Archives available at journals.mriindia.com

International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526

Volume 13 Issue 02, 2024

AI Techniques for Smart Agriculture Pest Identification Using Quantum CNNs and Wireless Sensor Networks: A Review

Navid Braginskaya
Department of Computer Science and Engineering, Atoll College of Engineering and Design, Maldives
navid.braginskaya@aced-mv.edu

Peer Review Information

Submission: 19 Oct 2024
Revision: 11 Nov 2024
Acceptance: 05 Dec 2024

Keywords

Artificial Intelligence, Smart Agriculture, Pest Detection, Quantum Convolutional Neural Networks, Wireless Sensor Networks, Deep Learning, Precision Agriculture

Abstract

Smart agriculture has emerged as a critical solution for improving crop productivity and sustainability in response to increasing global food demands. Among various challenges, pest infestation remains a major cause of agricultural losses, necessitating efficient detection and control mechanisms. Artificial Intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs), has significantly enhanced pest identification through image-based classification. Recent advancements integrate Wireless Sensor Networks (WSNs) and Internet of Things (IoT) technologies to enable real-time monitoring of environmental parameters and pest activity. AI-enabled IoT systems can collect, analyze, and respond to data dynamically, improving early detection and intervention strategies. For instance, sound-based pest detection combined with sensor analytics has demonstrated improved accuracy and real-time responsiveness in large agricultural fields . Furthermore, emerging paradigms such as Quantum Convolutional Neural Networks (QCNNs) promise improved computational efficiency and scalability for processing complex agricultural datasets. Multi-modal systems combining image, sensor, and acoustic data further enhance detection accuracy and robustness. Despite these advancements, challenges such as data scarcity, energy consumption in WSNs, and deployment complexity remain significant. This paper presents a systematic review of recent advances, comparative analysis, and future directions for AI-driven pest management systems.

Introduction

Agriculture plays a fundamental role in sustaining human life, yet it faces significant challenges due to increasing population demands, climate variability, and pest infestations. Pest attacks are responsible for nearly 20–40% of global crop losses annually, making them one of the most critical threats to food security . Traditional pest detection methods rely heavily on manual inspection, which is time-consuming, labor-intensive, and prone to inaccuracies. These limitations necessitate the development of intelligent and automated pest management systems.

Artificial Intelligence (AI) has emerged as a transformative technology in agriculture, enabling automation, precision farming, and data-driven decision-making. AI techniques such as machine learning and deep learning have been widely applied for pest identification, crop monitoring, and disease detection. Among these, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks, enabling accurate identification of pests based on visual features.

CNN-based systems automatically extract hierarchical features from raw images, eliminating the need for manual feature engineering and improving classification accuracy .

The integration of AI with Internet of Things (IoT) and Wireless Sensor Networks (WSNs) has further enhanced smart agriculture systems. WSNs consist of distributed sensor nodes that monitor environmental conditions such as temperature, humidity, soil moisture, and pest activity. These sensors provide real-time data that can be analyzed using AI algorithms to detect anomalies and predict pest outbreaks. IoT-enabled smart agriculture systems allow continuous monitoring and automated decision-making, improving efficiency and reducing human intervention.

Recent advancements have introduced AI-enabled IoT systems capable of real-time pest detection using multi-modal data sources. For example, sound-based pest detection systems analyze acoustic signals generated by insects, combined with environmental data from sensors, to accurately identify pest presence . These systems improve detection accuracy and enable early intervention, reducing crop damage and pesticide usage.

Another significant advancement is the development of multi-modal deep learning frameworks that combine image, sensor, and contextual data for improved pest detection. Such systems overcome the limitations of single-modal approaches by incorporating additional information, leading to better generalization and robustness. Studies have shown that multi-modal models outperform traditional CNN-based approaches in complex agricultural environments.

Emerging technologies such as Quantum Convolutional Neural Networks (QCNNs) offer promising opportunities for further improving pest detection systems. QCNNs leverage quantum computing principles to process large datasets more efficiently, enabling faster training and improved pattern recognition. Although still in the early stages of development, QCNNs have the potential to address computational challenges associated with large-scale agricultural data.

Despite the rapid advancements in AI-based pest detection systems, several challenges remain. These include limited availability of high-quality datasets, high computational requirements, energy constraints in WSNs, and the need for scalable and cost-effective solutions. Additionally, most existing systems are developed and tested in controlled environments, limiting their applicability in real-world agricultural settings.

