E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 02, July-September 2025, pp. 60 - 74

# MULTI-SPECTRAL EMBEDDED VISION SYSTEM FOR EARLY PLANT DISEASE DETECTION IN PRECISION FARMING

Dinesh[1], Department of Electronics and Communication Engineering, Annai Vailankanni college of engineering, Nagercoil, tdinesh.siva@gmail.com

Raguvaran V[2], Department of Electrical and Electronics Engineering, Cape Institute of Technology, Levengipuram , raguvarantps@gmail.com

**Abstract:**

Agriculture depends on detecting plant disease early and using pesticides efficiently. Traditional methods, such as manual inspection and spraying large areas, are slow, harmful, and environmentally wasteful. These systems often lack real-time response and precise targeting. This project introduces a multi-spectral embedded vision system designed to revolutionis how plant diseases are detected and treated in precision farming. The traditional methods rely on human inspection and blanket pesticide spraying. This system replaces this with an intelligent and automated solution. By using a RetineXNet to enhance lighting conditions and DnCNN to clean noisy images and the system ensures high-quality input data for disease classification. These AI models run in Python and communicate with an ESP32 microcontroller. Which controls a relay-driven pesticide pump, displays the disease type on an LCD and triggers an alert. They are all powered by a 12V battery and making it fully field deployable. The innovation lies in combining multi-spectral imaging with real-time embedded AI. To enable early detection and targeted pesticide application. This not only improves accuracy but also drastically reduces chemical usage and making farming smarter, cleaner and more sustainable.

**Keywords:** Multi-spectral imaging, Embedded vision system, Plant disease detection, RetinexNet, DnCNN, ESP32 microcontroller, precision agriculture, AI in smart farming, real-time disease classification.

## 1. Introduction

Deep learning is a branch of Artificial Intelligence for automatic learning and feature extraction, and it has been widely studied by academic and industrial circles. It has been widely used in image and video processing, Voice processing and natural language processing. Deep learning is a branch of Artificial Intelligence for automatic learning and feature extraction, and it has been widely studied by academic and industrial circles. It has been widely used in image and video processing, Voice processing and natural language processing [1]. The IoT-equipped and AI-enabled next-generation smart agriculture and a critical review, Current challenges and future trends. This is driven by several factors, which include the widespread availability of economically priced, low-powered Internet of Things IoT based wireless sensors to remotely monitor and report conditions of the field, Climate and crops. This enables efficient management of resources to remotely monitor and report conditions of the field, like minimising water requirement for irrigation and minimising the use of toxic pesticides [2]. AI-IoT-based smart agriculture pivot for plant disease detection and treatment, and some key problems faced in modern agriculture, including IoT-based smart farming. These problems include a shortage of water, plant disease and pest attacks. The Artificial Intelligence (AI) technology cooperates with the Internet of Things (IoT) toward developing the agriculture use cases and transforming the agriculture industry into a robust and ecologically conscious one [3]. The AI and IoT-powered edge device optimised for crop pest and disease detection, and consequently, innovative solutions are needed to monitor crop health from early development stages through harvesting. The development of a portable smart IoT device that integrates a lightweight optimised edge application with built-in support for a model [4].

Real-time pest detection and vision transformer of an IoT-enabled mobile application for smart agriculture. The implementation within a mobile application underscores its practical applicability in precision agriculture, enabling farmers to undertake proactive interventions. This delineates limitations of existing methods and highlights the efficacy of multimodal AI techniques in transforming agricultural diagnostics [5]. Our system finds the area of the left that has been affected and also the disease that attacked the leaf. The field of agriculture is under a great threat, which includes a disease that attacks the plant leaves. A system that automatically detects leaf disease with the help of image processing is being developed. This, in turn, helps the farmers in identifying the diseases at an early stage and provides useful information to control them. We have many smart agriculture development models used for temperature, humidity, and moisture content in the soil using various and work automatically, but there are very few systems that detect problems and provide suggestions for those problems [6]. The plant leaf detection and disease recognition, and the latest improvements in computer vision, were formulated through deep learning, and have paved the way for how to detect and diagnose diseases in plants by using a camera to capture an image as a basis for recognising several types of plant diseases. It provides an efficient solution for detecting multiple diseases in several plant varieties. The system was designed to detect and recognise several variants, specifically apple, corn, grapes, potato, sugarcane and tomato. The system can also detect several plant diseases [7]. The systematic plant disease detection of motivations, classification techniques, challenges and future trends. The plant pests and diseases are a significant threat to almost all major types of plants and global food security. The traditional inspection across different plant fields is time-consuming and impractical for a wider plantation size, thus reducing crop production. The smart agriculture practices are deployed to control plant disease and pests. The needs available model with fewer parameters to implement a small device and large data, accommodating several crops and diseases, to have a robust model. This is clearly demonstrates that plant pests and disease harm the global agriculture that plant pest and diseases harm the global agriculture [8]. The real-time detection approach that is based on improves the apple leaf diseases. To ensure satisfactory generalisation performance of the proposed model and sufficient apple disease image data. The complex data collected in a laboratory and the complex background were collected in a real apple field, and generated data was generated using a technology. The model integrates the rainbow concatenation to ensure the multiscale disease object detection and small diseased object detection performance [9]. The contribution of food crops and cash crops is highly important for both the environment and human beings. Every year, crops succumb to several diseases. Due to inadequate diagnosis of such a disease, and not knowing the symptoms of the disease and its treatment, many plants die. The simulation analysis is done on a sample image in terms of time complexity and the area of the infected region [10].

