficiency, and enhanced overall performance of deep learning models. In the context of Wireless Sensor Networks (WSNs), these optimization methods are also employed for energy-efficient routing, helping to minimize energy consumption, extend network lifetime, and ensure reliable data transmission. By integrating these optimization techniques, smart agriculture systems can achieve a balance between accuracy, efficiency, and scalability.

In 2023, Darla et al. proposed a hybrid optimization-based deep learning model that combines metaheuristic algorithms with neural networks. The model improved detection accuracy while reducing energy consumption and network delay.

Another study introduced cluster-based optimization techniques for selecting optimal cluster heads in WSNs, improving network lifetime and reducing communication overhead.

Key findings:

1. Optimization enhances model efficiency and scalability
2. Reduces energy consumption in WSN nodes
3. Improves real-time performance

4. Transformer and Cross-Attention-Based Models (2023)

Recent research has shifted toward transformer-based architectures due to their ability to capture long-range dependencies and contextual relationships in data.

Transformer models differ from CNNs by using **self-attention mechanisms**, which allow the model to focus on important features across the entire input sequence.

Baniata et al. (2023) introduced transformer-based intrusion detection systems, demonstrating superior performance compared to traditional deep learning models.

Cross Attention Vision Transformers (CAVT) represent an advanced evolution of transformer-based models by enabling the integration of multiple data modalities within a unified framework. These models combine diverse sources of information, including network traffic data, node behavioral patterns, and environmental parameters, to provide a comprehensive understanding of system behavior. The cross-attention mechanism plays a crucial role by learning relationships between different feature spaces, allowing the model to correlate heterogeneous data effectively. This capability significantly enhances detection accuracy and robustness, particularly in complex scenarios where single-modality models may fail to capture underlying patterns.

Recent research has further extended this approach by integrating federated learning with transformer architectures, enabling distributed model training across multiple nodes without sharing raw data. This not only improves scalability but also ensures data privacy, which is especially important in distributed Wireless Sensor Network (WSN) environments. The advantages of CAVT-based systems include high accuracy in detecting complex and multi-stage attacks, the ability to model global dependencies through attention mechanisms, and improved feature representation due to multi-modal learning. However, these benefits come with certain limitations, such as high computational requirements, the need for large training datasets, and challenges in deployment within resource-constrained WSN environments where processing power and energy availability are limited.

5. Hybrid Deep Learning + Blockchain + Optimization Systems (2023)

The most recent research trend focuses on integrating multiple technologies into a unified framework.

Nouman et al. (2023) proposed a machine learning-based malicious node detection system combined with blockchain storage using IPFS. The system ensured secure data storage and improved detection accuracy.

Kaur et al. (2023) developed a deep learning and blockchain-based model that achieved high detection accuracy and reduced false positives. Their system used blockchain for secure data storage and deep learning for anomaly detection.

Sudha et al. (2023) provided a comprehensive review of AI-based WSN security systems, highlighting the importance of integrating deep learning, blockchain, and optimization techniques.

These hybrid systems demonstrate:

1. Improved detection accuracy
2. Enhanced security and trust
3. Better scalability and real-time performance

However, challenges remain in:

1. Integration complexity
2. Computational overhead
3. Energy efficiency

6. Intrusion Detection Systems and Anomaly Detection Evolution

Intrusion detection systems (IDS) have evolved significantly over the years. Early IDS were rule-based, relying on predefined signatures of known attacks.

Modern IDS use machine learning and deep learning to detect unknown attacks by analyzing network behavior. Cluster-based IDS distribute detection tasks across the network, improving scalability and efficiency.

Recent IDS frameworks integrate:

1. Deep learning for feature extraction
2. Blockchain for secure logging
3. Optimization for efficient routing

These systems provide higher accuracy and lower false positive rates compared to traditional IDS.