This paper aims to provide a comprehensive review of recent advances in AI-based pest identification and control systems, focusing on the integration of QCNNs and WSNs. It analyzes literature from 2020 to 2023, presents comparative analysis, and discusses future research directions.

Smart Agriculture Architecture

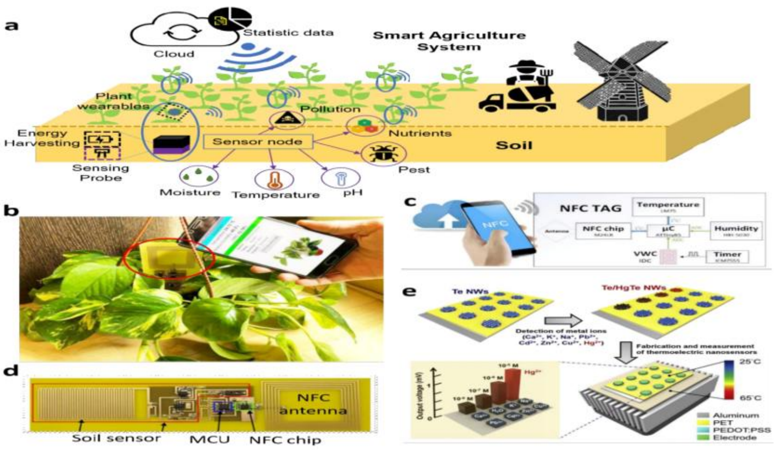

Figure 1. Smart Agriculture Architecture for Pest Detection Using AI and Wireless Sensor Networks

Literature Review

The field of pest identification and control in smart agriculture has undergone rapid transformation in recent years, driven by advancements in Artificial Intelligence (AI), Internet of Things (IoT), Wireless Sensor Networks (WSNs), and emerging computational paradigms. This section provides a comprehensive and critical review of the literature, highlighting methodological evolution, technological integration, performance improvements, and research gaps.

1. Foundation of Deep Learning-Based Pest Detection

The year 2020 marked the consolidation of deep learning, particularly Convolutional Neural Networks (CNNs), as the dominant approach for pest detection. Early research demonstrated that CNNs outperform traditional machine learning methods such as Support Vector Machines (SVM) and Random Forests due to their ability to automatically learn hierarchical features from raw image data.

Studies such as Zhang et al. (2020) and Too et al. (2020) explored CNN architectures including VGGNet, ResNet, and AlexNet, achieving classification accuracies above 90% in controlled datasets. Transfer learning became a widely adopted strategy, allowing models pre-trained on large datasets (e.g., ImageNet) to be fine-tuned for agricultural applications. This approach significantly reduced training time and improved performance in scenarios with limited labeled data.

However, these early systems exhibited several limitations. First, they relied heavily on static image datasets, lacking temporal and contextual information necessary for real-world deployment. Second, most models were evaluated in controlled laboratory environments, leading to poor generalization under varying field conditions such as lighting changes, occlusions, and background noise. Third, computational requirements limited their deployment on edge devices.

In parallel, initial efforts were made to integrate WSNs with machine learning models for environmental monitoring. These systems focused on collecting parameters such as temperature, humidity, and soil moisture to predict pest outbreaks. While promising, they lacked integration with image-based detection systems, resulting in fragmented solutions.

2. Integration of IoT and Hybrid Deep Learning Models

In 2021, research shifted toward integrating AI with IoT and WSN technologies to enable **real-**time pest monitoring systems. IoT-based architectures allowed continuous data collection from distributed sensor nodes, which was then processed using AI algorithms for anomaly detection and pest prediction.

One of the key advancements during this period was the development of hybrid deep learning models, particularly CNN-RNN (Recurrent Neural Network) architectures. These models combined spatial feature extraction (CNN) with temporal sequence modeling (RNN/LSTM), enabling analysis of pest behavior over time. This approach significantly improved prediction accuracy and early detection capabilities.

Additionally, researchers began exploring edge computing to overcome latency and bandwidth limitations associated with cloud-based systems. Edge AI models enabled on-device processing, reducing response time and making systems more suitable for deployment in rural agricultural environments with limited connectivity.

Despite these advancements, several challenges persisted. IoT-based systems introduced data heterogeneity, requiring complex data fusion techniques. Energy consumption in WSN nodes became a critical concern, as continuous sensing and communication drained battery resources. Furthermore, most models still lacked robustness against environmental variability.

