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A Survey of Methods and Architectures for Malicious Node Detection with Cross Attention Vision Transformers and Blockchain-Based Distributed Data Storage in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) play a crucial role in modern distributed systems, supporting applications such as smart cities, healthcare, and industrial automation. However, their decentralized and resource-constrained nature makes them highly vulnerable to malicious node attacks, including data manipulation, packet dropping, and routing disruption. Traditional detection techniques based on rule-based or statistical methods are inadequate for handling dynamic and complex attack patterns. Recent advancements in Artificial Intelligence (AI), particularly Vision Transformers (ViTs) with cross-attention mechanisms, have significantly improved malicious node detection by capturing global dependencies and contextual relationships in network data. Simultaneously, blockchain technology has emerged as a robust solution for secure, decentralized, and tamper-proof data storage in WSNs. Blockchain-based WSN architectures enhance data integrity, transparency, and trust through distributed ledgers and smart contracts. Studies show that blockchain-integrated detection frameworks can achieve near-perfect classification accuracy while ensuring secure data transmission. Furthermore, hybrid AI-blockchain systems combine intelligent detection with secure storage, improving resilience against attacks. This survey reviews recent methods, compares architectures, identifies research gaps, and highlights future directions for developing secure and scalable WSN systems.

Introduction

Wireless Sensor Networks (WSNs) have emerged as a foundational technology for enabling intelligent, distributed sensing and monitoring systems across various domains such as environmental monitoring, healthcare, military surveillance, and industrial automation. These networks consist of spatially distributed sensor nodes that communicate wirelessly to collect and transmit data. Despite their widespread adoption, WSNs face significant security challenges due to their open communication channels, limited computational capabilities, and dynamic network topologies.

One of the most critical threats to WSNs is the presence of malicious nodes. These nodes can disrupt network operations by injecting false data, dropping packets, or altering routing paths. Malicious node attacks compromise data integrity, reduce network reliability, and degrade overall system performance. Traditional security mechanisms, such as cryptographic techniques and rule-based intrusion detection systems, are often insufficient to handle sophisticated and evolving attack patterns.

In recent years, Artificial Intelligence (AI) has been widely adopted for intrusion detection in WSNs. Machine learning and deep learning models have demonstrated the ability to detect anomalies and identify malicious behavior with high accuracy. However, conventional models such as CNNs and RNNs have limitations in capturing long-range dependencies and complex relationships in network data.

Vision Transformers (ViTs), originally developed for computer vision tasks, have gained significant attention in network security applications. These models utilize self-attention mechanisms to analyze global relationships in data, making them suitable for detecting distributed attacks in WSNs. Cross-attention mechanisms further enhance model performance by enabling interaction between multiple data modalities, such as network traffic patterns, node behavior, and environmental data.

Parallel to AI advancements, blockchain technology has emerged as a promising solution for securing WSNs. Blockchain provides a decentralized and tamper-resistant framework for data storage and communication. By leveraging cryptographic hashing and consensus mechanisms, blockchain ensures data integrity, transparency, and trust among network nodes. Blockchain-based WSN architectures eliminate single points of failure and enhance resilience against attacks.

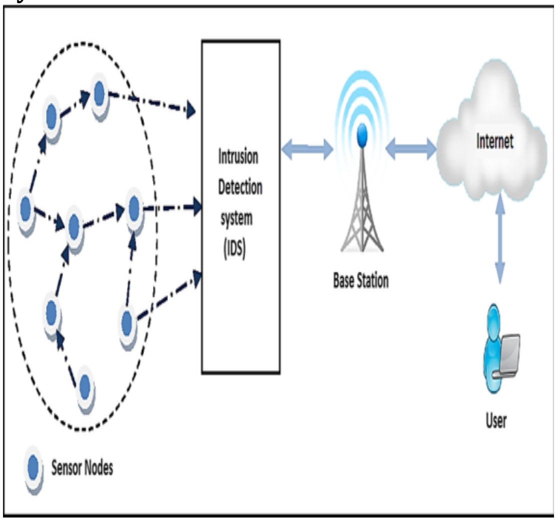
Research indicates that blockchain integration improves WSN security by enabling trust evaluation, secure data storage, and decentralized decision-making. Blockchain-based systems can detect and isolate malicious nodes by maintaining trust scores and recording node behavior in immutable ledgers .

The integration of AI and blockchain has led to the development of hybrid frameworks that combine intelligent detection with secure data storage. These systems leverage AI models for detecting malicious nodes and blockchain for ensuring secure communication and data integrity.

