International Journal of Science, Strategic Management and Technology
Volume **02** Issue **05** May-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

AI-Smart Plant Health Monitoring System using Deep Learning

Abitha E., Akesh S., Sruthi Jayaram J., Dr. R. Parameswari
Department of Computer Science and Information Technology, School of Computing Sciences,
Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai – 600 117, India

https://doi.org/10.55041/ijsmt.v2i5.019

Cite this Article: E, A., J, S. J. & S, A. (2026). AI-Smart Plant Health Monitoring System using Deep Learning. International Journal of Science, Strategic Management and Technology, *02*(05). https://doi.org/10.55041/ijsmt.v2i5.019

Abstract

The increasing demand for food production has made efficient plant health monitoring a critical aspect of modern agriculture. Traditional methods rely on manual inspection, which is time-consuming and often inaccurate. This paper proposes an AI-based smart plant health monitoring system that integrates Internet of Things (IoT) sensors with deep learning techniques to enable real-time monitoring and early detection of plant diseases. Environmental parameters such as temperature, humidity, and soil moisture are continuously collected using IoT devices, while leaf images are analyzed using a Convolutional Neural Network (CNN) model for accurate disease classification.

The collected data is transmitted to a cloud platform for analysis and monitoring, allowing farmers to receive timely alerts and recommendations. The proposed system improves accuracy, reduces manual effort, and helps prevent crop loss through early intervention. Overall, the integration of IoT and deep learning provides a scalable, cost-effective solution for precision agriculture and sustainable farming practices.

Keywords

Artificial Intelligence (AI), Internet of Things (IoT), Deep Learning, Convolutional Neural Network (CNN), YOLOv8, Plant Disease Detection, Smart Agriculture, Precision Farming, Image Processing, Real-Time Monitoring, Cloud Computing, Agricultural Automation

1. Introduction

Agriculture plays a vital role in ensuring food security and economic stability, especially in developing countries like India. However, plant diseases remain a major challenge, causing significant reductions in crop yield and quality. Studies indicate that plant diseases contribute to nearly 20–40% of global crop losses annually, leading to serious economic and food supply issues. Traditional methods of plant health monitoring rely on manual inspection by experts, which is time-consuming, costly, and often inaccessible to small-scale farmers.

With the advancement of modern technologies, Artificial Intelligence (AI) and the Internet of Things (IoT) have emerged as powerful tools for transforming agricultural practices. IoT enables continuous monitoring of environmental parameters such as temperature, humidity, and soil moisture, which directly influence plant health. At the same time, deep learning techniques, particularly Convolutional Neural Networks (CNN), have demonstrated high accuracy in image-based plant disease detection.

This paper proposes an AI-based smart plant health monitoring system that integrates IoT sensor data with deep learning-based image analysis for early and accurate detection of plant diseases. The system captures real-time environmental data and leaf images, processes them using advanced AI models such as CNN and YOLOv8, and provides instant results along with alerts and recommendations. The main objective is to develop a scalable, cost-effective, and user-friendly solution that assists farmers in identifying plant diseases at an early stage.

2. Literature Survey / Related Work

Plant disease detection has gained significant attention in recent years due to its impact on agricultural productivity and food security. Traditional approaches relied on manual inspection and laboratory analysis, which are time-consuming, costly, and often inaccurate. To overcome these limitations, researchers have explored machine learning and deep learning techniques for automated plant disease detection.

Early research focused on classical machine learning methods such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest algorithms combined with handcrafted features like color, texture, and shape. Although these methods improved detection accuracy, they required extensive feature engineering and were sensitive to environmental variations.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the most widely used technique for plant disease detection. CNN models automatically extract features from images, eliminating the need for manual feature engineering. Studies using datasets like PlantVillage have achieved accuracy above 90%, demonstrating the effectiveness of deep learning in agricultural applications.

Recent research has also explored advanced deep learning architectures such as ResNet, EfficientNet, and YOLO for real-time disease detection and localization. The integration of IoT with AI has further enhanced plant health monitoring systems, supporting precision agriculture by enabling continuous monitoring and automated decision-making.

3. Problem Statement

Plant diseases pose a major threat to global agricultural productivity, leading to significant crop losses and economic damage each year. Traditional plant health monitoring methods rely on manual inspection by experts, which is time-consuming, labor-intensive, and often inaccessible to small-scale farmers. These methods are not only inefficient but also prone to human error, resulting in delayed disease detection and improper treatment.

