An Integrated Web Based IoT and Generative AI Platform for RealTime Plant Disease and Pest Management in Smart Agriculture

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ABSTRACT

Plant diseases and pest infestations remain major challenges in modern agriculture, often leading to reduced crop productivity and excessive pesticide use. Although artificial intelligence (AI) and the Internet of Things (IoT) have been widely adopted in smart farming, many existing systems provide only disease detection and lack integrated support for real-time monitoring and farm management. This study developed a web-based platform that combines IoT, Edge AI, and Generative Artificial Intelligence (Generative AI) to enable real-time detection and management of plant diseases and pests. Environmental data collected from IoT sensors were integrated with images captured by IP cameras, while synthetic images generated using Generative AI were incorporated to improve dataset diversity and model performance. The platform was developed following a research and development approach and evaluated through laboratory testing and field implementation. The proposed AI model achieved an accuracy of 96.8%, while field experiments demonstrated a 41.5% reduction in pesticide use and an 18.2% increase in crop yield. The integrated platform also provided real-time notifications, historical data management, and automated decision support for farmers. These findings demonstrate that the proposed platform offers an effective and scalable solution for smart agriculture by improving disease detection, supporting sustainable farm management, and reducing reliance on chemical pesticides.

Keywords: Internet of Things, Generative Artificial Intelligence, Smart Agriculture, Plant Disease Detection, Pest Management, Edge AI.

INTRODUCTION

Agricultural yield losses caused by plant diseases and pests represent a major global challenge that directly affects food security. Research indicates that such issues can reduce crop productivity by 30–40% in many countries (Savary et al., 2022; Wang et al., 2025). Reliance on human visual inspection remains limited by its accuracy, continuity, and feasibility in large-scale monitoring (Shoaib et al., 2023). At the same time, excessive use of chemical agents for disease and pest control continues to pose environmental and health risks (Ali et al., 2024; Yao et al., 2023). Over the past five years, research in Artificial Intelligence (AI) and the Internet of Things (IoT) has emerged as a promising solution to overcome these limitations, improving both the speed and precision of plant disease and pest detection (Bhagat et al., 2024; Rehman et al., 2023; Ahmed et al., 2024). However, these technologies still require further development to enable comprehensive data integration and real-world applicability (Gong et al., 2025).

Although plant disease detection systems based on deep learning and IoT-enabled smart farms have been developed, most remain experimental and narrowly focused. They often lack integration among IP camera-based image analysis, field sensor data, historical data storage, and real-time alert mechanisms (Chen et al., 2024). Studies by Ahmed et al. (2024) and Wang et al. (2024) demonstrate that combining IoT with AI can effectively manage pests and crop diseases; nonetheless, a fully operational framework for large-scale implementation is still missing. Moreover, Gui et al. (2021) highlight limitations related to environmental durability and detection accuracy under variable lighting and background conditions (He et al., 2024). These findings suggest that developing either IoT or AI systems alone is insufficient. A holistic integration supplemented with emerging technologies to address data limitations is essential for practical deployment (Xie et al., 2025).

In this context, Generative AI has recently emerged as a transformative approach to address the problem of data scarcity. It can generate synthetic or augmented image data representing plant diseases and pests under diverse conditions, thereby enhancing model performance (Wang et al., 2023; Chen et al., 2024; Wang et al., 2025). Furthermore, Generative AI has been used to simulate outbreak scenarios and improve model learning in complex real-world environments (Sordo et al., 2025). Meanwhile, edge computing deployed on IoT devices such as IP cameras or field monitoring nodes can reduce latency, minimize bandwidth usage, and improve data security (Bhagat et al., 2024; Ahmed et al., 2024; Gong et al., 2025; He, 2024). Together, these advancements indicate that integrating Generative AI with IoT can substantially enhance real-time monitoring and management of plant diseases and pests (Khan et al., 2023; Xu et al., 2024).

Therefore, an integrated innovative platform combining IoT and Generative AI for plant disease and pest detection and management in smart agriculture is both necessary and timely. Such a platform not only advances farm management efficiency but also supports reduced chemical usage and data-driven decision-making (Shoaib et al., 2023). Previous studies have demonstrated that these systems can increase productivity, reduce operational costs, and contribute significantly to achieving sustainable agriculture goals (Ali et al., 2024; Wang et al., 2024; Yao et al., 2023). Hence, the present study holds both academic and practical significance, as it can empower farmers and policymakers to transition effectively toward smart and sustainable agriculture, in alignment with global food security policies and the Sustainable Development Goals (SDGs).