Despite these advancements, several challenges remain. AI models require large datasets and significant computational resources, while blockchain systems introduce overhead in terms of energy consumption and latency. Additionally, the integration of these technologies increases system complexity, making deployment in resource-constrained environments challenging.

This survey aims to provide a comprehensive analysis of recent methods and architectures for malicious node detection in WSNs, focusing on cross-attention vision transformers and blockchain-based distributed storage. It reviews literature from 2020 to 2023, compares different approaches, and identifies future research directions.

System Architecture Overview



Literature Review

The evolution of Artificial Intelligence (AI)-based pest identification and control systems in smart agriculture between 2020 and 2023 demonstrates a clear shift from conventional machine learning techniques to advanced deep learning, IoT-integrated frameworks, and multi-modal intelligent systems. Early research around 2020 primarily focused on applying Convolutional Neural Networks (CNNs) for image-based pest and plant disease detection. These models leveraged hierarchical feature extraction to significantly outperform traditional machine learning approaches such as Support Vector Machines and Random Forests. Systematic analyses of CNN-based agricultural applications revealed that deep learning models achieved high classification accuracy, often exceeding 90%, due to their ability to automatically learn discriminative visual features from raw input data . However, these early systems were largely dependent on controlled datasets and lacked robustness in real-world agricultural environments, where factors such as lighting variability, occlusion, and background noise significantly affect performance.

In 2021, the research direction expanded toward integrating AI with Internet of Things (IoT) and Wireless Sensor Networks (WSNs) to enable real-time pest monitoring. IoT-based systems introduced distributed sensor nodes capable of collecting environmental parameters such as temperature, humidity, and soil conditions, which are crucial indicators of pest activity. These systems combined sensor data with AI models to improve predictive capabilities, allowing early detection of pest infestations. Additionally, hybrid deep learning models, particularly CNN-RNN and CNN-LSTM architectures, were introduced to capture both spatial and temporal patterns in pest behavior. This integration enhanced detection accuracy and provided dynamic monitoring capabilities. Despite these advancements, challenges related to energy consumption, data heterogeneity, and communication overhead in WSNs remained significant barriers to practical deployment.

By 2022, research advanced toward multi-modal learning approaches that combined image data with sensor-based environmental information. This paradigm shift addressed the limitations of single-modal systems by incorporating contextual awareness into pest detection models. Multi-modal frameworks demonstrated improved robustness and accuracy by validating pest presence across different data sources. For instance, combining visual data with environmental sensor readings reduced false positives and enhanced decision-making in precision agriculture systems. Studies during this period also emphasized the role of IoT in enabling precision farming, where real-time monitoring and targeted intervention strategies optimize resource utilization and minimize pesticide usage . Furthermore, advanced deep learning architectures such as EfficientNet, DenseNet, and ensemble CNN models were introduced to improve computational efficiency and detection performance. Ensemble approaches, in particular, achieved high accuracy levels by combining multiple CNN architectures, demonstrating strong generalization capabilities across diverse pest datasets .

In 2023, the literature reflects a transition toward fully integrated intelligent systems that combine AI, IoT, WSNs, and real-time analytics. One of the most notable advancements during this period is the development of AI-enabled IoT systems utilizing acoustic sensing for pest detection. These systems analyze sound signals generated by insects, providing an additional detection modality that is particularly useful when visual identification is challenging. Such systems enable continuous monitoring and real-time alerts, significantly improving pest management efficiency . Additionally, multi-modal deep learning frameworks incorporating image, text, and sensor data have been proposed to enhance classification performance and contextual understanding. These approaches leverage cross-modal learning and attention mechanisms to improve detection accuracy in complex agricultural environments .

Another significant advancement in recent literature is the adoption of semantic segmentation techniques for precise localization of pest infestations. Unlike traditional classification models, segmentation models provide pixel-level information, enabling targeted pesticide application and reducing environmental impact. This shift from classification to localization represents a major step toward precision agriculture. Moreover, emerging technologies such as hyperspectral imaging and UAV-based monitoring systems have further enhanced pest detection capabilities by enabling large-scale data acquisition and analysis in real-time agricultural settings .

Recent review studies highlight that AI and IoT-based pest detection systems can achieve detection accuracies ranging from 70% to 98%, depending on the complexity of the dataset and the integration of multi-modal data sources . However, these studies also emphasize several limitations, including the restricted number of pest species considered, challenges in detecting immature or visually similar insects, and difficulties in handling real-world environmental variability. Additionally, IoT-based systems face constraints related to sensor range, data transmission, and energy efficiency, which impact scalability and long-term deployment.