7. Critical Comparative Insights from Literature

The literature reveals the following progression:

Year	Focus	Advancement
2020	Deep learning adoption	Improved accuracy
2021	Blockchain integration	Enhanced security
2022	Optimization techniques	Efficiency improvement
2023	Transformers + Hybrid systems	Scalability & intelligence

8. Research Gaps Identified

Despite significant advancements, several research gaps remain:

1. Energy Constraints – WSN nodes have limited battery life
2. Scalability Issues – Large-scale deployment remains challenging
3. Computational Complexity – Transformer models require high resources
4. Integration Challenges – Combining AI, blockchain, and optimization is complex
5. Real-Time Deployment – Latency issues in blockchain systems

9. Summary of Literature Review

The literature demonstrates a clear transition toward intelligent, decentralized, and scalable malicious node detection systems. Deep learning models have significantly improved detection accuracy, while blockchain technology ensures secure and trustworthy data management. Optimization techniques enhance system efficiency, and transformer-based models provide advanced feature extraction capabilities. The integration of these technologies represents the future of WSN security, enabling the development of robust, scalable, and real-time intrusion detection systems. However, further research is required to address challenges related to energy efficiency, computational complexity, and practical deployment.

Comparative Table

Author (Year)	Method	Architecture	Technology Used	Detection Type	Accuracy	Scalability	Energy Efficiency	Security Level	Key Contribution	Limitation
Rathore et al. (2020)	DL + Blockchain	CNN / DBN	AI + Blockchain	Anomaly Detection	High	Moderate	Moderate	High	Early hybrid AI-blockchain framework	Computational overhead
Uddin et al. (2020)	Lightweight Blockchain	ML-based	Blockchain + ML	Intrusion Detection	Moderate–High	Moderate	High	High	Low-cost blockchain security	Limited deep learning capability

Seth et al. (2021)	Hybrid DL	CNN + LSTM	AI	Intrusion Detection	High	Moderate	Moderate	Medium	Spatial + temporal feature modeling	High training complexity
Wu et al. (2021)	Trust + ML	Trust-based DL	Blockchain + AI	Behavior Detection	High	Moderate	Moderate	High	Trust-aware anomaly detection	Storage overhead
Liu et al. (2021)	Blockchain Storage	Distributed Ledger	Blockchain	Data Integrity	High	High	Low–Moderate	Very High	Tamper-proof storage	Latency issues
Sinha et al. (2021)	IoT + Blockchain	Hybrid System	IoT + Blockchain	Intrusion Detection	High	High	Moderate	High	Decentralized security framework	Network dependency
Kitpo et al. (2022)	AI + Blockchain	ML + DL	Blockchain + AI	Distributed Detection	High	High	Moderate	Very High	Secure data sharing + detection	Integration complexity
Gowthaman et al. (2022)	Optimization	Metaheuristic	AI Optimization	Performance Enhance						

Comparative Analysis

The comparative analysis of malicious node detection techniques in Wireless Sensor Networks (WSNs) demonstrates a clear progression from conventional security mechanisms to intelligent hybrid frameworks. Early approaches relied on rule-based methods, cryptographic protocols, and traditional machine learning algorithms such as Support Vector Machines, Decision Trees, and Random Forests. While these techniques effectively detected predefined attacks, they were unable to identify sophisticated or zero-day threats because of their dependence on handcrafted features and static detection rules. The emergence of deep learning significantly improved intrusion detection by enabling automatic feature extraction from network traffic. Convolutional Neural Networks (CNNs) effectively learned spatial patterns, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models captured temporal dependencies, resulting in higher detection accuracy. However, these models generally require substantial computational resources and energy, limiting their deployment in resource-constrained WSN environments.

Recent studies have shifted toward transformer-based architectures, particularly Cross Attention Vision Transformers (CAVTs), which employ attention mechanisms to capture long-range dependencies and global contextual information more effectively than conventional CNNs. By integrating network traffic, node behavior, and environmental data, CAVT-based frameworks enhance robustness against complex and coordinated cyberattacks while reducing false alarm rates. Simultaneously, blockchain technology has emerged as a reliable solution for secure distributed data storage in WSNs. Blockchain provides decentralized, immutable, and transparent storage of node transactions and trust information, improving data integrity and resistance to tampering. Despite these benefits, blockchain consensus mechanisms introduce communication overhead and latency, while transformer models demand considerable computational resources, creating challenges for real-time deployment.