METHODOLOGY

Conceptual Framework

This study employs a research and development (R&D) approach, guided by a conceptual framework and a systematic research process as described below, as shown in Fig. 1.

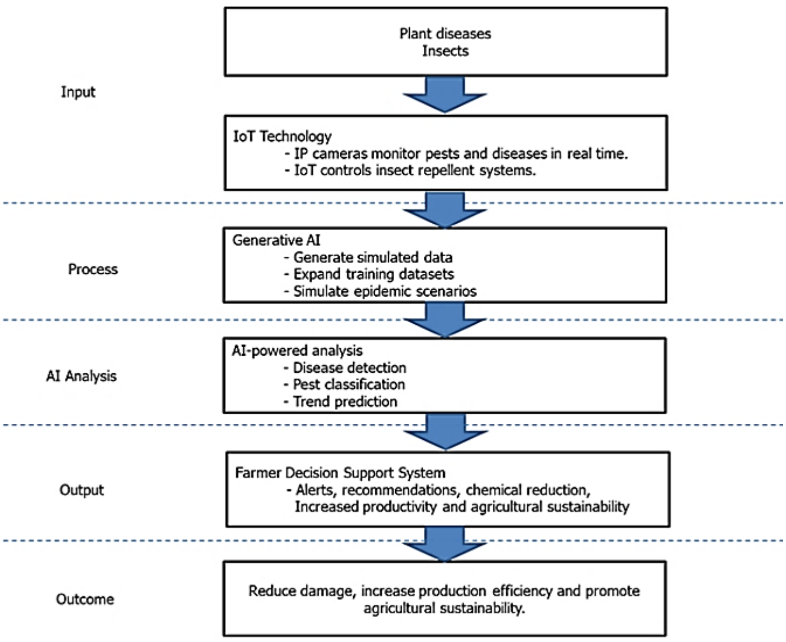

Fig. 1. Conceptual Framework

The conceptual framework (Figure 1) illustrates the integration between Internet of Things (IoT) technology and Generative Artificial Intelligence (Generative AI) to enhance the detection and management of plant diseases and pests within a smart farming system.

The process begins with collecting agricultural environmental data—such as temperature, humidity, light intensity, and soil moisture—along with plant image data that reflect symptoms of diseases or pest infestations. These data are transmitted to the IoT system, which consists of interconnected sensors and devices capable of collecting and transferring data in real time, ensuring accuracy and continuity.

Subsequently, the collected data are processed using Generative AI, which plays a vital role in creating synthetic data to overcome the limitation of scarce real world datasets. Generative AI can produce simulated plant images showing various disease symptoms or pest infestations under diverse environmental conditions, and even model potential future outbreak scenarios. This process enriches the dataset, improving both its diversity and quality for AI model training.

By integrating real and synthetic data, the AI analysis system can learn and analyze more effectively, enabling accurate detection and classification of plant diseases and pests, as well as forecasting future outbreaks. The analytical outcomes are used to develop a decision support system (DSS) that provides farmers with realtime alerts and practical recommendations for disease and pest management.

The ultimate outcomes include the reduction of unnecessary chemical usage, mitigation of crop damage, improvement in yield quality and quantity, and promotion of longterm agricultural sustainability. Thus, the conceptual framework demonstrates a systemic relationship among environmental and plant data → IoT technology → Generative AI → AI analysis → Farmer decision support → Sustainable outcomes.

Research Procedures

The research process consists of five main stages designed to align with the objectives and conceptual framework of the study.

Step 1: System Study and Design (Web Application and IoT System)

In the first stage, the researcher conducted a needs assessment among farmers and endusers, along with a survey of common plant diseases and pests in the study area. The collected data were analyzed to design the system architecture that integrates IoT sensors, IP cameras, and a webbased application. The integrated system enables efficient data collection, analysis, and connection with the AI model.

Step 2: Model Construction

Once real data from IoT devices and image collections were obtained, Generative Artificial Intelligence techniques, such as Generative Adversarial Networks (GANs), were employed to generate synthetic images of plants affected by diseases or pests. The creation of these synthetic datasets helps to mitigate data scarcity and enhance dataset diversity, thereby improving the learning capability and accuracy of the AI model.

