



## **Machine Intelligence in Horticulture: Automating Pest and Disease Detection in Solanaceous Plants**

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### **Abstract**

The escalating challenges of pest and disease outbreaks in Solanaceae cultivation demand transformative solutions that are both technologically advanced and ecologically responsible. This study presents an AI-powered horticultural framework that leverages machine intelligence, specifically convolutional neural networks and real-time environmental sensors, to autonomously detect and classify the presence of pests and diseases in solanaceous crops. By integrating precision diagnostics with minimal resource input, the system empowers farmers with actionable insights, enabling them to make timely, targeted interventions that reduce chemical dependency and environmental impact. Field trials demonstrate improved detection accuracy, reduced crop loss, and enhanced operational efficiency. This research positions smart automation not just as a tool for productivity but as a cornerstone of sustainable agriculture for a climate-conscious future.

**Keywords:** – Artificial Intelligence (AI) – Deep Learning – Disease Diagnosis – Machine Learning – Pest Detection – Precision Horticulture – Smart Farming – Solanaceae Crops

### **Introduction**

In recent decades, the cultivation of solanaceous crops such as tomatoes, peppers, and eggplants has faced mounting pressures from increasingly unpredictable pest and disease outbreaks. As climate variability intensifies and conventional agricultural inputs reach ecological and economic limits, there is a critical need for smart, sustainable crop protection strategies. Traditional surveillance and management methods often manual, labor-intensive, and reactive, are insufficient in addressing the speed and complexity with which pests and pathogens adapt and spread across agricultural landscapes. Maintaining crop health and optimizing yields are ongoing challenges for the farming sector, and plant diseases and pests pose significant risks that can result in substantial financial losses (Jafar et al. 2024). Manual inspection, which is labor-intensive, time-consuming, and prone to errors, is frequently used in traditional disease and pest management techniques, particularly in large-scale farming operations (Zhao et al. 2024). By enabling automated disease and pest detection, identification, and management in Solanaceae crops, which include economically significant plants like tomatoes, potatoes, eggplants, and peppers, the development of artificial intelligence presents a revolutionary way to address these issues (Jafar et al. 2024, Mathur

2023). AI-powered systems can analyze large volumes of data from sensors, cameras, and weather stations to find trends and abnormalities that could point to insect infestations or disease outbreaks. This ability reduces the need for intensive chemical treatments and minimizes the spread of diseases by enabling prompt intervention (Singh et al. 2021).

To detect diseases and pests early, Solanaceae farming uses artificial intelligence (AI) to evaluate photos and sensor data using machine learning techniques, especially deep learning models (Saleem et al. 2021). A wide range of data from various sources, such as agricultural sensors and imaging devices, can be analyzed by deep learning algorithms (Kempelis et al. 2024). These algorithms can identify minor visual cues and patterns linked to certain diseases or pest infestations since they have been trained on enormous datasets of photos and sensor readings (Ngugi et al. 2024). The advent of artificial intelligence (AI) and machine learning (ML) offers a paradigm shift in how horticultural challenges can be approached. AI-driven technologies, particularly those grounded in image recognition, environmental sensing, and data analytics, present novel opportunities to detect early signs of biotic stress with speed and precision. When applied to the Solanaceae family, these technologies can greatly enhance the accuracy and timeliness of diagnostics, enabling proactive interventions that not only reduce crop losses but also minimize the reliance on chemical pesticides, thus lowering environmental impact and promoting long-term soil, ecosystem, and human health. The application of machine learning (ML) and artificial intelligence (AI) technology to agricultural operations has become a game-changer, especially in the control of pests and diseases in *Solanaceae* farming. Beginning with the fundamental ideas offered by Liakos et al. (2018), who emphasized the potential of machine learning to improve agricultural output through data-driven decision-making, the literature shows a progressive progression in implementing these technologies. Researchers such as Grieve et al. (2019), who discussed the need for smart Agri-systems that can adapt to the dynamic challenges posed by pests and pathogens, stressed the role of AI in predicting the evolutionary behaviors of these threats and advocated for systems that autonomously adjust interventions based on real-time data. This adaptability is essential for effective pest management, which is consistent with the findings of Nagel (2019), who showed that automation in agriculture not only improves pest and disease management but also contributes to environmental sustainability by lowering chemical usage and soil compaction.