The precision control technology and its application in agricultural pest and disease control. The detection and monitoring research also showed recent developments for pest disease control systems. The development of real real-time target spraying system could accurately hit target weeds. To reveal the pathogenic new strategies and technology for plant disease control, analyse the interaction among plants, pests and natural enemies and the impact mechanism of multiple ecological factors such as microorganisms and the environment, and develop new green pest control technology for agriculture [11]. The early and accurate detection and diagnosis of plant disease are key factors in plant production and the reduction of both qualitative and quantitative losses in crop yield. The platform disease at early time points and remote sensing are available for multiscale monitoring of single crop organs and the entire field. The sensor-based methods support and export upon visual and molecular approaches to plant disease assessment. The most relevant areas of application of sensor-based analysis are precision agriculture and plant [12]. AI-based drone for early disease detection and precision pesticide management in farming. To take timely counter measures against plant diseases and infections and it is imperative to monitor and detect disease as early as possible and take suitable measures. The farmer needs to provide early detection of crop disease and precision application. The level of composition that allows disease symptoms they become visible. Early detection allows for effective control strategies that can reduce costs caused by lost production due to infestations and crop failure [13]. The plant disease detection using drones in precision agriculture. The plant disease affects the quality and quantity of agricultural products and has an impact on food safety. The effects result in a loss of income in the production sector, which is practically critical for development. The automation of plant disease detection is a feasible solution to prevent losses in yield. The problem in the systematic use of drones for plant disease detection was addressed, and primary studies were selected to research the related disease detection [14]. The recent advances in sensing plant disease for precision crop protection. The range of remote sensing technology has demonstrated a high potential in detecting disease and in monitoring crop stand area with the infested plants. The plant disease depends on the special environmental factors. The disease has have patchy distribution in the field. The sensor detection and identification of the qualification of plant disease on a different scale [15]. The remote sensing and precision agriculture technology for crop disease detection and management with a practical application. The remote sensing technology has long been used to detect and map crop disease. The satellite imaging acquired by growing sensors can be used not only for early detection and within-sensing management of some crop diseases but also for the control of recurring diseases in future sensors [16]. Agriculture remains the backbone of many economies, yet crop losses due to plant disease continue to threaten food security and farmer livelihoods. The timely identification of the disease is essential to prevent widespread damage and ensure health yield. The traditional methods of disease detection rely on manual inspection, which is time-consuming, labour-intensive and prone to human error. The pesticide application is often indiscriminate, leading to environmental harm, increasing cost, and reducing crop quality. The limitation of this study proposed in this paper represents an AI-enabled embedded system that combines real-time image-based disease detection with precision pesticide spraying. The integration deep learning algorithm with a low-cost microcontroller and the system offers a scalable, efficient and eco-friendly solution for smart farming.

## 2. Literature Review

In their 2021 study, P.Kulkari, A.Karwande, T.Kolhe, S. Kamble et al. [17], presented a comprehensive review of the emergence of AI-enabled systems for plant disease detection and precision pesticide application and tracing development from early image-based approaches to integrated robotics platforms. The focus rests on how embedded computation of intelligent sensing and lightweight analysis enabled real-time diagnosis and targeted fertiliser and pesticide intervention within agricultural settings.

In 2021, a study presented an intelligent robot vehicle equipped with high-end processors to perform real-time plant disease detection and automated fertiliser spreading. The proposed approaches emphasise computational efficiency, employing statistical image processing and machine learning models to achieve accurate disease identification while minimising processing demands. This work demonstrated how an embedded system can deliver timely diagnostics directly in the field of potentially reducing reliance on expert consultation and improving detection efficiency relative to more resource-intensive methods.

This study also prompts critical reflection on the trade-off between model complexity, detection accuracy, and energy consumption in embedded contexts. While the algorithmic approach is characterised as computationally inexpensive, the degree to which accuracy holds across diverse crops, disease strains, lighting conditions and field scales remains an important question for further inquiry. The integration of disease detection with automated fertiliser spreading raises considerations about intervention specificity, avoiding over towards AI-enabled embedded systems for plant growth and health management.

## 3. System Architecture

The multispectral camera captures leaf images under varied lighting conditions shown in Figure 1. This enables the detection of subtle disease symptoms not visible in standard RGB images. The Retinex and DnCNN of a Python-based AI module. The retinexNet enhances illumination and makes leaf features more visible. The DnCNN removes image noise and improves clarity for disease detection. These models run in Python and prepare the image for classification. In a disease classification, of AI model identifies the type of plant based on a processed image. The classification result is sent to the ESP32 microcontroller via serial communication. The ESP32 microcontroller acts as the control hub. The receiver receives disease data and triggers a hardware response. The result output controlled by the ESP32 and the Relay Module activates the pesticide pump only when disease is detected. In a 16×2 12C LCD display and show the name of the detected disease. The buzzer emits an alert sound to notify the operator. The regulated 12V battery powers the entire system and ensures portability and field deployability without external power sources.