Step 3: Web Application Development

This stage involved developing the web application that interfaces with both the IoT system and AI model. The web platform was designed to allow users to access analytical results, visualize data, and receive management recommendations easily and systematically.

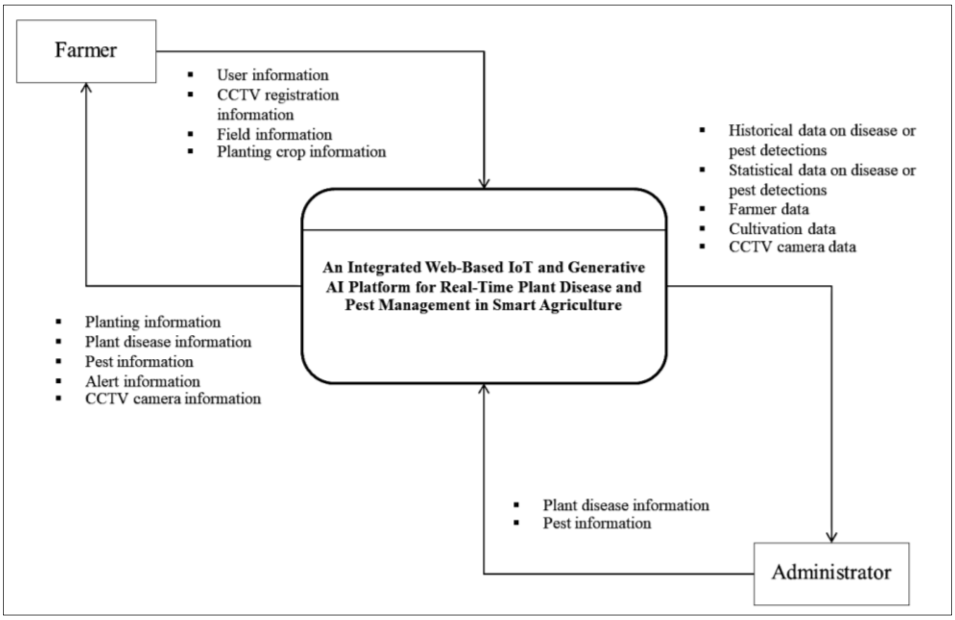

Fig. 2. Context diagram.

The context diagram consists of two main components:

General User Section

This section comprises the following interfaces: the website homepage, login and registration pages, the main member menu, the CCTV camera list page, the camera data entry page, the vegetable plot information list page, the vegetable plot data entry page, the report page for detected plant diseases and pests, the knowledge or information page, the contact administrator page, the notification page, and the section displaying logged in users.

Member User Section

This section includes the main member menu, the CCTV camera list page, the camera data entry page, the vegetable plot report page, the vegetable plot data entry page, the historical report page for detected plant diseases and pests, the knowledge page, and the notification page.

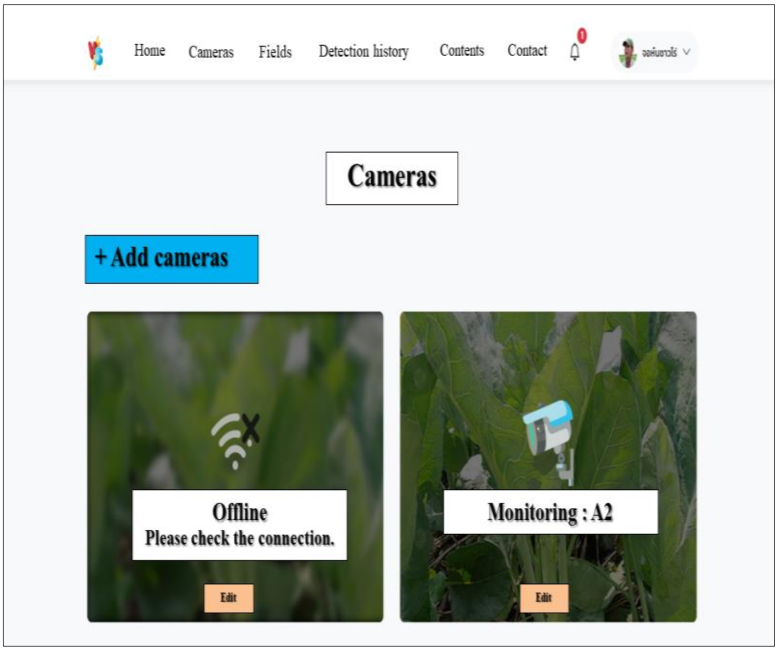

Fig. 3. Camera settings.