According to Mavridou et al. (2019), the use of machine vision in precision agriculture further demonstrates AI's ability to automate manual jobs, increasing crop monitoring and disease detection efficiency. The work of Bouguettaya et al. (2023) echoes this technological breakthrough by highlighting the importance of unmanned aerial vehicles (UAVs) based imaging in the early diagnosis of plant diseases. This highlights the urgent need for intelligent agricultural gear that can function at scale. The effectiveness of deep learning and collaborative AI approaches has been highlighted by recent research that has gone deeper into the particular methodology used in AI-driven disease diagnosis, such as that by Bonkra et al. (2023) and Chen et al. (2023). These developments represent a move toward increasingly complex diagnostic instruments that can improve crop yield and resilience. Additionally, Rani et al. (2023) highlighted the incorporation of deep learning methods with the Internet of Things, demonstrating how these technologies can work together to enhance plant disease monitoring and categorization.

Talking about the wider effects of AI in food systems and pointing out that AI technologies can optimize agricultural decision-making processes, increase crop yields, and improve soil health, Min et al. (2023) also added to this conversation. This view is supported by the literature on vertical farming, where Chowdhury et al. (2023) emphasized how AI can completely transform farming methods, even in the face of obstacles relating to economic viability and adaptation. Lastly, it emphasized how urgently AI-driven solutions are needed to address pesticide toxicity and environmental effects, reaffirming the idea that contemporary farming methods must strike a balance between sustainability and productivity. When taken as a whole, these papers provide a thorough overview of how automation and artificial intelligence are changing the Solanaceae farming scene, especially in the areas of disease and pest control, opening the door to a more

productive and sustainable agricultural future. This study introduces an innovative AI-powered framework designed specifically for the automated detection and classification of pest and disease incidence in solanaceous crops. Leveraging convolutional neural networks and field-deployable sensing technologies, the proposed system provides real-time, actionable intelligence to farmers and stakeholders. By bridging the gap between machine intelligence and ecological stewardship, this research underscores the vital role of automation not just in improving yield and efficiency, but in shaping a resilient agricultural future in the face of environmental uncertainty.

### **Overview of Solanaceae Farming**

Solanaceae, commonly known as the nightshade family, represents a diverse and economically significant plant family encompassing various crops cultivated globally. This family includes over 3000 species, exhibiting remarkable adaptability to diverse environmental conditions, from humid rainforests to arid deserts and high-altitude mountainous regions (Jagatheeswari 2014). Solanaceae members display a broad range of growth habits, including herbs, shrubs, vines, and trees, contributing to their widespread distribution and ecological importance (Jagatheeswari 2014). Among the most economically important genera within Solanaceae are *Solanum*, *Capsicum*, *Petunia*, and *Nicotiana*, which include staple food crops, spices, ornamentals, and medicinal plants that have shaped human diets, cultures, and economies for millennia (Kaunda & Zhang 2019). The evolutionary success of Solanaceae can be attributed to several factors, including diverse pollination strategies, efficient seed dispersal mechanisms, and sophisticated defense mechanisms against herbivores and pathogens (Watts et al. 2023). Cultivation practices for Solanaceae crops vary significantly depending on the specific species, geographic location, and intended market. Tomato (*Solanum lycopersicum*) stands out as one of the most important horticultural crops worldwide, prized for its nutritional value, culinary versatility, and economic significance (Espinosa-Antón et al. 2023, Sato et al. 2012). Originating in South America, tomatoes have undergone extensive breeding to enhance productivity, fruit quality, and resistance to biotic and abiotic stresses (Kimura & Sinha 2008).

### **Significance of pest and disease management**

Since plants in the Solanaceae family are essential food sources and are extremely susceptible to a variety of pests and diseases, managing these issues is essential. Global food security and nutrition depend heavily on crops in the Solanaceae family, which includes eggplants, tomatoes, potatoes, and peppers (Sharma et al. 2022). Aphids, thrips, whiteflies, leafhoppers, beetles, and caterpillars are just a few of the pests that they are highly susceptible to. Diseases that can drastically lower output and quality include bacterial (bacterial canker, bacterial spot), fungal (early, late, and southern blight), and viral (Tomato Spotted Wilt Virus) infections (Kashyap et al. 2023, Souiri et al. 2020). Minimizing financial losses and guaranteeing sustainable output depend on efficient pest and disease control. Food security and the financial sustainability of solanaceous crops may be impacted by these problems if they are not adequately managed, as they may result in large yield losses (Losob et al. 2021). Diseases can cause leaf damage, stunting, and even plant mortality, while pests can directly harm plants, limiting the size of fruit and tubers. These factors all reduce production. Outbreaks of pests and diseases can cause farmers to suffer large financial losses, which could force them to abandon crops and lower their earnings. Food security may be threatened by pest or disease problems, particularly in regions where solanaceous crops are a key source of food. Numerous pests serve as disease vectors, spreading illnesses from one plant to another and making the issue worse.