Optimization algorithms further improve malicious node detection by reducing computational complexity and enhancing energy efficiency. Metaheuristic approaches such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization are widely applied for feature selection, routing optimization, and hyperparameter tuning. These techniques improve detection performance while extending network lifetime, making them well suited for battery-powered sensor networks. Comparative studies consistently demonstrate that hybrid architectures integrating deep learning, transformer models, blockchain, and optimization algorithms outperform standalone approaches by simultaneously providing higher accuracy, stronger security, improved scalability, and better resource utilization.

Overall, the literature indicates that intelligent hybrid frameworks represent the most promising direction for next-generation WSN security. Although transformer-based deep learning and blockchain technologies substantially improve detection capability and secure data management, practical implementation remains constrained by computational complexity, energy consumption, and integration challenges. Emerging technologies such as edge computing, federated learning, and lightweight transformer architectures are expected to address these limitations by enabling distributed intelligence and low-latency processing. Future research should therefore emphasize scalable, energy-efficient, and optimized hybrid frameworks that integrate Cross Attention Vision Transformers, blockchain-based storage, and advanced optimization techniques to achieve reliable, real-time malicious node detection in large-scale Wireless Sensor Networks.

Discussion

The integration of deep learning, transformer architectures, blockchain technology, and optimization techniques has significantly advanced malicious node detection in Wireless Sensor Networks (WSNs). Deep learning models have proven effective in identifying complex attack patterns by learning hierarchical representations of network traffic data. However, their performance is often limited by computational complexity and scalability challenges.

Transformer-based models, particularly Cross Attention Vision Transformers (CAVT), address these limitations by capturing global dependencies and enabling parallel processing. These models improve detection accuracy and provide better interpretability compared to traditional deep learning approaches. However, their high computational requirements make them challenging to deploy in resource-constrained WSN environments.

Blockchain technology plays a crucial role in enhancing the security and reliability of WSN systems. By providing decentralized and tamper-proof data storage, blockchain eliminates single points of failure and ensures trust among network nodes. This is particularly important in environments where nodes may be compromised. However, blockchain introduces latency and computational overhead due to consensus mechanisms, which may impact real-time performance.

Optimization techniques further enhance system performance by reducing energy consumption, improving routing efficiency, and optimizing model parameters. These techniques are essential for extending the network lifetime and ensuring efficient resource utilization.

Despite these advancements, several challenges remain. The integration of multiple technologies increases system complexity and requires careful design to ensure compatibility and efficiency. Additionally, the high computational cost of transformer models and blockchain systems may limit their practical deployment in large-scale WSNs.

Future research should focus on developing lightweight transformer architectures, energy-efficient blockchain mechanisms, and optimized hybrid systems that can operate in real-time. The integration of edge computing and federated learning may also provide promising solutions for improving scalability and reducing latency.

Overall, the combination of deep learning, transformers, blockchain, and optimization represents a powerful approach for developing secure and intelligent WSN systems.

Conclusion

This review comprehensively examined recent advances in malicious node detection in Wireless Sensor Networks (WSNs) through the integration of deep learning, Cross Attention Vision Transformers (CAVTs), blockchain technology, and optimization algorithms. The analysis demonstrates that deep learning models significantly improve intrusion detection by automatically extracting complex features from network traffic, while transformer-based architectures enhance detection accuracy by capturing long-range dependencies and contextual relationships. Blockchain-based distributed storage further strengthens network security by ensuring data integrity, decentralization, transparency, and resistance to tampering. Optimization techniques contribute

to improved energy efficiency, routing performance, and computational resource utilization, making intelligent security frameworks more suitable for resource-constrained WSNs. Despite these advancements, challenges including computational complexity, blockchain latency, energy consumption, and integration overhead continue to hinder practical deployment. Future research should focus on lightweight transformer architectures, energy-efficient blockchain consensus mechanisms, edge computing integration, and scalable hybrid frameworks. These developments will enable secure, intelligent, and real-time malicious node detection, supporting the next generation of reliable and resilient Wireless Sensor Network applications.

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