Existing automated approaches using classical image processing and traditional machine learning techniques have limitations in accuracy and reliability, especially under varying environmental conditions such as lighting, background noise, and image quality. Moreover, most current systems focus only on disease detection through images and do not consider environmental factors like temperature, humidity, and soil moisture.

Therefore, there is a need to develop an efficient, accurate, and scalable system that integrates IoT-based environmental monitoring with deep learning-based disease detection to enable real-time plant health analysis and early intervention.

4. Proposed System

To overcome the limitations of existing plant health monitoring methods, this paper proposes an AI-based smart plant health monitoring system that integrates IoT technology with deep learning techniques for accurate, real-time analysis. The system is designed as a cloud-based platform that continuously monitors environmental conditions and performs intelligent plant disease detection using image processing.

The proposed system consists of two main components: IoT-based environmental monitoring and AI-based disease detection. IoT sensors collect real-time data such as temperature, humidity, and soil moisture. Simultaneously, plant leaf images are captured and processed using CNN for disease classification and YOLOv8 for disease localization.

The system architecture includes a user-friendly web interface that allows farmers to upload plant images, view sensor data, and receive real-time alerts. The integration of cloud computing ensures scalability and accessibility from any location.

5. System Architecture

The proposed AI-based smart plant health monitoring system follows a layered architecture that integrates data acquisition, processing, cloud storage, and user interaction. The architecture consists of four major layers:

5.1 Data Acquisition Layer

International Journal of Science, Strategic Management and Technology
Volume **02** Issue **05** May-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

This layer is responsible for collecting input data from the field. It includes IoT sensors such as temperature, humidity, and soil moisture sensors that continuously monitor environmental conditions. A camera module or smartphone captures images of plant leaves for disease detection.

5.2 Processing and AI Layer

In this layer, the collected data is processed and analyzed. Environmental data from sensors is checked against predefined threshold values to identify abnormal conditions. The captured leaf images are processed using deep learning models — CNN for disease classification and YOLOv8 for detecting and localizing infected regions.

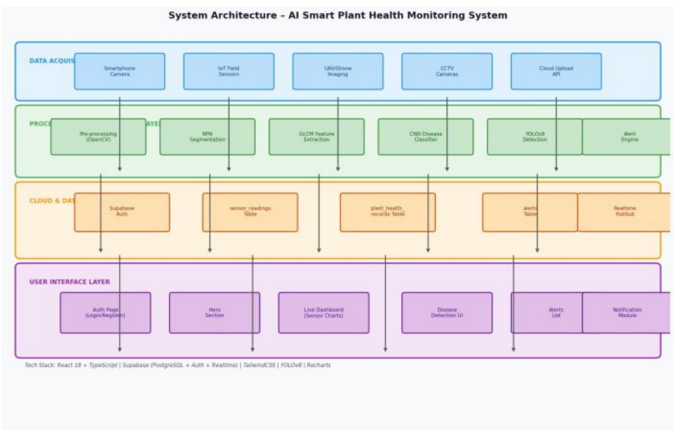

Fig. 1: System Architecture – Four-Layer AI Plant Health Monitoring Stack

5.3 Cloud and Database Layer

All processed data, including sensor readings and disease detection results, are stored in a cloud database. This layer ensures data availability, scalability, and real-time synchronization. It also supports data analysis, historical tracking, and integration with AI services.

5.4 User Interface Layer

This layer provides interaction between the system and users. A web or mobile application allows farmers to view real-time sensor data, upload plant images, and receive disease detection results. The system also generates alerts and notifications when abnormal conditions or diseases are detected.

Working Flow

- IoT sensors collect environmental data continuously
- Leaf images are captured using a camera or mobile device
- Data is transmitted to the cloud server
- Deep learning models analyze images for disease detection
- Sensor data is evaluated for threshold violations
- Results and alerts are sent to the user through the interface

6. Methodology

The proposed system follows a structured methodology that integrates IoT-based data collection with deep learning-based image analysis for effective plant health monitoring. The methodology consists of multiple stages ensuring accurate disease detection and real-time environmental monitoring.

6.1 Data Collection

The system collects two types of data: Environmental Data (temperature, humidity, and soil moisture monitored using IoT sensors) and Image Data (plant leaf images captured using a camera or smartphone for disease detection).