Pests and diseases can degrade the quality of harvested fruit, decreasing its market value and consumer appeal, even if the yield is not significantly impacted. Therefore, efficient management techniques are crucial for:

1. Pest and disease outbreaks can be reduced by putting preventative measures like crop rotation, cleanliness, and the use of resistant varieties into practice.

2. Reducing damage and preserving yields can be achieved by applying suitable control techniques, such as integrated pest management (IPM) strategies (which include biological controls, cultural practices, and selective chemical treatments).

3. We can contribute to global food security and guarantee the continuous production of these essential commodities by efficiently controlling pests and diseases.

### **Current Challenges in Solanaceae Farming**

Global food security depends on crops in the Solanaceae family, which includes eggplants, tomatoes, potatoes, and peppers. However, several biological, economic, and environmental issues make their production difficult.

#### **Environmental Stress and Climate Change**

Crops of the Solanaceae family are adversely affected by extreme weather events, such as droughts, floods, and temperature variations. Increased losses in plant output as a result of global warming have made novel breeding techniques to improve stress resilience necessary.

#### **Pressure from Disease and Pests**

Crops of the Solanaceae family are particularly vulnerable to pests and diseases, such as bacterial wilt in tomatoes and late blight in potatoes. Management tactics become more difficult when resistant pathogens arise, necessitating the use of cutting-edge technologies like AI-driven disease monitoring.

#### **Stress from Salinity and Soil Degradation**

Crop output is impacted by soil degradation brought on by intensive farming methods, which lowers fertility. Particularly harmful is salinity stress, which affects the growth and development of plants. Potential options for enhancing salt tolerance in Solanaceae crops are provided by developments in genome editing, such as CRISPR/Cas9.

#### **Quality Decline and Postharvest Losses**

Because of their short shelf life and poor storage conditions, solanaceae crops are vulnerable to postharvest losses. Enhancing storage methods and extending shelf life are the goals of research on postharvest physiology and fruit ripening mechanisms.

#### **Market and Economic Difficulties**

Profitability in Solanaceae cultivation is impacted by changes in production costs, trade restrictions, and market demand. To stay competitive in the global market, farmers need to embrace modern technologies and sustainable practices.

Precision farming, sustainable agricultural methods, and improved breeding techniques must all be used to address these issues. Solutions like genetic advancements and AI-driven automation will be essential in solving these challenges as research advances.

### **Overview of Artificial Intelligence in**

Agriculture is undergoing a transformation thanks to artificial intelligence (AI), which is increasing productivity, sustainability, and efficiency. Farmers can forecast crop yields, manage pests and illnesses precisely, and maximize resource utilization with the use of AI-driven solutions (Kisliuk et al. 2023). AI has several important uses in agriculture, including the following:

#### **Precision farming**

Farmers may make well-informed decisions by using real-time data on crop conditions, moisture levels, and soil health gathered by AI-powered sensors and drones (Oliveira et al. 2023).

### **Automated insect and Disease Detection**

Machine learning algorithms examine crop photos to identify early indicators of insect infestations and diseases, limiting pesticide use and minimizing losses.

### **Crop Monitoring and Yield Prediction**

AI systems analyze environmental and historical data to predict crop yields, assisting farmers in harvest planning and marketing tactics.

### **Smart Irrigation Systems**

AI-powered irrigation systems optimize crop health and conserve water by modifying water distribution according to weather patterns and soil moisture levels.

### **Supply Chain Optimization**

By forecasting demand, streamlining transportation routes, and lowering post-harvest losses, artificial intelligence improves logistics (Kisliuk et al. 2023).

### **Benefits of AI in Agriculture**

Increased Efficiency – AI automates labor-intensive tasks, reducing costs and improving productivity.