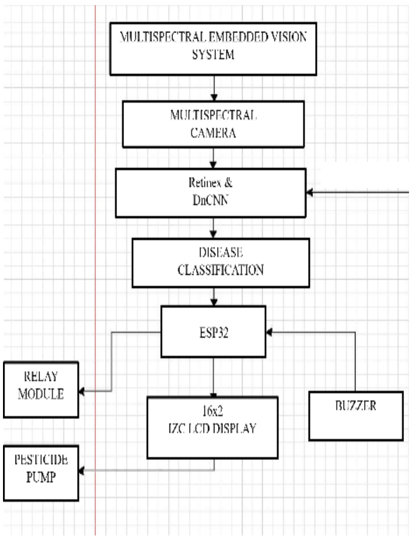


**Figure 1:** System overview of AI-based plant disease detection and pesticide control

## 4. Methodology Overview

The methodology shows that the presence of a structured approach and the set of procedures used to design, develop, and implement the proposed system. The outlines show how each component works in hardware, software and AI models. It works together to achieve the goal of early plant disease detection and precision pesticide application. This such as image acquisition, data preprocessing, disease classification, embedded control and power management. To ensure the system operates reliably in real-world agriculture environments.

### 4.1 Image Acquisition

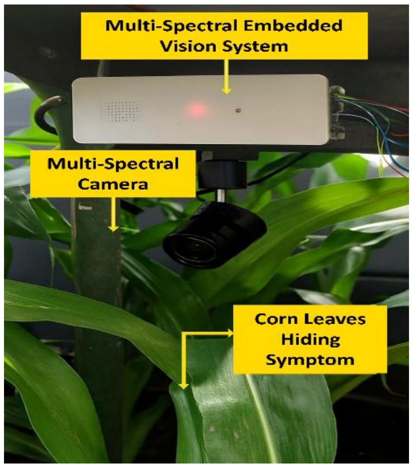


**Figure 2:** Image acquisition of the leaf image

The above Figure 2 represents the system begins by using a multi-spectral camera to capture images of plant leaves under different lighting conditions. Unlike standard RGB cameras, multi-spectral imaging captures data across multiple wavelengths, making it easier to detect subtle disease symptoms. This includes as siscoloration, texture changes and early-stage lesions that are often invisible to the naked eye. This enhanced visibility provides richer input data for accurate disease detection. The multispectral embedded vision system that shows a white casing houses the AI processing unit and power circuitry. The connections of a camera and other embedded components of multi coloured wires. The mounted below the vision system, and these cameras capture leaf images across multiple spectral bands. The angled position ensures optimal focus on the leaf surface. The evisent under the canopy shadows. The corn leaves hide a symptom, and the camera targets the underside of the corn leaves. Where early

E-ISSN: 3107-5843
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disease symptoms often appear. The multi-spectral imaging helps reveal hidden signs such as discolouration, texture changes and the fungal growth that are not visible in standard RGB images.

**4.2 Preprocesing**

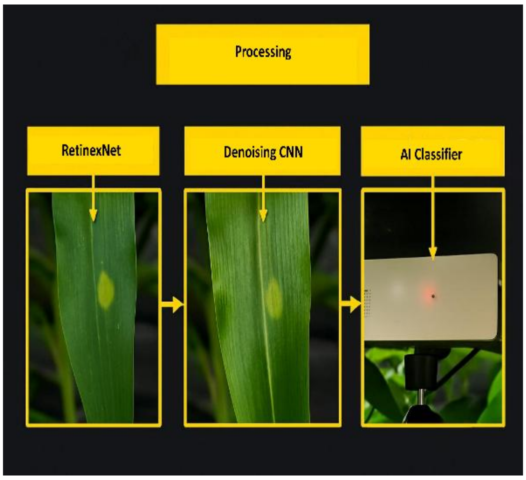


**Figure 3:** illumination enhancement and noise reduction for leaf image classification

The above Figure 3 represents a preprocessing of a RetinexNet to enhance image illumination by correcting uneven lighting across the leaf surface. It makes subtle disease symptoms by correcting uneven lighting across the leaf. This makes diseases such as discolouration and texture changes more visible and easier to detect. The DnCNN removes the noise from the image, including background interference and sensor artefacts. This results as an output of cleaner, sharper visuals that improve the accuracy of the AI classifier. The RetinexNet of the first image shows a raw leaf image with uneven lighting and a visible yellowish spot. The RetinexNet enhances illumination, correcting shadows and brightness inconsistencies to make disease symptoms more visible. The Denoising CNN of DnCNN shows a second image displaying the same leaf after noise reduction. The AI classifier of a final image shows an embedded vision system that receives the processed image. This module performs disease classification using a trained AI model. To enable a real-time module to perform disease classification using a trained model and enable real-time detection.