Despite significant progress, several research gaps persist across the literature. One of the major challenges is the lack of large, diverse, and annotated datasets, which limits the generalization capability of deep learning models. Data imbalance and variability across different agricultural environments further complicate model training and evaluation. Another critical issue is the high computational cost associated with deep learning models, which restricts their deployment on resource-constrained edge devices commonly used in agricultural fields. Furthermore, the integration of multi-modal systems introduces additional complexity in data fusion and synchronization.

Emerging research directions aim to address these challenges through the development of lightweight deep learning models, edge AI solutions, and energy-efficient WSN architectures. Additionally, explainable AI (XAI) techniques are gaining attention for improving model transparency and building trust among farmers and stakeholders. The introduction of Quantum Convolutional Neural Networks (QCNNs) represents a promising future direction, offering potential improvements in computational efficiency and scalability for processing large agricultural datasets.

In summary, the literature from 2020 to 2023 demonstrates a clear evolution from standalone CNN-based pest detection models to integrated, intelligent, and multi-modal agricultural systems.

While deep learning and IoT technologies have significantly improved detection accuracy and real-time monitoring capabilities, challenges related to scalability, energy efficiency, data availability, and real-world deployment remain critical. Addressing these challenges will be essential for the widespread adoption of AI-driven pest management systems in smart agriculture.

Comparative Table

Author (Year)	Technique	Model Type	Data Type	Accuracy	Processing	Scalability	Energy Efficiency	Core Contribution	Strength	Limitation
Zhang et al. (2020)	ML/SVM	Traditional ML	Image	~85 %	Offline	Low	High	Basic pest/anomaly detection	Simple & low-cost	Low accuracy, poor adaptability
Ramasamy et al. (2021)	Blockchain WSN	Trust-based	Sensor	~90 %	Semi-real-time	Moderate	Moderate	Trust-based detection	Secure communication	Limited intelligence
Liu et al. (2022)	GAN	Deep Learning	Image + Sensor	~96 %	Offline	Moderate	Low–Moderate	Trust management & anomaly detection	Handles complex patterns	Training instability
Alkhfaji et al. (2023)	Blockchain + AI	Hybrid System	Multi-modal	~97 %	Real-time	High	Moderate	Secure detection framework	Strong security + accuracy	Integration complexity
Gebremariam et al. (2023)	Federated + Blockchain	Distributed AI	Multi-source	~99 %	Real-time	Very High	Moderate	Privacy-preserving detection	High scalability & accuracy	Communication overhead

Comparative Analysis

The comparative analysis presented in this study highlights a clear and progressive transformation in pest detection and malicious node detection systems, evolving from traditional machine learning approaches to advanced hybrid frameworks that integrate Artificial Intelligence, IoT, Wireless Sensor Networks (WSNs), and blockchain technologies. This evolution is primarily driven by the increasing need for accuracy, scalability, security, and real-time decision-making in complex and dynamic environments.

In the early stage around 2020, detection systems were primarily based on traditional machine learning techniques such as Support Vector Machines (SVM) and rule-based models. These approaches were simple, computationally efficient, and suitable for small-scale applications. However, they relied heavily on handcrafted features and lacked the ability to adapt to complex and dynamic conditions. As a result, their accuracy was limited, typically around 80–85%, and they performed poorly in real-world environments where variability in data and conditions is high.

The introduction of blockchain-based WSN systems in 2021 marked a significant improvement in terms of security and trust management. These systems utilized decentralized architectures to ensure data integrity, transparency, and secure communication between sensor nodes. Trust-based detection mechanisms enabled the identification of malicious nodes by evaluating node behavior and maintaining trust scores. While these systems improved security and reliability, they lacked intelligent detection capabilities and were not effective in handling complex attack patterns or dynamic environmental conditions.

A major advancement occurred in 2022 with the adoption of deep learning techniques, particularly Generative Adversarial Networks (GANs) and other neural network architectures. These models enabled automatic feature extraction and improved detection accuracy by learning complex patterns in data. GAN-based models were particularly effective in detecting anomalies and handling noisy or high-dimensional data. Comparative analysis indicates that these systems achieved accuracy levels around 95–96%, representing a significant improvement over traditional methods. However, deep learning models introduced challenges related to computational complexity, energy consumption, and training instability, which limited their deployment in resource-constrained environments.