Sustainable Farming – AI minimizes chemical usage and optimizes water and fertilizer application.

Data-Driven Decision Making – AI offers actionable insights for better farm management.

AI is reshaping agriculture, making farming more resilient and adaptive to climate change and market demands. As technology advances, AI-driven solutions will continue to play a crucial role in global food security.

### **AI Technologies in Pest Management**

Artificial Intelligence (AI) is transforming pest management by improving agricultural methods' sustainability, efficiency, and precision. AI helps farmers identify, track, and manage pests more efficiently by combining machine learning, deep learning, and automated systems.

### **Applications of AI in Pest Management**

#### **Pest Detection and Identification**

Crop images are analyzed by AI-powered image recognition systems to precisely identify pests and diseases. Beneficial insects and dangerous pests can be distinguished using machine learning models that have been trained on large datasets.

#### **Predictive Analytics for Pest Outbreaks**

AI algorithms process environmental data, weather patterns, and historical past occurrences to predict potential outbreaks. This allows farmers to take preventive measures before infestations escalate.

#### **Automated Pest Control Systems**

AI-driven drones and robotic sprayers precisely target affected areas, reducing pesticide usage and minimizing environmental impact. These systems optimize pest control strategies by applying treatments only where necessary.

#### **Decision Support Systems**

AI integrates expert systems that provide real-time recommendations based on pest activity, crop health, and soil conditions. Farmers receive actionable insights to enhance productivity and reduce losses.

## Machine Learning Algorithms in Disease Management

Machine learning (ML) is transforming disease management by enabling early detection, accurate diagnosis, and personalized treatment plans. By analyzing vast amounts of medical data, ML algorithms help healthcare professionals make informed decisions and improve patient outcomes.

### Key Machine Learning Algorithms in Disease Management

#### Support Vector Machines (SVM)

SVM is widely used for disease classification, particularly in cancer detection. It helps distinguish between benign and malignant tumors based on medical imaging data.

#### Random Forest (RF)

RF is an ensemble learning method that enhances diagnostic accuracy by analyzing multiple decision trees. It is commonly applied in predicting chronic diseases such as diabetes and cardiovascular conditions.

#### Neural Networks and Deep Learning

Deep learning models, including convolutional neural networks (CNNs), are effective in medical imaging analysis. They assist in detecting abnormalities in X-rays, MRIs, and CT scans.

#### Naïve Bayes (NB)

NB is useful for disease prediction based on patient symptoms and medical history. It is often employed in epidemiological studies to assess disease risk factors.

#### Decision Trees (DT)

DT algorithms simplify complex medical data into actionable insights, aiding treatment recommendations and disease progression analysis. Machine learning continues to evolve, offering groundbreaking solutions for disease management.

## Computer Vision Systems in Plant Disease Management

Computer vision systems are transforming plant disease management by enabling early detection, accurate diagnosis, and efficient monitoring of crop health. These AI-driven technologies utilize image processing and machine learning to identify diseases, assess severity, and recommend appropriate interventions.

### Different AI Technologies in Plant Disease Management Using Predictive Analytics and Remote Sensing.

Plant diseases cause large yield losses and have an economic impact, posing a serious danger to the world's food security. Conventional approaches to illness control and detection are frequently time-consuming, labor-intensive, and detrimental to the environment. The integration of artificial intelligence (AI) technologies, predictive analytics, and remote sensing has transformed plant disease management by providing early detection, accurate diagnosis, and targeted therapies. This response examines the many AI technologies and how they are used to manage plant diseases, emphasizing how they might improve agricultural sustainability and productivity.