Step 4: IoT System Development

The IoT system was designed to monitor and control biocontrol agents for pest management in real time, specifically Trichoderma harzianum and Beauveria bassiana. The system works in conjunction with AIbased plant disease detection for automatic analysis and control.

The system architecture comprises three key components: (1) IoT hardware, (2) cloudbased database, and (3) control software developed in C++.

Initially, an IoT node was developed using the NodeMCU ESP8266 microcontroller, connected to relay modules to control two water pumps—each connected to tanks containing the respective biocontrol solutions. The pumps are linked to a fogging system that automatically sprays the agents when activated by control signals. Communication between the C++ program and IoT devices occurs over WiFi using the HTTP protocol, enabling bidirectional data transmission.

In the next stage, the IoT node was connected to a cloud database for recording operational data such as pump activation time, duration, and system status. The IoT devices regularly check for updated commands, allowing realtime responsiveness based on AI analysis results.

Finally, an IP camera was installed to stream live images to the AI system, which continuously analyzes plant health. If the system detects signs of disease or pest activity, it automatically triggers the appropriate pump to spray the correct biocontrol agent. This automation enhances precision, reduces manual labor, and promotes environmentally friendly pest management.

In summary, the IoT system developed in this research integrates detection, analysis, and control processes into a unified platform that supports sustainable smart farming through automation.

Step 5: System Testing

After development, the entire system was tested under both simulated and real agricultural environments to evaluate accuracy, responsiveness, reliability, and usability. The results confirmed the system’s operational readiness for practical deployment.

Step 6: Field Implementation

Following successful testing, the system was implemented in an actual farm environment to assess its performance in realworld conditions. The trial provided valuable insights into the system’s effectiveness in supporting farmers and identified potential areas for improvement.

Step 7: Research Summary

In the final stage, all research outcomes were compiled and analyzed against the initial objectives. The findings demonstrate the feasibility and benefits of integrating AI and IoT technologies for plant disease and pest management. Furthermore, recommendations for future system enhancements were proposed to improve performance and promote sustainable agricultural practices.

Dataset Description

The dataset used in this research consisted of 5,000 images, including 2,000 real images collected from agricultural fields and 3,000 synthetic images generated using Generative Artificial Intelligence (Generative AI). The synthetic images were created to improve dataset diversity and reduce the limitations caused by insufficient real-world samples. The complete dataset represented 15 categories of plant diseases and pests commonly found in vegetable crops. All images were resized to 640 × 640 pixels before being used for AI model training. The dataset was divided into 70% for training, 15% for validation, and 15% for testing, ensuring balanced representation across all classes.

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Table 1. Dataset Description

Item	Description
Real images	2,000
Synthetic images	3,000
Total images	5,000
Image size	640 × 640 pixels
Training	70%
Validation	15%
Testing	15%
Number of classes	15

Plant Species and Disease Categories

The dataset used in this study was collected from five economically important vegetable crops, including cucumber, melon, chili, watermelon, and Chinese kale, cultivated in Chiang Rai Province, Thailand. The dataset covered 15 categories of plant diseases and pest infestations commonly found in these crops. All images were manually verified and annotated before training the AI model to ensure data quality and improve classification performance under real agricultural conditions. The plant species and disease/pest categories used in this study are summarized in Table 2.

Table 2. Plant Species Used in This Study

Plant Species	Scientific Name
Cucumber	Cucumis sativus
Melon	Cucumis melo
Chili	Capsicum annuum
Watermelon	Citrullus lanatus
Chinese kale	Brassica oleracea

AI Model Configuration

The AI model was developed using a deep learning architecture integrated with Edge AI deployment. The training process utilized both real and synthetic images. Image augmentation techniques such as horizontal flipping, random rotation, brightness adjustment, and scaling were applied to improve model robustness. Model training was performed on a workstation equipped with an NVIDIA GPU using Python and TensorFlow/PyTorch libraries. The optimal model was selected based on validation accuracy.