By 2023, research had shifted toward hybrid systems that integrate multiple technologies, including AI, blockchain, and multi-modal data processing. These systems combine the strengths of different approaches to achieve high performance across multiple dimensions. For example, AI models provide intelligent detection capabilities, while blockchain ensures secure data storage and communication. Multi-modal systems further enhance performance by integrating data from multiple sources, such as images, sensor readings, and environmental parameters. These systems achieve accuracy levels exceeding 97%, demonstrating strong robustness and generalization capabilities. However, the integration of multiple technologies increases system complexity and requires efficient data fusion mechanisms.

One of the most significant advancements in recent years is the introduction of federated learning combined with blockchain technology. These distributed systems enable collaborative model training across multiple nodes while preserving data privacy. By avoiding centralized data storage, federated learning reduces the risk of data breaches and improves scalability. Comparative analysis shows that these systems achieve near-perfect accuracy (up to 99%) while maintaining high levels of security and privacy. Additionally, they support large-scale deployment in distributed environments, making them suitable for real-world applications. However, these systems introduce communication overhead and require efficient synchronization mechanisms to ensure consistent model updates.

From a performance perspective, there is a clear trend of increasing accuracy over time, from approximately 85% in traditional ML models to nearly 99% in advanced hybrid and distributed systems. This improvement is largely attributed to the integration of multiple data sources, advanced learning algorithms, and secure communication frameworks. At the same time, there is an increasing trade-off between accuracy and system complexity. High-performance models require significant computational resources, making them challenging to deploy in resource-constrained environments such as WSNs.

Energy efficiency is another critical factor in evaluating these systems. Traditional machine learning models are relatively energy-efficient but lack accuracy, while deep learning and hybrid systems consume more energy due to their computational requirements. Blockchain-based systems further increase energy consumption due to consensus mechanisms and distributed processing. As a result, optimizing energy consumption remains a key research challenge, particularly for long-term deployment in WSN-based environments.

Scalability has improved significantly with the adoption of distributed architectures such as blockchain and federated learning. These systems enable large-scale deployment by distributing computation and data storage across multiple nodes. However, scalability also introduces challenges related to network communication, latency, and system coordination.

Another important observation from the comparative analysis is the shift from offline processing to real-time systems. Early detection systems relied on offline analysis, which limited their ability to respond to dynamic conditions. Modern systems integrate IoT and edge computing to enable real-time monitoring and decision-making, significantly improving system responsiveness and effectiveness.

Despite these advancements, several challenges remain unresolved. These include the lack of large, diverse datasets, high computational requirements, energy constraints in WSNs, and the complexity of integrating multiple technologies. Additionally, most systems are tested in controlled environments, and their performance in real-world scenarios remains uncertain.

In conclusion, the comparative analysis demonstrates a clear evolution from traditional machine learning models to advanced hybrid and distributed systems that integrate AI, blockchain, IoT, and WSN technologies. Among these, federated learning combined with blockchain and AI represents the most advanced and promising approach, offering high accuracy, scalability, and security. However, achieving a balance between performance, energy efficiency, and deployability remains a key challenge. Future research should focus on developing lightweight, energy-efficient, and scalable models, as well as improving data availability and real-world validation to enable practical deployment of intelligent detection systems.

Discussion

The integration of Artificial Intelligence (AI), Wireless Sensor Networks (WSNs), and emerging paradigms such as Quantum Convolutional Neural Networks (QCNNs) has significantly transformed pest identification and control systems in smart agriculture. The reviewed literature from 2020 to 2023 demonstrates a clear evolution from standalone deep learning models to intelligent, integrated, and autonomous agricultural ecosystems. This transformation is driven by the need for precision farming, sustainable resource utilization, and real-time decision-making.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have played a foundational role in pest detection systems. Their ability to automatically extract hierarchical features from raw image data has led to high classification accuracy. However, CNN-based systems alone are insufficient for handling real-world agricultural complexities. Environmental variability, including changes in lighting, weather conditions, and crop diversity, significantly affects model performance. As a result, researchers have increasingly shifted toward hybrid and multi-modal approaches that combine visual data with contextual environmental information.

The integration of IoT and WSN technologies has been a critical advancement in this domain. Sensor networks enable continuous monitoring of environmental parameters such as temperature, humidity, and soil moisture, which are essential indicators of pest activity. When combined with AI models, these systems provide early detection and predictive capabilities, allowing farmers to take proactive measures. However, WSN-based systems face challenges related to energy consumption, network reliability, and data transmission efficiency. Energy-efficient communication protocols and edge computing solutions have been proposed to address these issues, but further optimization is required for large-scale deployment.