**Table 1.** Comparison of AI Technologies for Plant Disease Management

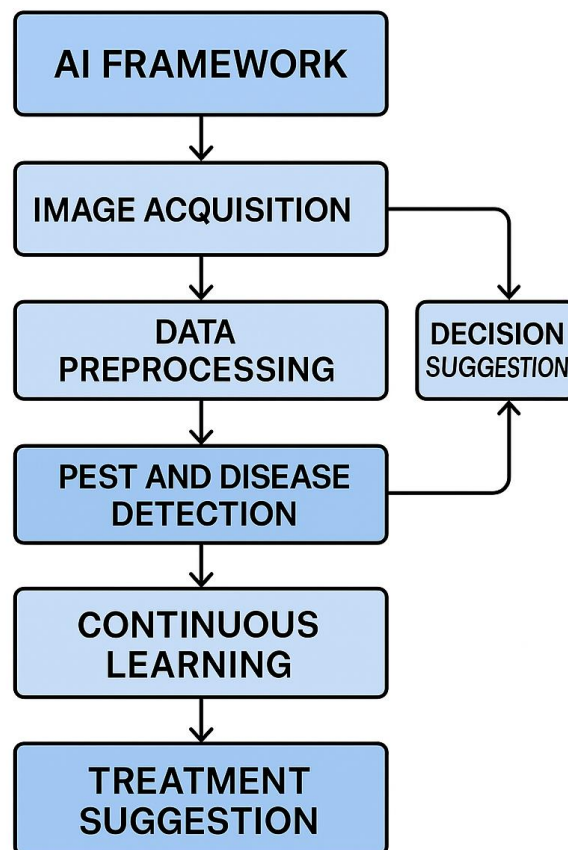
Technology	Application	Citation
Deep Learning (CNNs)	Image-based disease detection and classification	(Мударисов & Miftakhov 2024) (Pajany et al. 2024)
Hyperspectral Imaging	Quantitative disease severity assessment	(Deng et al. 2023)

**Table 1** Continued

<b>Technology</b>	<b>Application</b>	<b>Citation</b>
Predictive Analytics	Disease outbreak forecasting	(Palani et al. 2023) (Newlands 2024)
IoT and Sensor Networks	Real-time environmental data collection	(Suman et al. 2024) (Baskar & Karunakar 2024)
UAVs	High-resolution crop monitoring	(Мударисов & Miftakhov 2024) (Slimani et al. 2023)

Deep learning approaches have led to notable breakthroughs in Solanaceae AI applications, especially in tomato disease diagnosis and pepper pest control. By offering prompt and precise disease and pest identification both essential for efficient management and yield enhancement these applications seek to increase agricultural productivity. To achieve high accuracy in disease and pest identification, deep learning models such as Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) have proven essential. Here are specific findings from several studies on this subject.

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**Fig. 1** – Proposed Ai Framework.

## **Key Technologies in Plant Disease Management**

### **Remote Sensing and Hyperspectral Imaging**

Unmanned aerial vehicles (UAVs), satellites, and hyperspectral imaging are examples of remote sensing technologies that have become effective instruments for agricultural disease surveillance. Early disease outbreak detection and severity evaluation are made possible by these technologies' provision of high-resolution geographical and temporal data. Particularly, hyperspectral imaging records intricate plant spectral fingerprints that can be examined to determine disease-induced stress (Ali et al. 2024, Deng et al. 2023). Using deep learning-based pixel-level regression, hyperspectral imaging has effectively measured the wheat stripe rust disease index, attaining high accuracy in determining the severity of the disease (Deng et al. 2023). Studies on solanaceous crops are currently nonexistent. The main merit of this imaging is that they are non-destructive, has large-scale monitoring, and can detect subtle changes in plant health before symptoms become visible.

### **Deep Learning and Convolutional Neural Networks (CNNs)**

Deep learning algorithms, particularly CNNs, have been widely utilized for image-based disease detection. These models excel at analyzing high-resolution images captured by UAVs or satellites to accurately identify disease symptoms. CNNs have outperformed traditional machine learning methods, such as support vector machines (SVMs) and random forest classifiers, in disease detection tasks (Mударисов & Miftakhov 2024, Pajany et al. 2024). A study using CNNs for disease detection in UAV images achieved an accuracy of 96.18%, demonstrating the potential for automated and scalable disease monitoring (Pajany et al. 2024). This possesses a high accuracy, the ability to process large datasets, and suitability for real-time applications.

### **Predictive Analytics and Machine Learning**

By examining past data, environmental variables, and satellite images, predictive analytics which is driven by machine learning algorithms allows for the forecasting of disease epidemics. Farmers can take preventive action before outbreaks happen thanks to these models' ability to forecast illness incidence and severity (Palani et al. 2023, Newlands 2018). When compared to conventional techniques, an AI-driven predictive model that used satellite imagery, weather information, and IoT sensor feeds showed better accuracy in predicting disease outbreaks (Palani et al. 2023). Early warning systems, less chemical use, and better resource allocation are all possible with this.