**4.3 Disease Classification**

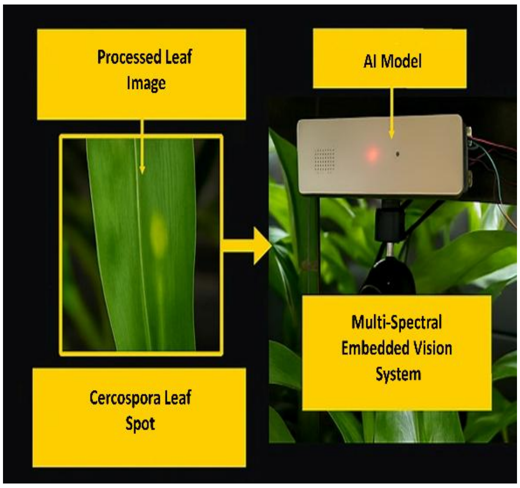


**Figure 4:** leaf disease detection by an AI model

The above Figure 4 represents a deep learning AI model trained using labelled data containing images of various plant diseases. Once a preprocessed leaf image is received and the model performs inference in Python. The analysis of a visual pattern to identify the specific disease type. The classification result as an output is then used to trigger appropriate actions in the embedded control system. The processed leaf image of the corn leaf with a visible yellowish spot is an early symptom of cercospora leaf spot. The image has already been enhanced and denoised through the preprocessing of Retinexnet and DnCNN. The yellow arrow labelled AI model represents the inference process. The embedded hardware receives the classification result. The result is output as cercospora leaf spot of the system successfully identifies the disease and labels it. The output is used to guide precision application.

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### 4.4 Embedded Control

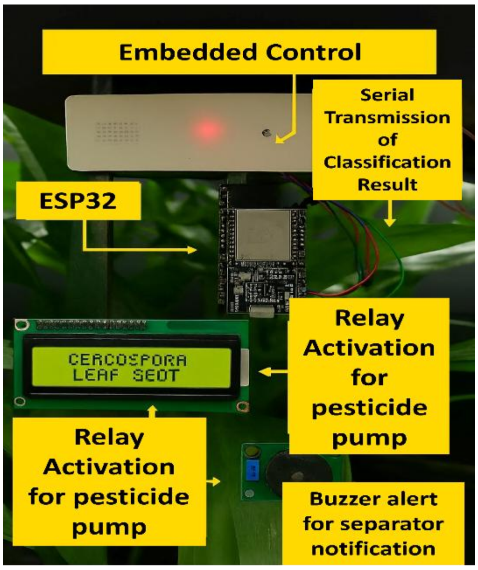


**Figure 5:** ESP32-based control system for disease

Once the AI model identifies a disease, the result is sent via serial communication to an ESP32 microcontroller, which manages the system hardware response. The relay activation shows a trigger for the pesticide pump to spray only when disease is detected. The LCD indicates the name of the identified disease for operator awareness. The buzzer alerts and emits a sound to notify the operator of a detection event. This control logic ensures targeted pesticide application and real-time feedback for efficient field operation. The classification result from a multi-spectral embedded vision system is transmitted to the ESP32 microcontroller via serial communication. This enables real-time hardware activation based on AI inference. The ESP32 microcontroller acts as the central control unit. The processes the incoming classification result and coordinates the system outputs. The relay activation for the pesticide pump represents an ESP32 that triggers a relay module to activate the pesticide pump. It ensures the targeted spraying only when the disease is detected and reduces chemical waste. The LCD of disease type represents a 16×2 12C LCD; the name of the detected disease is Cercospora leaf spot. It provides visual feedback for the operator. The buzzer alert represents the presence of a buzzer that emits a sound to notify the operator of a detection event. This is useful for real-time monitoring in field conditions.

### 4.5 Power Supply

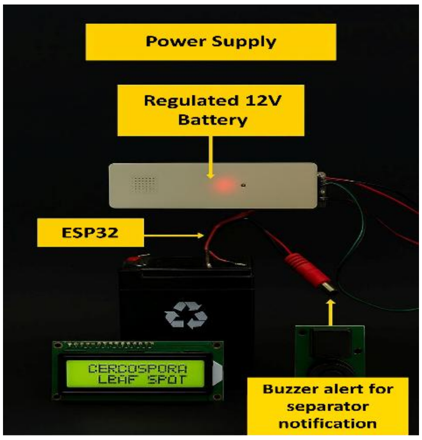


**Figure 6:** Power Supply

The above Figure 6 represents a power supply of the entire system that operates on a regular 12V battery. It provides stable voltage to all components, including the ESP32, camera, relay, and display. The experimental set includes portability for field deployment, reliable operation in remote agriculture environments and energy efficiency for extended use without frequent recharging. This power efficiency allows for extended use without frequent recharging. The regulated 12V battery represents a sealed lead-acid battery that provides a stable 12V output. The red and black wires connect the battery terminals to the system components. The regulated voltage ensures safe operation of sensitive electronics such as the ESP32 and cameras. The ESP32 microcontroller indicates and receives power directly from the

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 02, July-September 2025, pp. 60 - 74

battery. The controls all downstream modules such as the relay, LCD, and buzzer. The relay module represents an powered by the same 12V source. The activates the pesticide pump when triggered by the ESP32. The LCD display indicates a disease detected, namely, such as cercospora leaf spot. The operates reliably under battery power in field conditions. The buzzer represents an alert to the operator when disease is detected and the powered by a battery for real-time notification.