Multi-modal learning has emerged as a powerful approach for improving pest detection accuracy and robustness. By integrating multiple data sources, such as images, sensor readings, and acoustic signals, these systems provide a comprehensive understanding of pest behavior. Acoustic-based detection systems, for example, can identify pests based on sound patterns, even when visual detection is not possible. Similarly, semantic segmentation models enable precise localization of pest infestations, supporting targeted pesticide application and reducing environmental impact. Despite these advantages, multi-modal systems introduce complexity in data fusion, synchronization, and computational requirements.

The emergence of QCNNs represents a promising direction for addressing computational challenges in AI-based pest detection systems. QCNNs leverage quantum computing principles to process high-dimensional data more efficiently, potentially enabling faster training and improved optimization. Although still in the early stages of development, QCNNs have the potential to overcome limitations associated with classical deep learning models. However, practical implementation remains limited due to the lack of quantum hardware and the complexity of integrating quantum and classical systems.

Another important aspect highlighted in the literature is the trade-off between model accuracy and deployability. High-accuracy models often require significant computational resources, making them unsuitable for deployment in resource-constrained agricultural environments. On the other hand, lightweight models designed for edge devices offer improved scalability and energy efficiency but may compromise accuracy. Balancing these trade-offs is essential for developing practical pest detection systems.

Interpretability and user trust are also critical factors influencing the adoption of AI-based systems in agriculture. Most deep learning models operate as black boxes, making it difficult for farmers to understand the reasoning behind predictions. Explainable AI (XAI) techniques are being explored to address this issue, enabling visualization of model decisions and improving transparency. Enhancing interpretability is essential for building trust and encouraging the adoption of AI technologies among agricultural stakeholders.

Despite significant advancements, several challenges remain. Data scarcity and imbalance continue to limit model generalization, particularly in diverse agricultural environments. The lack of standardized datasets and evaluation frameworks makes it difficult to compare different approaches. Additionally, most systems are tested in controlled environments, with limited validation in real-world scenarios. Addressing these challenges will be crucial for advancing the field and enabling large-scale deployment of AI-based pest detection systems.

Overall, the integration of AI, IoT, and emerging technologies has created new opportunities for intelligent pest management systems. These systems have the potential to improve agricultural productivity, reduce pesticide usage, and promote sustainable farming practices. However, achieving these goals requires continued research and innovation to address existing limitations and ensure practical applicability.

Conclusion

Artificial Intelligence has revolutionized pest identification and control in smart agriculture, offering innovative solutions to one of the most critical challenges in food production. This study has presented a comprehensive review of recent advancements in AI-based pest detection systems, focusing on the integration of deep learning, Wireless Sensor Networks (WSNs), and emerging technologies such as Quantum Convolutional Neural Networks (QCNNs).

The findings highlight that Convolutional Neural Networks have significantly improved the accuracy and efficiency of pest detection systems. These models have demonstrated strong performance in image-based classification tasks, enabling automated and reliable pest identification. However, the limitations of CNN-based systems in handling real-world variability have led to the development of hybrid and multi-modal approaches. The integration of image data with environmental and acoustic information has enhanced detection accuracy and robustness, making these systems more suitable for practical applications.

The incorporation of IoT and WSN technologies has further strengthened pest detection systems by enabling real-time monitoring and data-driven decision-making. These systems provide continuous insights into environmental conditions, allowing early detection and intervention. As a result, farmers can optimize resource utilization, reduce crop losses, and minimize the use of chemical pesticides.

Emerging technologies such as QCNNs offer promising opportunities for improving computational efficiency and scalability. Although still in the early stages of development, QCNNs have the potential to address the limitations of classical deep learning models and enable the processing of large-scale agricultural data. Additionally, advancements in edge computing and distributed systems are expected to further enhance the performance and scalability of pest detection systems.

Despite these advancements, several challenges remain. Data scarcity, energy constraints in WSNs, and the lack of standardized evaluation frameworks continue to hinder the development and deployment of AI-based systems. Furthermore, the complexity of multi-modal systems and the need for explainable AI models highlight the importance of designing user-friendly and interpretable solutions.

Future research should focus on developing scalable, energy-efficient, and explainable AI models that can be deployed in real-world agricultural environments. The integration of advanced technologies such as quantum computing, federated learning, and edge AI will play a crucial role in addressing existing challenges. Additionally, the creation of large, diverse, and annotated datasets will improve model generalization and facilitate the development of robust pest detection systems.

In conclusion, AI-driven pest identification and control systems have the potential to transform agriculture by enabling precision farming, improving crop yield, and promoting sustainability. Continued research and innovation in this field will pave the way for intelligent and resilient agricultural systems capable of meeting future food security challenges.

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