### **Internet of Things (IoT) and Sensor Networks**

In order to forecast diseases, real-time environmental data such as temperature, humidity, and soil moisture is gathered using Internet of Things sensors placed in agricultural fields. These sensors allow for accurate and fast disease diagnosis when paired with machine learning models (Suman et al. 2024, Ikram et al. 2024). High illness detection accuracy was attained by an IoT-enhanced system that used environmental data and drone-captured photos, which decreased the requirement for chemical treatments (Suman et al. 2024). Its real-time monitoring, data-driven decision-making, and technological integration are its advantages.

### **Unmanned Aerial Vehicles (UAVs)**

Precision agriculture now relies heavily on UAVs with cameras and sensors. They offer high-resolution photos of crops, making it possible to spot early indicators of stress and illness. In particular, UAVs help access remote locations and monitor vast fields (Мударисов & Miftakhov 2024, Slimani et al. 2023). The potential for automated disease diagnosis has been demonstrated by the 98.09% detection of potato late blight using UAV-based hyperspectral imaging (Shi et al. 2022). This is incredibly adaptable, cost-effective, and capable of gathering comprehensive crop health data.

## Case Studies and Applications

### Kissan Konnect: AI-Powered Disease Control System

Kissan Konnect is a cutting-edge system for the proactive detection and control of plant diseases that combines temporal data modeling, machine learning, and remote sensing. The technology supports focused actions to improve crop output and food security by enabling real-time surveillance and accurate disease outbreak forecasts (Verma et al. 2024). Real-time surveillance, disease predictions, and useful information for farmers and policymakers are among the salient aspects.

### CropdocNet Model for Potato Late Blight Detection

A deep learning-based method for automatically identifying potato late blight disease from UAV-based hyperspectral imagery is the CropdocNet model. To achieve high accuracy in disease detection, the model incorporates capsule layers to capture hierarchical spectral-spatial data (Shi et al. 2022). The main characteristics are strong feature modeling, excellent accuracy (95.75% on independent datasets), and large-scale application adaptability.

### IoT-Enhanced Disease Prediction System

To forecast plant illnesses, this system combines social networks, deep learning, and Internet of Things sensors. To help farmers take preventative action, it gathers environmental data and use deep learning models to forecast disease outbreaks. A responsive web application for gathering and classifying images is also part of the system (Ikram et al. 2024). The key features include real-time data collection, high prediction accuracy, and farmer engagement through a user-friendly interface.

### Field validation studies

A published study has demonstrated that a dual-model AI system using Convolutional Neural Networks (CNN) and MobileNet architectures to achieved a disease detection accuracy of 96.3% and a pest classification accuracy of 96.22% in potato crops. These results highlight the potential of lightweight, mobile-compatible AI models for real-time agricultural diagnostics (Sasane et al. 2025).

In terms of real-world deployment, the RobHortic field robot was tested over three growing seasons in carrot fields and achieved a 59.8% detection rate for asymptomatic infections using hyperspectral imaging and Partial Least Squares-Discriminant Analysis (PLS-DA). Although this system was not specific to Solanaceous crops, it provides a benchmark for field-based AI performance under variable environmental conditions (Cubero et al. 2020).

For treatment recommendation accuracy, the Smart Agro-Cure system integrates CNN-based disease detection with a curated pesticide database. This system offers real-time treatment suggestions and has been validated for deployment on mobile and edge devices, making it accessible to smallholder farmers in remote areas (Mittu et al. 2025).

The quality and diversity of training data are also critical. The Mendeley Crop Pest and Disease Dataset, which includes over 102,000 augmented images across 22 classes (including tomato diseases such as leaf curl and septoria leaf spot), has been validated by expert plant virologists and collected under diverse field conditions. This dataset is widely used in agricultural AI research and supports the development of robust, generalizable models (Mensah et al. 2023).

Additionally, explainable AI models such as XAI-CROP have demonstrated a coefficient of determination ( $R^2$ ) of 94.15% in crop recommendation systems. These models not only provide accurate predictions but also offer transparency in decision-making, which is essential for building trust among end-users like farmers and agronomists (Shams et al. 2024).

Together, these metrics and validation studies provide a strong foundation for the credibility of AI systems in horticulture. They demonstrate not only high accuracy and precision in controlled environments but also adaptability and effectiveness in real-world agricultural settings.