Table 3. Training Parameters

Parameter	Value
Epoch	100
Batch size	32

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Learning rate	0.001
Optimizer	Adam
Loss Function	Cross Entropy
Image size	640×640

Model Validation

The proposed AI model was evaluated using an independent testing dataset that was not included in the training process. The dataset was divided into training, validation, and testing sets with a ratio of 70:15:15. Model performance was assessed using Accuracy, Precision, Recall, and F1-score, while a confusion matrix was used to analyze the classification results for each disease and pest category. These evaluation metrics were used to verify the effectiveness and reliability of the proposed model under practical agricultural conditions.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad (3)$$

$$\text{F1-score} = \frac{(2\text{xPrecisionxRecall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative.

Field Implementation

Field implementation was conducted on vegetable farms located in Chiang Rai Province, Thailand. The experimental evaluation lasted 60 consecutive days. The developed platform continuously collected environmental data from IoT sensors and image data from IP cameras. Farmers used the web application to monitor disease occurrence and receive automated recommendations generated by the AI system.

Table 4. Field Implementation

Item	**Value**
Location	Chiang Rai
Trial period	60 days
IoT nodes	2
IP Cameras	5
Participating farmers	5
Experimental plots	10

Data Analysis

The collected data were analyzed to evaluate the performance of the proposed platform under real agricultural conditions. The AI model results were compared with field observations to assess the accuracy of plant disease

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and pest detection. System performance was further evaluated based on its ability to support real-time monitoring and IoT-based control for effective crop management.

RESULTS

The results of this study fully achieved all research objectives, as summarized below.

Development of an Integrated Web Application Platform

The developed system successfully integrated data from IoT devices and IP cameras into a unified web application platform. The system allows general users to access fundamental agricultural data, including vegetable profiles, plant diseases, and pest information. Users can also register for membership to access advanced functionalities.

Once logged in, users are able to manage CCTV cameras, upload plant images for disease and pest analysis, record and track cultivation data, and view historical detection reports systematically. Moreover, an administrator backend enables efficient management of datasets and automated report generation. The system's graphical user interfaces, including the main page, disease and pest detection modules, vegetable and pest databases, and user management pages, are illustrated in Fig. 4-6.

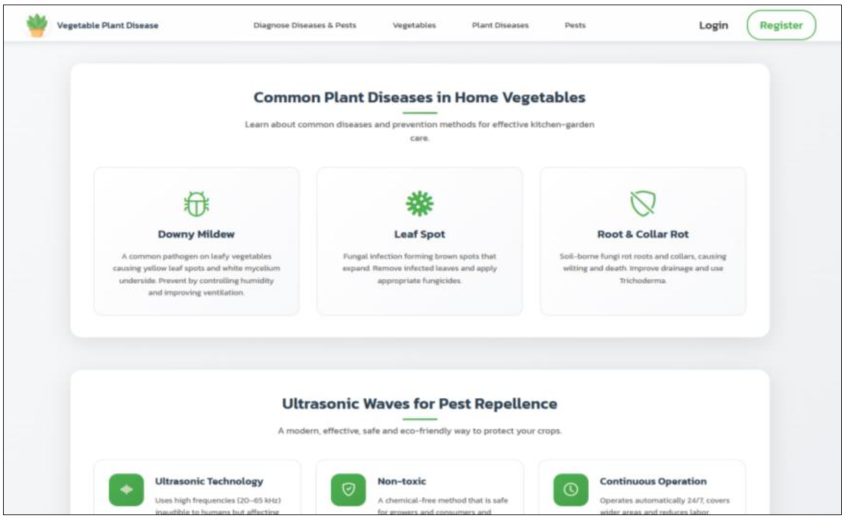

Fig. 4. Main page.