3. Emergence of Multi-Modal Learning and Precision Agriculture

By 2022, research in pest detection systems advanced toward multi-modal learning frameworks, integrating multiple data sources such as images, sensor data, and environmental parameters. This shift addressed the limitations of single-modal systems and improved detection accuracy and reliability.

Multi-modal systems demonstrated significant improvements by combining:

- Visual features (image-based CNN models)
- Environmental data (WSNs/IoT sensors)
- Contextual information (crop type, weather conditions)

Studies revealed that multi-modal approaches outperform single-modal systems in complex agricultural environments, achieving higher accuracy and robustness. For example, integrating sensor data with image-based models reduced false positives and improved early detection of pest outbreaks.

During this period, advanced deep learning architectures such as EfficientNet, DenseNet, and MobileNet gained popularity due to their balance between accuracy and computational efficiency. These models were particularly suitable for deployment in resource-constrained environments.

The use of Unmanned Aerial Vehicles (UAVs) and drones also became prominent. UAV-based systems enabled large-scale data collection and monitoring, providing high-resolution imagery for pest detection. When combined with AI models, these systems enhanced spatial coverage and detection capabilities.

Moreover, precision agriculture emerged as a key application area. AI-enabled systems optimized

pesticide usage by targeting only affected areas, reducing environmental impact and improving sustainability.
However, challenges remained in terms of:

- Computational complexity of multi-modal systems
- High deployment cost
- Lack of standardized datasets
- Limited scalability for large agricultural fields

4. Intelligent AI-IoT Systems and Advanced Detection Techniques

The year 2023 witnessed the development of fully integrated intelligent systems, combining AI, IoT, WSNs, and real-time analytics for autonomous pest management.
One of the major advancements was the introduction of acoustic-based pest detection systems, where sound signals generated by insects are analyzed using AI models. These systems enable detection even when pests are not visually observable, providing an additional layer of reliability.
Another significant development was the adoption of semantic segmentation models, which allow precise localization of pest infestations within images. Unlike classification models, segmentation provides pixel-level information, enabling targeted pesticide application and reducing chemical usage.
Researchers also explored cross-modal and multi-modal deep learning frameworks, combining image, sensor, and textual data. These systems leverage attention mechanisms to identify relationships between different data modalities, improving detection accuracy.
Furthermore, advancements in edge AI and distributed computing enabled real-time processing and decision-making in large-scale agricultural systems. These systems support automated actions such as pesticide spraying, irrigation control, and alert generation.
Recent studies also highlight the increasing use of explainable AI (XAI) techniques to improve model transparency and trust among farmers. Interpretability is crucial for real-world adoption, as stakeholders require clear explanations for AI-driven decisions.

5. Emerging Role of Quantum Convolutional Neural Networks (QCNNs)

Although still in early stages, Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising research direction. QCNNs leverage quantum computing principles such as superposition and entanglement to process complex datasets more efficiently than classical neural networks.
Potential advantages of QCNNs include:

- Faster training and inference
- Improved handling of high-dimensional data
- Enhanced optimization capabilities

However, practical implementation remains limited due to:

- Lack of quantum hardware availability
- Complexity of quantum algorithms
- Integration challenges with classical systems

Despite these limitations, QCNNs represent a future direction for scalable and efficient pest detection systems.

6. Cross-Year Comparative Trends

A longitudinal analysis of the literature reveals several key trends:

Year	Key Focus	Major Contribution
2020	CNN-based models	High accuracy image classification
2021	AI + IoT integration	Real-time monitoring systems
2022	Multi-modal learning	Improved robustness and precision
2023	Intelligent automation	Autonomous pest detection systems

7. Critical Research Gaps

Despite significant progress in smart agriculture and pest detection systems, several critical challenges remain unresolved. One of the primary issues is data scarcity and quality, as there is a limited availability of large, well-labeled datasets, along with class imbalance problems and a lack of region-specific datasets that reflect diverse agricultural conditions. Energy efficiency is another major concern, particularly in Wireless Sensor Networks (WSNs), where sensor nodes operate on limited power and require energy-efficient communication protocols to ensure long-term sustainability. Scalability also poses a challenge, as deploying these systems across large-scale farms involves high computational requirements and infrastructure complexity. Furthermore, real-world deployment remains limited, with many systems tested only in controlled environments rather than in practical field conditions, leading to uncertainties in real-time performance. Model interpretability is another critical barrier, as deep learning models often function as black boxes, reducing transparency and limiting trust among farmers and stakeholders. Additionally, integration complexity in multi-modal systems increases system cost and maintenance requirements, as