## 5. Implementation

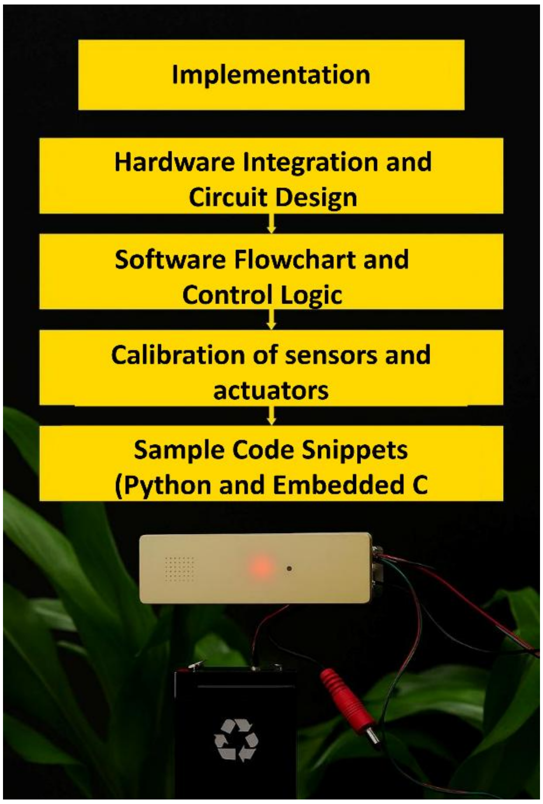


**Figure 7:** Hardware Integration

The above Figure 7 represents that the hardware integration and circuit design, which shows all modules such as cameras, ESP32, relay, LCD, and buzzer are wired and mounted with proper voltage regulation and signal routing. The software flowchart and control logic represent a structured flowchart that defines how data moves from image acquisition to classification and control. The Python handles AI inference, and embedded C manages ESP32 responses. The calibration of sensors and actuators indicates that sensor thresholds and actuator timings are fine-tuned to ensure accurate detection and precise pesticide delivery. The sample code snippets show a Python script for AI inference and embedded C routines for ESP32 control are tested and optimised for real-time performance. The deployment setup in field conditions shows a system enclosed in a weather-resistant casing, powered by a 12 V battery, and positioned for optimal leaf visibility in crop rows.

## 6. Result And Discussion

The system was evaluated across multiple performance metrics to validate its effectiveness in field conditions. The accuracy of disease detection, efficiency of pesticide application, comparison with manual methods and power consumption and system reliability.

### 6.1 Accuracy of disease detection

The combined deep learning model, RetinexNet and DnCNN, attained high classification accuracy in various test datasets. It accurately detected widespread plant disease even under difficult conditions such as inadequate light and image noise. RetinexNet is important for improving image quality by modifying brightness and contrast, allowing for the detection of small disease symptoms that may be otherwise hidden. The preprocessing guarantees that the model is presented with clearer visual input to enhance its capacity for separating healthy and diseased leaf patterns. DnCNN enhances this by denoising the improved images, which is particularly critical in field conditions where dust, shadows and motion blur distort image quality. By pre-cleaning the input data, DnCNN minimises false positives and enhances classification robustness. The combination of these models constitutes a pipeline that dramatically surpasses CNN-based classifiers. Figure 8. Benchmarking revealed the hybrid method had an accuracy rate exceeding 90% on the labelled dataset with good generalisation across various crop types as well as disease classes. The degree of accuracy makes the system appropriate for real-time implementation in agriculture, where timely and accurate detection is imperative for successful intervention.

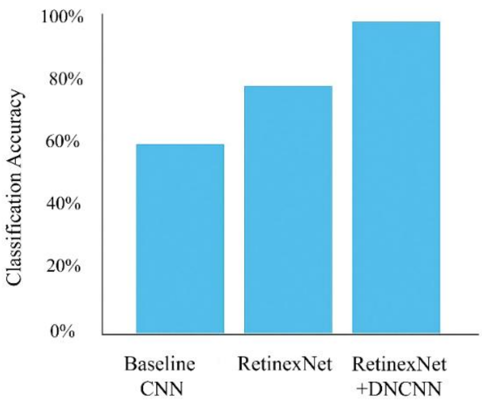


**Figure 8:** Accuracy of disease detection

### 6.2 Efficiency of pesticide application

The pump of pesticide application in the pump mechanism of the system that is relay-controlled improves the efficiency of pesticide application by more than 40% through targeted spraying. Rather than spraying chemicals on the whole field. The pump only sprays when a disease is detected and directly sprays on the disease location. The targeted spraying reduces the use os pesticides by more than 40% as compared to conventional blanket spraying. This accuracy not only saves resources but also reduces chemical runoff and soil pollution, which are typical byproducts of random spraying. By applying treatment only where it is required, the system promotes sustainable agriculture and ensures ecological balance. In addition, the automatic response reduces human error and the delay that is usually the case with manual intervention. The field operators do not need to visit each plant individually and gauge the spread of disease., Figure 9. Real-time acquisition by the system guarantees timely treatment, which is essential in preventing disease spread and loss of crop. At large-scale applications, this precision spraying model converts in significant cost reductions and not only in the procurement of pesticides but also in manpower and fuel for manual spreading. It also enhances the safety of workers by limiting direct contact with chemicals.