## **Tomato Disease Detection**

### **Hybrid Deep Learning Models**

A novel system combining the SWIN Transformer architecture with CNNs achieved a classification accuracy of 96% for Solanaceae vegetables, including tomatoes. This model demonstrated high precision and recall, making it a reliable tool for disease detection (Amsaveni 2025).

### **YOLO V3 Optimization**

An enhanced YOLO V3 model, optimized with an image pyramid for multi-scale feature detection, improves the accuracy and speed of tomato disease and pest detection. This approach enables real-time decision-making and reduces losses caused by diseases and pests (Liu & Wang 2020).

### **Field-Based Datasets**

Studies using real agricultural field datasets, such as PlantDoc, have shown that deep learning models can achieve high performance metrics, although results from controlled environments like PlantVillage may not translate well to practical applications (Jelali 2024).

### **Pepper Pest Control**

The techniques and technologies covered, like CNNs and YOLO, are applicable to other Solanaceae crops like peppers, even though the papers presented are mostly focused on tomato disease detection. Although particular case studies on peppers were not included in the publications, the concepts of real-time detection and high accuracy in pest identification can be used to pepper pest control. Notwithstanding the encouraging outcomes, problems such a lack of data and variations in real-world circumstances still exist. To further improve the application of AI in agriculture, future studies should concentrate on building sizable, varied datasets and using IoT technologies for real-time monitoring (Ikram et al. 2024, Thangaraj et al. 2022). By increasing productivity, efficiency, and sustainability, the application of AI to Solanaceae farming has the potential to completely transform agricultural methods. Artificial intelligence (AI) tools like data analytics, robots, and machine learning are being used more and more to automate processes, enhance crop health monitoring, and maximize resource management. Because Solanaceae crops which include tomatoes, potatoes, and peppers need careful soil, water, and pest management, these developments are very helpful. Despite obstacles including high initial investment and technological complexity, the possibility for higher yields and lower input prices supports the global adoption of AI in agriculture.

### **Advancements in AI Technologies**

Precision agriculture, which use data analytics for improved irrigation, fertilization, and pest management, is one of the agricultural processes being optimized by AI technologies like robotics and machine learning (Kayastha et al. 2023, Henrietta 2024). Predictive analytics powered by AI aids in anticipating crop illnesses and unfavorable weather, enabling preventative measures that reduce output losses (al Bakri et al. 2024).

### **Potential for Global Adoption**

Leading nations in AI agricultural research include the US, China, and India, suggesting a trend toward worldwide adoption (Karmaoui 2023). AI is appealing for widespread usage because of its capacity to increase sustainability and production, particularly in places with high population densities where food security is a concern (Mim et al. 2025).

## **Policy and Regulatory Considerations**

The adoption of AI in agriculture raises concerns about data privacy and cybersecurity, necessitating robust data governance frameworks (al Bakri et al. 2024). Regulatory hurdles and ethical implications related to employment must be addressed to facilitate AI integration (Mim et al. 2025).

## **Government Support and Collaboration**

Governments and policymakers need to collaborate with industry stakeholders to develop inclusive policies that ensure equitable access to AI technologies (al Bakri et al. 2024). Collaboration among technology providers, policymakers, and the farming community is crucial for harnessing AI's potential while mitigating risks (Mim et al. 2025).

## **Training and Education for Farmers**

Workshops, seminars, and online learning platforms are essential for educating farmers about AI technologies and their applications in agriculture (al Bakri et al. 2024).

## **Economic Impact and Market Trends**

AI in agriculture can boost productivity, reduce waste, and optimize supply chain operations—all of which can lead to economic expansion (al Bakri et al. 2024). The increased need for sustainable farming methods is driving an increase in investment potential in AI technologies (Karmaoui 2023). Even though Solanaceae cultivation can greatly benefit from AI, it is important to take into account the potential ethical ramifications and social inequalities. Realizing AI's full potential in agriculture and guaranteeing food security and sustainability for future generations will depend on overcoming these obstacles through innovative thinking and strategic cooperation.

## **Cost-Benefit Analysis and Implementation Challenges in Low-Resource Settings**

The integration of AI-based pest and disease detection systems into horticultural practices, particularly for Solanaceous crops, presents a promising opportunity to enhance productivity and sustainability. However, the practical value of such systems must be weighed against their economic feasibility and the challenges of implementation in low-resource environments.