6.2 Data Preprocessing

- Image resizing and normalization
- Noise removal and enhancement
- Formatting sensor data for analysis

6.3 Feature Extraction

Important features are extracted from the input data — color, texture, and shape features from images, and environmental patterns and threshold values from sensors. This step helps the model focus on relevant information for accurate prediction.

6.4 Model Training (Deep Learning)

A Convolutional Neural Network (CNN) is used for plant disease classification. The model is trained using a dataset of healthy and diseased plant images. Multiple layers extract hierarchical features, and the model learns to classify different disease categories. YOLOv8 is additionally used for detecting and localizing diseased regions in the leaf images.

6.5 Disease Detection and Analysis

- The trained model analyzes new input images
- Classifies whether the plant is healthy or diseased
- Identifies the type of disease
- Marks affected regions using bounding boxes (YOLOv8)

6.6 Cloud Integration & Alerts

- All data is sent to a cloud server and stored in a database

• Alerts generated when disease is detected or sensor values exceed safe limits
• Notifications sent to users through the application

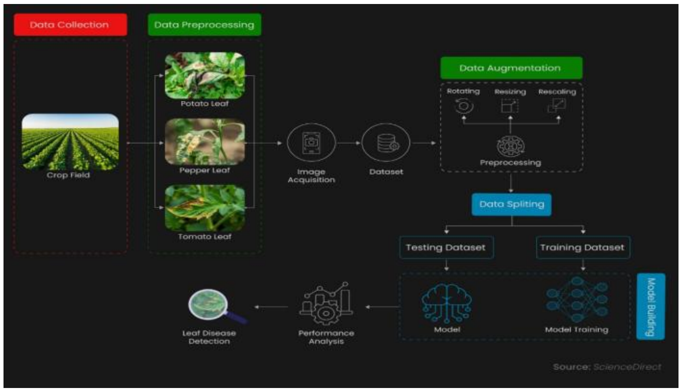

Fig. 2: Workflow of the Proposed Plant Disease Detection System

7. Hardware & Software Requirements

7.1 Hardware Requirements

The hardware components are mainly responsible for collecting environmental data and capturing plant images:

• Microcontroller / Development Board: Arduino Uno, ESP32, Raspberry Pi
• Temperature Sensor – Measures ambient temperature
• Humidity Sensor – Measures air moisture level
• Soil Moisture Sensor – Detects water content in soil
• Camera Module / Smartphone Camera – Captures leaf images

Component	Min Spec	Recommended
Processor	Intel Core i5 (8th Gen)	Intel Core i7 / Apple M1
RAM	8 GB DDR4	16 GB DDR4 or more
Storage	128 GB SSD	256 GB NVMe SSD
GPU	Integrated graphics	NVIDIA GTX 1060 6 GB
Internet	5 Mbps broadband	25 Mbps fiber or faster
Camera	8 MP smartphone	12 MP+ with macro lens
Display	1280×720 HD	1920×1080 Full HD

7.2 Software Requirements

• Python (for AI and backend development)
• TensorFlow / Keras / PyTorch (Deep Learning Frameworks)
• Firebase / Supabase / ThingSpeak (IoT Platforms)
• HTML, CSS, JavaScript (Web Technologies)
• Google Colab / Jupyter Notebook / VS Code

Category	Technology	Version
Operating System	Windows 10/11, macOS 12+, Ubuntu 20.04	Latest LTS
JS Runtime	Node.js	18.x or higher
Frontend	React	18.3.1
Language	TypeScript	5.8.3
Build Tool	Vite	5.4.19
CSS Framework	TailwindCSS	3.4.17

8. Algorithm / Model Description

The proposed system utilizes deep learning techniques — a Convolutional Neural Network (CNN) for plant disease classification and YOLOv8 for disease detection and localization. The algorithm is designed to process both image data and IoT sensor inputs to provide accurate and real-time plant health analysis.