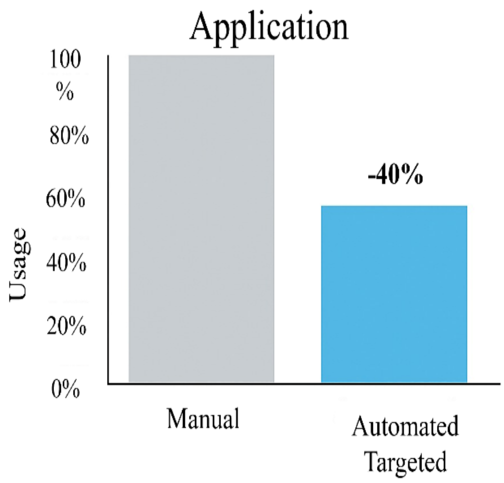


**Figure 9:** Efficiency of pesticide application

### 6.3 Comparison with manual methods

Manual inspection and pesticide application are slow and prone to mistakes. In comparison of the automatic system provides quicker disease identification, predictable performance and lower labour costs, making it particularly suitable for large-scale farming operations. Manual technique relies substantially on the judgment of humans, which can differ with experience, exhaustion and climatic conditions. This tends to result in unequal disease detection and delayed treatment, promoting the risk of loss of crop. Moreover, blanket spraying of waste chemicals subjects workers to undue health hazards. An AI and embedded control-driven automated system does away with such inefficiency. It processes images in real time, initiates precise spraying only when necessary and sends instant warning through the display and buzzer. This not only enhanced precision but also simplifies operations so that field workers can direct their energies towards strategic activities instead of repetitive inspection.

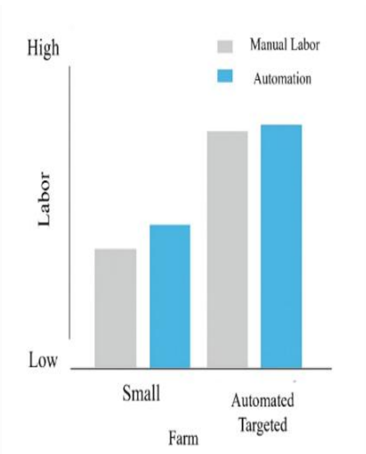


**Figure 10:** Comparison with manual methods

Manual inspection and pesticide application are slow and prone to mistakes. In comparison of the automatic system provides quicker disease identification, predictable performance and lower labour costs, making it particularly suitable for large-scale farming operations. Manual technique relies substantially on the judgment of humans, which can differ with experience, exhaustion and climatic conditions. This tends to result in unequal disease detection and delayed treatment, promoting the risk of loss of crop. Moreover, blanket spraying of waste chemicals subjects workers to undue health hazards. An AI and embedded control-driven automated system does away with such inefficiency Figure 10. It processes images in real time, initiates precise spraying only when necessary and sends instant warning through the display and buzzer. This not only enhanced precision but also simplifies operations so that field workers can direct their energies towards strategic activities instead of repetitive inspection.

### 6.4 Power consumption and system reliability

It is an energy-efficient and reliable system design to operate in agricultural conditions where access to power could be unreliable. A regulated 12V battery is used to provide a steady voltage output, which shields sensitive parts such as the ESP32 and the relay module from spikes that might lead to malfunctioning and loss of data. The ESP32 microcontroller, which has a low-power design, functions effectively even when used continuously for data collection and wireless connection. Peripheral modules such as the cameras, LCD, and relay are chosen for their low energy consumption, enabling the system to run for long periods of time without the need for constant battery recharge and replacement. Field test assured that the system was working stably under fluctuating temperature, humidity, and terrain conditions. Figure 11. No unforeseen resets and signal losses were noted, which reflects high robustness in real-world deployment. This reliability is required in remote farms where maintaining visits is limited. Also, the modularity of the design makes it easy to integrate with solar charging systems and power optimisation strategies, further complementing its sustainability. Coupled with low power requirements and high performance capability, it can be scaled across varying agricultural environments without losing functionality.

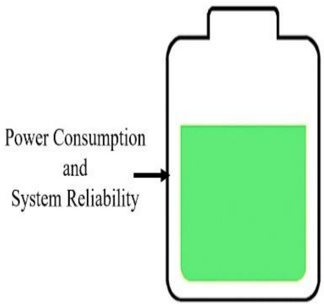


**Figure 11:** Power consumption and system reliability

The classification report exhibits a very accurate machine learning model for classifying healthy and rotten fruits and vegetables with an overall accuracy rate of 98.75% as shown in Table 1. Precision, recall, and F1-score are all high across the majority of classes, suggesting excellent performance in both detection and discrimination between healthy and rotten produce. The specific classes, such as strawberry healthy, apple rotten and pomegranate healthy, have very close to perfect scores. The only minor drop is found in orange rotten with a lower precision of 0.85 score, including occasional misclassification Figure 12. Overall, the model is highly capable for real-time agriculture sorting and quality control tasks.