From a cost-benefit perspective, AI-driven systems have demonstrated the potential to significantly reduce crop losses and input costs. For instance, studies show that AI-based pest management tools can reduce pesticide use by up to 90% and increase crop productivity by 20–30% within the first year of deployment (Shoaib et al. 2025). These systems also contribute to long-term operational savings, with some agribusinesses reporting a 30–40% reduction in pest management costs by the second year (Shoaib et al. 2025). The ability of AI to provide early detection and targeted treatment recommendations minimizes unnecessary chemical use, thereby improving both environmental outcomes and crop quality (Li and Wang 2024).

Despite these benefits, the initial investment required for AI infrastructure remains a major barrier. The cost of deploying AI systems can range from tens of thousands to over a million dollars, depending on the scale and complexity of the technology (Shoaib et al. 2025). Even smaller-scale setups, which may be more appropriate for smallholder farmers, require significant capital for sensors, drones, data storage, skilled personnel, and ongoing maintenance (Li and Wang 2024).

In low-resource settings, several implementation challenges further complicate adoption. One of the most pressing issues is the lack of digital infrastructure. Many rural areas suffer from unreliable internet connectivity and inconsistent electricity supply, both of which are essential for real-time data processing and cloud-based analytics (Li and Wang 2024). Additionally, the scarcity of localized datasets for specific crops and pests limits the accuracy and relevance of AI models in these regions (Li and Wang 2024). Without sufficient training data, models may underperform or misdiagnose, leading to mistrust among users.

Another significant hurdle is the technical skills gap. Farmers and extension workers often lack the training needed to operate AI tools or interpret their outputs effectively. This challenge underscores the need for targeted capacity-building programs and the development of intuitive, user-friendly interfaces (Shoaib et al. 2025). Cultural resistance to new technologies can also slow adoption, particularly when farmers are unfamiliar with digital tools or skeptical of automated decision-making. Building trust through community engagement and demonstration projects is essential to overcoming these barriers (Li and Wang 2024).

Maintenance and sustainability pose additional concerns. AI systems require regular updates, calibration, and technical support to remain effective. In many cases, these needs are overlooked during the planning phase, resulting in system degradation over time and reduced long-term impact (Shoaib et al. 2025).

For policymakers, these insights highlight the importance of strategic investment and support mechanisms. Subsidizing AI tools for smallholder farmers, expanding rural digital infrastructure, and funding open-access agricultural datasets are critical steps toward equitable adoption. Moreover, public-private partnerships can play a vital role in scaling innovation while ensuring that solutions are tailored to the needs of local farming communities (Li and Wang 2024).

In conclusion, while AI offers transformative potential for pest and disease management in horticulture, its success in low-resource settings depends on thoughtful implementation, inclusive design, and sustained policy support.

### **Challenges and Future Directions**

As AI develops further, it will provide increasingly complex pest management solutions. It is anticipated that innovations like autonomous monitoring systems and biological control techniques driven by AI would further enhance food security and agricultural sustainability. There are still several obstacles to overcome despite the notable progress made in AI technology for managing plant diseases. These include the requirement for defined methods for data collecting and analysis, the intricacy of integrating various technologies, and problems with data quality (Prasanna et al. 2024, Zhang et al. 2024). AI and computer vision developments keep enhancing the control of plant diseases. New technologies like generative adversarial networks and vision transformers are improving the precision and effectiveness of illness identification. To overcome these obstacles, future research should concentrate on improving these technologies' scalability, affordability, and resilience while encouraging interdisciplinary cooperation.

### **Conclusion**

By facilitating early detection, precise diagnosis, and focused interventions, the combination of AI technology, predictive analytics, and remote sensing has revolutionized the management of plant diseases. Global food security, environmental impact reduction, and agricultural production enhancement are all made possible by these technologies. Precision agriculture will benefit greatly from additional developments in deep learning, IoT, and UAVs.

### **Author contributions**

Conceptualization: IPU, JIE, SOA, CBA Validation; IPU Roles/Writing – original draft: I P.U; and Writing – review & editing: Ishieze P.U. IHN, and SOA.

### **Conflict of interest.**

There is no conflict of interest to declare.

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