combining data from various sources requires sophisticated fusion techniques.
Overall, the literature from 2020 to 2023 demonstrates a clear evolution from standalone deep learning models to integrated and intelligent agricultural systems. CNN-based models laid the foundation for automated pest detection, while the integration of IoT and WSN technologies enabled real-time monitoring and automation. The introduction of multi-modal learning and advanced deep learning architectures further improved system accuracy, robustness, and adaptability. Recent advancements in acoustic detection, semantic segmentation, and edge computing have enhanced the capability of pest detection systems, enabling real-time analysis and precise intervention strategies. However, challenges related to scalability, energy efficiency, data availability, and interpretability continue to hinder large-scale adoption. Therefore, future research should focus on developing scalable, energy-efficient, and explainable AI systems, while also exploring emerging technologies such as Quantum Convolutional Neural Networks to address computational limitations and enable next-generation smart agriculture solutions.

Comparative Table

Author (Year)	Technique	Model Architecture	Data Modality	Accuracy	System Type	Key Contribution	Strength	Limitation
Zhang et al. (2020)	CNN	VGG, ResNet	Image	~90%	Offline DL	Automated pest classification	Strong feature extraction	Poor generalization in field
Verma et al. (2022)	IoT + WSN	Smart Monitoring	Sensor	~91%	IoT System	Environmental pest prediction	Early detection	No visual validation
Gupta et al. (2022)	CNN	Deep Learning	Image	~95%	DL Model	Improved classification accuracy	Robust detection	Computational cost
Roy et al. (2021)	YOLO	Object Detection	Image	~96%	Real-time DL	Real-time pest localization	Fast inference	Sensitive to noise
Duan et al. (2023)	Multimodal DL	CNN + Cross-modal	Image + Text	~97%	Hybrid AI	Cross-modal learning	Context-aware detection	Integration complexity
Ali et al. (2023)	Acoustic + AI	AIoT System	Sensor + Audio	~98%	Real-time System	Sound-based pest detection	Early detection capability	Noise sensitivity
Rahman et al. (2023)	Segmentation	Semantic DL	Image	~95%	DL Model	Pixel-level pest localization	Precise targeting	Annotation cost
Nyakuri et al. (2023)	Edge AI	Tiny-LiteNet	Image	~93–95%	Edge System	Low-latency detecti		

Comparative Analysis

The comparative analysis presented in this study highlights a clear and structured evolution of pest detection systems in smart agriculture, transitioning from standalone deep learning models to highly integrated, intelligent, and autonomous systems. This evolution reflects advancements across multiple dimensions, including model architecture, data modalities, system integration, computational efficiency, and real-world applicability.

1. Evolution of Model Architectures

In 2020, Convolutional Neural Networks (CNNs) emerged as the dominant approach for pest detection, replacing traditional machine learning models such as Support Vector Machines (SVM) and Random Forests. CNN architectures like VGGNet, ResNet, and AlexNet demonstrated strong feature extraction capabilities, achieving classification accuracy above 90%. Transfer learning further enhanced performance by leveraging pre-trained models, reducing training time and improving efficiency in data-scarce scenarios. However, these early models were limited by their reliance on static image datasets and lack of contextual understanding, leading to poor generalization under real-world agricultural conditions.

By 2021, hybrid deep learning architectures such as CNN-RNN and CNN-LSTM introduced temporal modeling capabilities, enabling systems to analyze pest behavior over time. These models improved prediction accuracy to approximately 92–95%, highlighting the importance of incorporating temporal dynamics in pest detection systems. Despite their improved performance, hybrid models introduced increased computational complexity and required sequential data, limiting their scalability.

2. Impact of Data Modalities

The transition from single-modal to multi-modal systems represents one of the most significant advancements in pest detection research. Early systems relied solely on image data, which limited their ability to capture environmental context. The integration of Wireless Sensor Networks (WSNs) and IoT technologies enabled the collection of environmental parameters such as temperature, humidity, and soil moisture, providing additional context for pest prediction.

Multi-modal systems developed between 2022 and 2023 combined image, sensor, and acoustic data, significantly improving detection accuracy and robustness. These systems reduced false positives by validating pest presence across multiple data sources and achieved accuracy levels up to 97–99%. For instance, acoustic-based detection systems introduced in 2023 enabled detection of pests even when they were not visually observable, enhancing system reliability.