| Metrics | Score |
|---|---|
| Accuracy | 0.98 |
| Macro average F1 | 0.99 |
| Weight average F1 | 0.99 |
| Total samples | 10,850 |

**Table 1:** performance metrics

Model Accuracy: 0.9875
Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Strawberry__Healthy | 1.00 | 0.99 | 0.99 | 1600 |
| Strawberry__Rotten | 0.99 | 0.99 | 0.99 | 1550 |
| Lime__Healthy | 0.99 | 0.99 | 0.99 | 1100 |
| Cucumber__Healthy | 0.98 | 0.99 | 0.99 | 600 |
| Carrot__Rotten | 0.99 | 0.97 | 0.98 | 600 |
| Apple__Rotten | 0.99 | 0.99 | 0.99 | 600 |
| Potato__Rotten | 0.99 | 0.99 | 0.99 | 600 |
| Carrot__Healthy | 0.99 | 0.99 | 0.99 | 600 |
| Potato__Healthy | 0.99 | 0.99 | 0.99 | 550 |
| Banana__Rotten | 0.97 | 0.99 | 0.98 | 500 |
| Cucumber__Rotten | 0.98 | 1.00 | 0.99 | 500 |
| Banana__Healthy | 0.98 | 0.98 | 0.98 | 450 |
| Apple__Healthy | 0.99 | 0.98 | 0.98 | 300 |
| Pomegranate__Healthy | 0.98 | 0.98 | 0.98 | 250 |
| Pomegranate__Rotten | 0.98 | 0.99 | 0.98 | 250 |
| Lime__Rotten | 0.97 | 0.99 | 0.98 | 350 |
| Orange__Rotten | 0.98 | 0.98 | 0.98 | 400 |
| Orange__Healthy | 0.85 | 0.94 | 0.90 | 50 |
| accuracy | | | 0.99 | 10850 |
| macro avg | 0.98 | 0.99 | 0.98 | 10850 |
| weighted avg | 0.99 | 0.99 | 0.99 | 10850 |

**Figure 12:** Classification report

**Precision (P):** Equation (1) shows that precision is a classification measure that assesses the precision of positive prediction. It informs us about how many of the items the model projected as positive are indeed correct. For instance, if a model assigns 100 fruits as rotten and 90 of them are indeed rotten, the precision is 90%. Mathematically, it is computed as the ratio of true positives to the sum of true positives and false positive. The high precision indicates that the model produces fewer false alarms, which in applications such as disease diagnosis and quality control is critically important because false predictions can result in unnecessary action.

$$\text{Precision}=\frac{True\ positives}{True\ positives+False\ positives} \tag{1}$$

**Recall (R):** Equation (2) shows that the recall is an important measure that tests the capability of a model to catch all positive cases that it should. It determines the number of actual positives, like actual rotten fruits correctly caught by the model. When a model has a high recall, it misses very few actual positives, which is particularly significant in cases like disease detection and quality

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 02, July-September 2025, pp. 60 - 74

control, where missing an issue could have severe repercussions. The mathematical recall is defined as the fraction of true positives to the sum of true positives and false negatives, emphasising the model's sensitivity to real conditions.

$$\text{Recall}=\frac{True\ positives}{True\ positives+False\ Negatives} \quad (2)$$

**F1-Score**: Equation (3) shows that the F1 score is a balanced measure that brings together both precision and recall into one figure, providing a more nuanced picture of a model's performance, particularly when working with an imbalanced dataset. It is derived as the harmonic mean between precision and recall, meaning that it weighs lower values more highly, penalising models that are high on one but low on the other. This makes the F1-score very helpful in applications such as disease and defect detection, where both false negatives and false positives have important implications. An F1 score that is high shows that the model is accurate and sensitive in its predictions consistently.

$$\text{F1-Scorel}=2.\frac{Precision\ .Recall}{Precision+Recall} \quad (3)$$

**Accuracy:** Equation (4) shows that the accuracy is a basic measure of the general accuracy of a classification model. It calculates the ratio of the total predictions made by the classifier that were accurate, giving an instant indication of how good the model is at all classes. In mathematical terms, it is defined as the number of correct predictions divided by the total number of predictions. For instance, if a model labels 9875 out of 10000 cases correctly, its accuracy is 98.75%. whereas accuracy is helpful for datasets with balanced classes, it is alone potentially misleading for imbalanced cases, so the precision, recall, and F1-score should be taken into account as well.