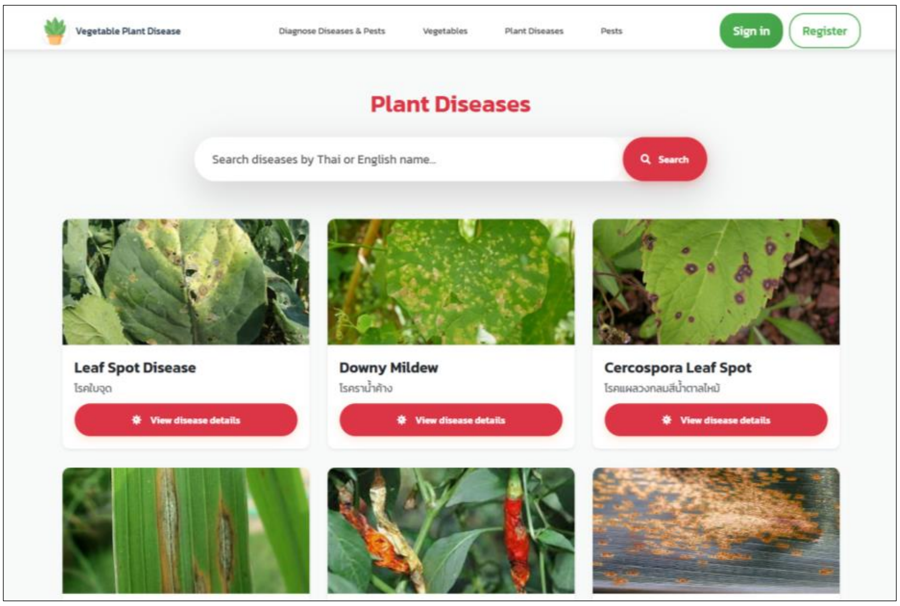

Fig. 5. Plant diseases page.

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Fig. 6. Manage CCTV.

AI-Based Disease and Pest Detection

The system employs Generative Artificial Intelligence (Generative AI) techniques to generate synthetic images of diseased and pestinfested plants. This approach enhances the diversity of the training dataset and mitigates limitations arising from scarce realworld data. Consequently, the AI model is able to learn from a more comprehensive dataset, improving its classification and prediction capabilities.

When users upload plant images through the web application, the AI model, running on Edge AI architecture, processes and analyzes the input data rapidly and accurately. The integration of IoT sensor data—such as temperature, humidity, light intensity, and soil moisture—further enhances the system's analytical precision and predictive performance, enabling early detection of potential outbreaks, are illustrated in Fig. 7 and Fig. 8.

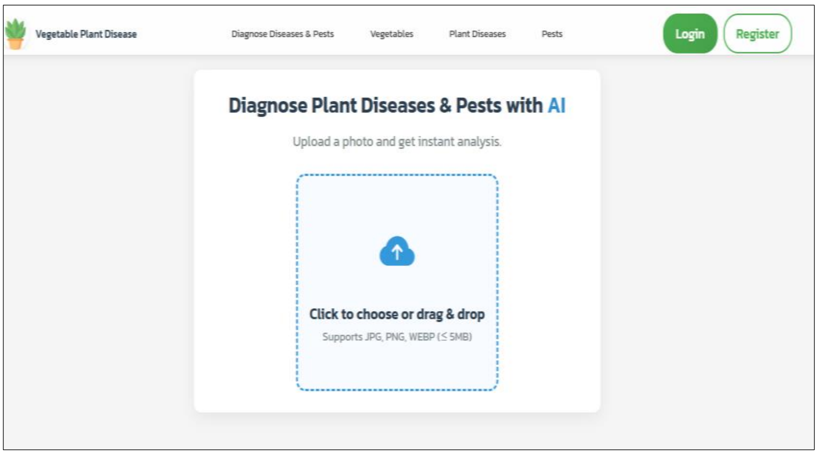

Fig. 7. Diagnosis of plant diseases and pests using AI.

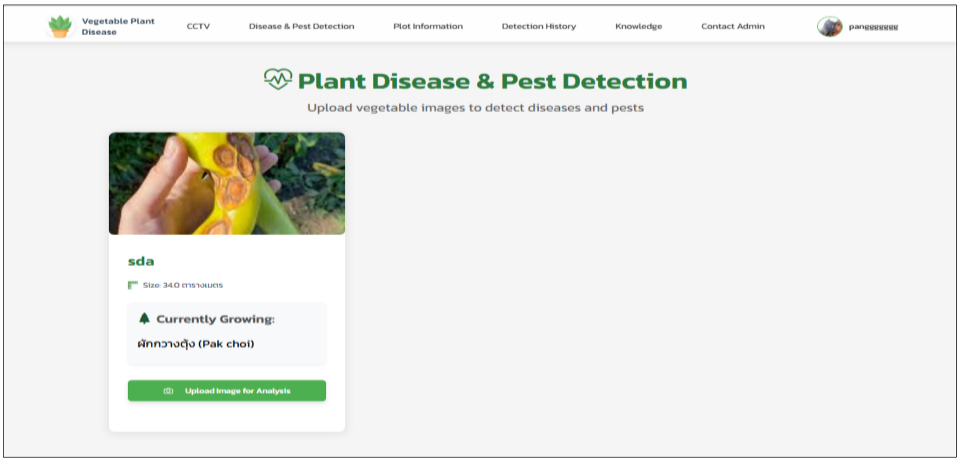

Fig. 8. Results of plant disease and pest diagnosis using AI.