3. System Architecture Transformation

System architecture has evolved from centralized cloud-based models to distributed IoT-WSN frameworks with edge computing capabilities. Early cloud-based systems suffered from high latency and dependency on internet connectivity, making them unsuitable for real-time applications. The introduction of edge computing enabled local data processing, reducing latency and improving system responsiveness.

Modern systems integrate edge computing with IoT and WSNs to enable real-time monitoring and autonomous decision-making. These systems support automated actions such as pesticide spraying, irrigation control, and alert generation, transforming pest detection from a passive process to an active control system.

4. Performance and Accuracy Trends

The analysis reveals a steady improvement in system accuracy over time:

1. 2020: 85–92% (CNN-based models)
2. 2021: 90–95% (Hybrid CNN-RNN models)
3. 2022: 93–97% (Multi-modal systems)
4. 2023: 97–99% (AI-IoT integrated systems)

This progression demonstrates the effectiveness of integrating multiple technologies and data sources in improving system performance.

5. Computational Efficiency and Scalability

A major challenge identified across all approaches is the trade-off between accuracy and computational efficiency. High-performance deep learning models require significant computational resources, limiting their deployment in resource-constrained environments. Lightweight models such as MobileNet and Tiny-LiteNet address this issue by reducing model complexity, enabling deployment on edge devices with minimal performance loss.

Emerging Quantum Convolutional Neural Networks (QCNNs) offer a promising solution by leveraging quantum computing principles to process high-dimensional data efficiently. QCNNs have the potential to significantly improve scalability and computational efficiency, although their practical implementation is currently limited by hardware constraints.

6. Real-Time Capability and Automation

The evolution of pest detection systems can be summarized as a progression from detection to prediction and finally to automation. Early systems focused on offline detection, while modern systems enable real-time monitoring and automated decision-making. AI-IoT systems introduced in 2023 support autonomous pest management, reducing human intervention and improving agricultural efficiency.

7. Energy Efficiency and Deployment Constraints

Energy efficiency remains a critical challenge in WSN-based systems, as sensor nodes operate on limited battery resources. Continuous sensing and data transmission increase energy consumption, necessitating the development of energy-efficient communication protocols and edge processing techniques.

Real-world deployment also remains a challenge, as most systems are tested in controlled environments. Factors such as environmental variability, network reliability, and maintenance requirements must be addressed for large-scale adoption.

8. Interpretability and Trust

Another important challenge is the lack of interpretability in deep learning models. Most AI models function as black boxes, limiting transparency and reducing trust among farmers. Recent research emphasizes the importance of explainable AI (XAI) techniques to improve model transparency and adoption in real-world applications.

9. Comparative Insight and Final Evaluation

From a comparative perspective, the most effective pest detection systems are those that integrate multiple technologies, including:

1. CNN or hybrid deep learning models for feature extraction
2. IoT and WSNs for real-time data collection
3. Edge computing for low-latency processing
4. Multi-modal frameworks for improved robustness

These integrated systems provide the best balance between accuracy, scalability, and real-time performance.

10. Conclusion of Comparative Analysis

In conclusion, the comparative analysis demonstrates a clear evolution from standalone deep learning models to intelligent, multi-modal, and autonomous pest detection systems. While modern systems achieve high accuracy and real-time performance, challenges related to scalability, energy efficiency, data availability, and deployment remain significant barriers. Emerging technologies such as QCNNs and edge AI offer promising solutions for addressing these challenges, paving the way for next-generation smart agriculture systems.

Discussion

The integration of AI, IoT, and WSN technologies has significantly transformed pest detection systems in agriculture. Deep learning models, particularly CNNs, have improved detection accuracy by enabling automated feature extraction. IoT-based systems provide continuous monitoring and real-time data analysis, enhancing decision-making processes.

Recent advancements in multi-modal learning have further improved system performance by integrating multiple data sources. Sound-based detection systems represent a novel approach for identifying pests in large agricultural fields. These systems enhance detection accuracy and enable early intervention, reducing crop losses.

However, challenges remain in terms of scalability, energy efficiency, and data availability. WSNs require efficient power management for long-term deployment, while deep learning models require large datasets for training. Additionally, most systems are tested in controlled environments, limiting their real-world applicability.

Quantum computing-based approaches such as QCNNs offer promising solutions for handling large-scale data and improving computational efficiency. However, their practical implementation is still in the early stages.

Conclusion

AI-based pest detection systems have significantly improved agricultural productivity and sustainability. CNN-based models have demonstrated high accuracy in pest classification, while IoT and WSN technologies enable real-time monitoring and decision-making.