8.1 Step-by-Step Algorithm

Input: Plant leaf image, sensor data (temperature, humidity, soil moisture)

Output: Disease classification, detection result, and alert notification

• Step 1: Initialize IoT sensors and connect to cloud server
• Step 2: Collect environmental data continuously
• Step 3: Capture plant leaf image using camera or mobile device
• Step 4: Preprocess image – resize, normalize pixel values, remove noise
• Step 5: Input preprocessed image into trained CNN model
• Step 6: Perform feature extraction using convolutional and pooling layers
• Step 7: Classify image into healthy or diseased categories

- Step 8: Apply YOLOv8 model to detect and localize disease regions
- Step 9: Analyze sensor data and compare with threshold values
- Step 10: Combine image analysis and sensor data results
- Step 11: Generate disease name, confidence score, and bounding box output
- Step 12: Trigger alert if disease detected or abnormal conditions occur
- Step 13: Store results in cloud database and display via interface

8.2 Model Description

Convolutional Neural Network (CNN)

CNN is used for image classification due to its ability to automatically extract features from images. The architecture includes an Input Layer (accepts resized plant leaf images), Convolutional Layers (extract features such as edges, textures, and patterns), Pooling Layers (reduce dimensionality), Fully Connected Layer (performs classification), and Output Layer (produces probability scores for disease classes).

YOLOv8 (You Only Look Once)

YOLOv8 is used for real-time object detection and localization. It detects infected regions in leaf images, provides bounding boxes around diseased areas, and offers high speed and accuracy for real-time applications. This model enhances the system by not only identifying the disease but also visually highlighting affected areas.

Sensor Data Analysis Model

- Threshold-based analysis of environmental parameters
- Detects abnormal conditions affecting plant health
- Supports decision-making along with AI prediction

9. Implementation

The implementation of the proposed AI-based smart plant health monitoring system involves the integration of IoT hardware components with deep learning models and cloud-based services. The system is developed in a modular manner to ensure flexibility, scalability, and efficient performance.

9.1 System Setup

The hardware components, including IoT sensors (temperature, humidity, and soil moisture), are connected to a microcontroller such as ESP32 or Arduino. The microcontroller is programmed to collect real-time environmental data and transmit it to a cloud platform via Wi-Fi.

9.2 Data Collection and Transmission

Sensor data is continuously monitored and sent to the cloud server using IoT protocols such as HTTP or MQTT. Plant leaf images are either captured through a camera module or uploaded manually through the user interface. The collected data is stored in a cloud database (Firebase or Supabase) for further processing.

9.3 Model Development and Training

The deep learning model is developed using Python and trained on a dataset of plant leaf images. A Convolutional Neural Network (CNN) is used for disease classification, while YOLOv8 is implemented for detecting and localizing infected regions. The model is trained using Google Colab or Jupyter Notebook, ensuring high accuracy and efficient performance.

9.4 Model Deployment

After training, the model is deployed on a cloud server or integrated into a web application using frameworks such as Flask or Django. The deployed model processes incoming images in real time and generates predictions, including disease type and confidence score.

9.5 Integration of IoT and AI

The system integrates IoT sensor data with AI-based image analysis. Sensor readings are compared with predefined threshold values to identify abnormal environmental conditions. The results from both sensor analysis and image classification are combined to provide a comprehensive plant health status.

9.6 User Interface Development

A web-based or mobile application is developed using HTML, CSS, and JavaScript to provide a user-friendly interface. The interface allows users to view real-time sensor data, upload plant images, and receive disease detection results.

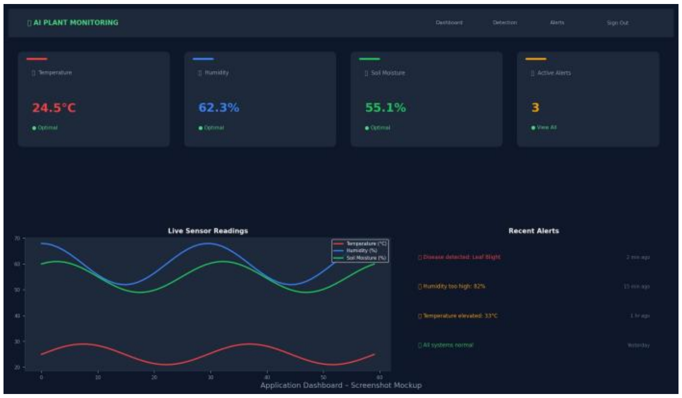

Fig. 3: Application Dashboard – Live Sensor Cards, Chart, and Alerts Panel

10. Results and Discussion

The proposed AI-based smart plant health monitoring system was evaluated using a dataset of plant leaf images along with real-time environmental data collected from IoT sensors. The performance of the system was analyzed based on accuracy, precision, recall, and response time. The CNN model demonstrated high classification accuracy in identifying plant diseases, while the YOLOv8 model effectively detected and localized infected regions in the leaf images.