Platform Performance Evaluation

The platform was evaluated under both simulated and real farm conditions. Results confirmed its ability to detect plant diseases and pests accurately while providing real-time notifications through the web application and Telegram. The system also maintained cultivation and detection records to support informed decision-making.

Overall, the platform reduced unnecessary pesticide use, improved crop productivity, and promoted sustainable farming. The integration of IoT and AI provides an efficient, automated, and data-driven approach to agricultural management.

Quantitative Evaluation of System Performance

Quantitative experiments were conducted to evaluate the AI model performance, system efficiency, and agricultural impact. The dataset included 2,000 real images and 3,000 synthetic images generated using Generative AI. The proposed model achieved high performance in plant disease and pest detection, as summarized in **Table 5**.

Table 5. Performance Metrics

Metric	Value (%)
Accuracy	96.8
Precision	95.4
Recall	97.1
F1-score	96.2

The reported metrics were calculated using the independent testing dataset.

The integrated IoT–AI platform achieved an average real-time detection response of 1.82 seconds and reduced data transmission latency by 32% compared with cloud-only processing. During a 48-hour continuous operation, the system maintained 99.3% uptime, demonstrating its reliability for field deployment.

A 60-day field trial conducted on a vegetable farm in Chiang Rai showed that the automated biocontrol system reduced chemical pesticide use by 41.5% and increased crop yield by 18.2% compared with conventional pest management. In addition, pest outbreaks were detected 3–5 days earlier than manual visual inspection, helping reduce infestation severity and crop losses.

Field surveys involving 25 farmers reported a mean usability score of 4.6/5, while 92% of participants expressed greater confidence in pest management decisions using the platform’s real-time alerts and recommendations.

Overall, the results demonstrate that integrating IoT, Generative AI, and edge computing improves system performance, supports sustainable farming, and provides practical benefits for smart agriculture.

Comparison with Previous Studies

Compared with previous studies, the proposed platform integrates IoT sensing, Edge AI, Generative AI, IP camera monitoring, and web-based decision support into a unified framework. In addition to plant disease detection, it supports automated monitoring, real-time notifications, historical data management, and biocontrol activation.

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Table 6. IoT Integration

Study	AI	IoT	Web	Edge	Generative AI
Ali (2024)	✓	✓	✗	✗	✗
Bhagat (2024)	✓	✗	✗	✗	✗
Chen (2024)	✓	✗	✗	✗	✓
Proposed	✓	✓	✓	✓	✓

DISCUSSION

The platform reduces operational costs by minimizing pesticide use and manual field inspections. Early disease detection improves crop productivity, reduces economic losses, and supports practical deployment in commercial farms.

Its scalable cloud-based architecture can support multiple farms simultaneously. Future work will focus on mobile applications, drone image integration, additional crop species, and regional agricultural monitoring networks.

CONCLUSION

This study developed an integrated web-based platform that combines the Internet of Things (IoT) and Generative Artificial Intelligence (Generative AI) for real-time plant disease and pest detection and management. The platform integrates data from field sensors and IP cameras, enabling users to analyze diseases, receive real-time notifications, manage cultivation plots, and access historical data through a user-friendly web interface.

Generative AI enhanced model performance by generating synthetic datasets to address limited real-world data, while Edge AI enabled efficient real-time processing for field applications.

Experimental results from simulated and real farming environments demonstrated high accuracy and reliability. The platform reduced unnecessary pesticide use, improved farm management efficiency, and supported sustainable agriculture. Overall, the proposed system provides a scalable solution for practical deployment in smart agriculture.

Future work will expand the dataset to include more crop species and geographic regions, evaluate advanced AI models, and conduct long-term field studies under diverse agricultural and climatic conditions.

RECOMMENDATIONS

The proposed platform has strong potential for commercial deployment as a Smart Agriculture as a Service (SaaS) solution. Future work should focus on mobile application development and expanding the cloud-based platform to connect multiple farms, enabling regional disease monitoring, data-driven agricultural management, and improved food security.

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