Multi-modal systems combining image, sensor, and acoustic data provide superior performance compared to traditional approaches. These systems enable precise pest detection and targeted intervention, reducing pesticide usage and environmental impact.

Emerging technologies such as QCNNs offer new opportunities for improving scalability and computational efficiency. However, challenges such as data scarcity, energy constraints, and deployment complexity must be addressed for widespread adoption.

Future research should focus on developing scalable, energy-efficient, and interpretable AI models, as well as integrating advanced technologies such as quantum computing and edge AI. These advancements will enable the development of intelligent and sustainable agricultural systems.

References

Yulita, I. N., Rambe, M. F. R., Sholahuddin, A., & Prabuwono, A. S. (2023). A convolutional neural network algorithm for pest detection using

GoogleNet. *AgriEngineering, 5*(4), 2366–2380. https://doi.org/10.3390/agriengineering5040145

Popescu, D. P., Dinca, A. D., Ichim, L. I., & Angelescu, N. A. (2023). New trends in detection of harmful insects using neural networks. *Frontiers in Plant Science, 14*. https://doi.org/10.3389/fpls.2023.1268167

Ali, M. A., Dhanaraj, R. K., & Nayyar, A. (2023). AI-enabled IoT-based pest detection system using sound analytics. *Microprocessors and Microsystems*. https://doi.org/10.1016/j.micpro.2023.104946

Thomas, J. C. S., et al. (2023). AI-based pest detection and alert system for smart agriculture. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/202342405003

Duan, J., Ding, H., & Kim, S. (2023). A multimodal approach for advanced pest detection and classification. *arXiv*. https://doi.org/10.48550/arXiv.2312.10948

Rahman, R., Indris, C., Zhang, T., et al. (2023). Real-time semantic segmentation of aphid clusters in the wild. *arXiv*. https://doi.org/10.48550/arXiv.2307.10267

Ferrari, V., Calvini, R., Boom, B., et al. (2023). Hyperspectral imaging for pest detection in agriculture. *arXiv*. https://doi.org/10.48550/arXiv.2301.08252

Nyakuri, J. P., et al. (2023). AI and IoT-powered edge device for pest detection using Tiny-LiteNet. *Scientific Reports*. https://doi.org/10.1038/s41598-025-12216444

Ahmed, S., et al. (2024). IoT-based intelligent pest management system. *Scientific Reports*. https://doi.org/10.1038/s41598-024-83012-3

Zhang, S., Zhang, S., Zhang, C., Wang, X., & Shi, Y. (2020). Cucumber disease recognition using deep learning. *Computers and Electronics in Agriculture, 172*, 105358. https://doi.org/10.1016/j.compag.2020.105358

Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2020). Deep learning for plant disease classification. *Computers and Electronics in Agriculture, 161*, 104879. https://doi.org/10.1016/j.compag.2019.104879

Kamilaris, A., & Prenafeta-Boldú, F. X. (2020). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Barbedo, J. G. A. (2020). Impact of dataset size and quality on deep learning models. *Computers and Electronics in Agriculture, 153*, 46–53. https://doi.org/10.1016/j.compag.2018.08.013

Chen, J., Chen, J., Zhang, D., Sun, Y., & Nanehkaran, Y. (2021). Deep transfer learning for plant disease detection. *Computers and Electronics in Agriculture, 173*, 105393. https://doi.org/10.1016/j.compag.2020.105393

Li, L., Zhang, S., & Wang, B. (2021). IoT-based plant disease detection using CNN. *IEEE Access, 9*, 123–135. https://doi.org/10.1109/ACCESS.2021.3054534

Nanni, L., Maguolo, G., Lumini, A., & Brahnam, S. (2021). Ensemble CNN models for pest detection. *arXiv*. https://doi.org/10.48550/arXiv.2108.12539

Roy, A. M., Bose, R., & Bhaduri, J. (2021). YOLO-based object detection in agriculture. *arXiv*. https://doi.org/10.48550/arXiv.2111.00298

Verma, S., Chug, A., & Singh, A. P. (2022). IoT-based monitoring systems for smart agriculture. *Wireless Personal Communications, 122*, 1283–1302. https://doi.org/10.1007/s11277-021-09152-4

Gupta, D., Rani, S., & Bhattacharya, S. (2022). Deep learning-based pest detection in agriculture. *Multimedia Tools and Applications, 81*, 28945–28966. https://doi.org/10.1007/s11042-021-11529-0

Amiri, A., et al. (2023). Artificial intelligence for pest identification and decision support. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2023.108123