The results indicate that the system performs efficiently in real-time conditions. The CNN model accurately classifies plant diseases, and the YOLOv8 model enhances visualization by marking affected regions. The integration of IoT sensor data further improves reliability by considering environmental conditions that influence plant health.

10.1 Discussion

The experimental analysis shows that the proposed system provides significant improvements over traditional manual inspection methods. The use of deep learning eliminates the need for manual feature extraction and ensures higher accuracy even under varying conditions. Additionally, the integration of IoT sensors allows continuous monitoring of environmental parameters, enabling early detection of unfavorable conditions.

The system is capable of delivering real-time alerts and recommendations, which helps farmers take timely action and reduce crop losses. However, the performance of the model depends on the quality and diversity of the training dataset. In real-world scenarios, factors such as lighting variations, background noise, and image quality may affect accuracy.

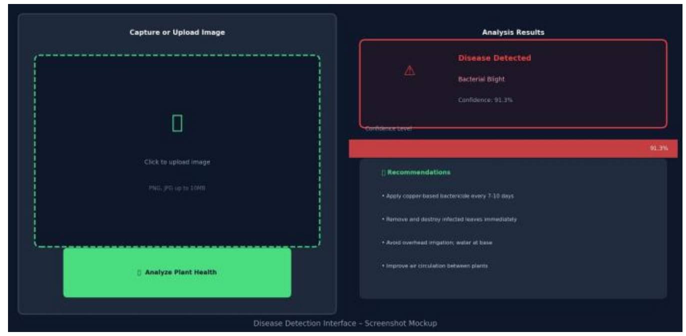

Fig. 4: Disease Detection Interface – Upload / Camera + AI Analysis Results

11. Future Scope

Although the proposed AI-based smart plant health monitoring system demonstrates high accuracy and efficiency, there are several opportunities for further enhancement to improve its performance, scalability, and real-world applicability.

• Incorporate advanced deep learning models such as EfficientNet and Vision Transformers (ViT) to improve classification accuracy

• Deploy lightweight models using edge computing for offline disease detection in rural areas

• Integrate additional IoT sensors such as soil nutrient (NPK) sensors and weather data APIs

• Include a recommendation engine for suggesting fertilizers, pesticides, and treatment methods

• Develop a multilingual mobile application for broader farmer accessibility

• Integrate drone or satellite-based imaging for large-scale field monitoring

• Incorporate predictive analytics using time-series models to forecast disease occurrence

12. Conclusion

This paper presented an AI-based smart plant health monitoring system that integrates Internet of Things (IoT) technology with deep learning techniques for efficient and accurate plant disease detection. The proposed system combines real-time environmental monitoring using IoT sensors with image-based disease classification using CNN and disease localization using YOLOv8. This integrated approach enables early detection of plant diseases and continuous monitoring of factors affecting plant health.

The experimental results demonstrate that the system achieves high accuracy and reliability, making it suitable for real-world agricultural applications. By automating the process of disease detection and monitoring, the system reduces dependency on manual inspection and expert knowledge. The real-time alert mechanism further supports timely decision-making, helping farmers take preventive actions and minimize crop losses.

Overall, the proposed system provides a scalable, cost-effective, and user-friendly solution for smart agriculture. It contributes to improving crop productivity, promoting sustainable farming practices, and supporting precision agriculture. With further enhancements, the system has the potential to play a significant role in transforming modern

13. References

1. A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases," Sensors, vol. 17, no. 9, pp. 2022, 2017.
2. B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," Agronomy, vol. 11, no. 1, pp. 93, 2021.
3. E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019.
4. Google, "Gemini API Documentation," [Online]. Available: https://ai.google.dev/gemini-api/docs
5. J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," Computers and Electronics in Agriculture, vol. 173, pp. 105393, 2020.
6. J. Su et al., "Spatio-temporal monitoring of wheat yellow rust using UAV multispectral imaging," Computers and Electronics in Agriculture, vol. 162, pp. 103–112, 2019.
7. K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.
8. M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," Plants, vol. 8, no. 11, pp. 468, 2019.
9. PlantVillage Dataset, "PlantVillage Dataset," [Online]. Available: https://plantvillage.psu.edu/
10. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, pp. 1419, 2016.
11. S. S. Patil and S. A. Thorat, "Early detection of grape diseases using machine learning and IoT," in Proc. IEEE ICACCI, 2016, pp. 1–6.
12. Ultralytics,"YOLOv8 Documentation,"[Online]. Available: https://docs.ultralytics.com/