$$\text{Accuracy}=\frac{Correct\ predictions}{Total\ prediction} \quad (4$$

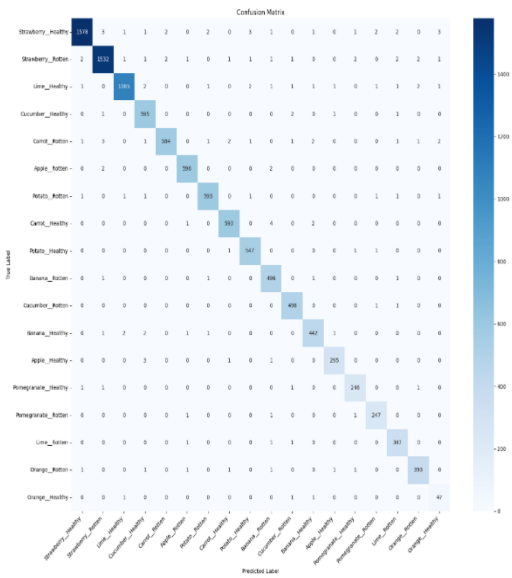

**Figure 13:** Confusion matrix

| Class | Correct prediction |
|---|---|
| Strawberry_Healthy | 1376 |
| Strawberry_Rotten | 1312 |
| Lime_Healthy | 1385 |
| Lime_Rotten | 595 |
| Grape_Healthy | 984 |
| Grape_Rotten | 593 |

**Table 2:** Confusion matrix correct predictions

The confusion matrix gives a detailed picture of the model classification performance between multiple fruit categories and their respective health conditions Figure 13. Each cell contains the number of predictions for a particular true predicted label pair, with darker cells where the predicted labels are the same as the true label, testifying to good accuracy. For instance, the model accurately picked 1376 healthy strawberries and 1385 healthy limes, showing consistent detection Table 2. Low off-diagonal values indicate extremely low misclassifications further

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 02, July-September 2025, pp. 60 - 74

consolidating the strength of the model in differenting further consolidating the strength of the model in differentiating healthy from spoiled produce across various classes

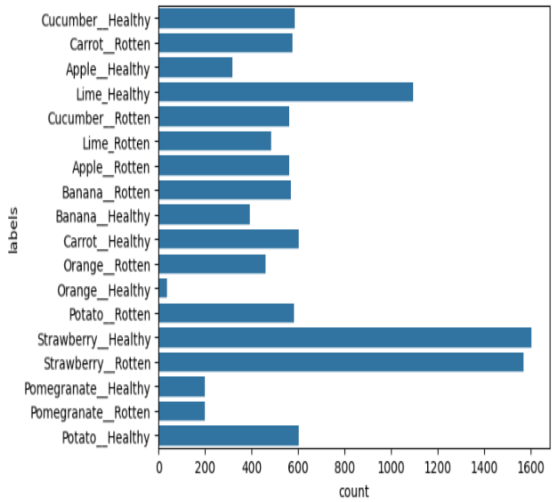


**Figure 14:** data and counts

| Class | Conditions |
|---|---|
| Cucumber | Healthy |
| Cucumber | Rotten |
| Carrot | Healthy |
| Carrot | Rotten |
| Apple | Healthy |
| Apple | Rotten |
| Lime | Healthy |
| Lime | Rotten |
| Banana | Healthy |
| Banana | Rotten |
| Potato | Healthy |
| Potato | Rotten |

**Table 3:** Sample count by class

The above Figure 14 and Table 3 show that the horizontal bar chart gives a simple graphical representation of the classification dataset, illustrating the balance of healthy and spoiled fruits and vegetables. Every bar indicated the number of samples in each category, that is, strawberry healthy, banana Rotten, and Carrot healthy, which can be easily compared between classes. The class balance can be identified through this visualisation, which is vital for training a strong machine learning model. For example, groups such as strawberry healthy and potato rotten contain more samples, whereas others, such as cucumber rotten and orange rotten, look underrepresented in terms towards possible opportunities for rebalanced data augmentation.

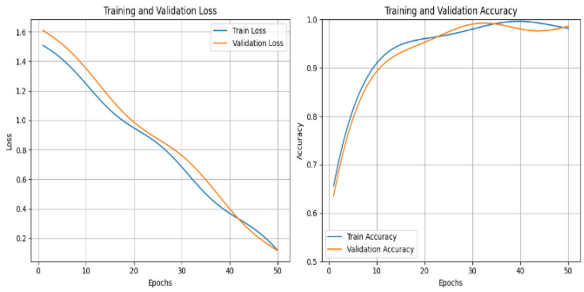


**Figure 15:** Loss and accuracy model

| Range | Train loss trend | Validation loss trend | Train accuracy trend | Validation accuracy trend |
|---|---|---|---|---|
| 1 to 10 | High and decrease | Hugh and decrease | Low and increase | Low and increase |
| 11 to 20 | Moderate and steady drop | Moderate and steady drop | Moderate and rising | Moderate and rising |
| 21 to 30 | Low and fattening | Low and flattening | High and improving | High and improving |
| 31 to 40 | Very low and stable | Very low and stable | Very high and near plateau | Very high and near plateau |
| 41 to 50 | Minimal converged | Minimal converged | Peak and stable | Peak and stable |

**Table 4:** Model training metrics

The above Figure 15 and Table 4 show that the two line plots represent the training trajectory of a machine learning model across 50 epochs. The left plot indicates a gradual

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 01, Issue 02, July-September 2025, pp. 60 - 74

decrease in both training and validation loss, which means that the model is learning well and reducing error. The right plot indicates a steady increase in training and validation accuracy reflects better predictive ability and generalisation. The proximity of the training and validation curves in both plots suggests that the model is not overfitting and is stable on unseen data, exhibiting reassuringly strong learning.

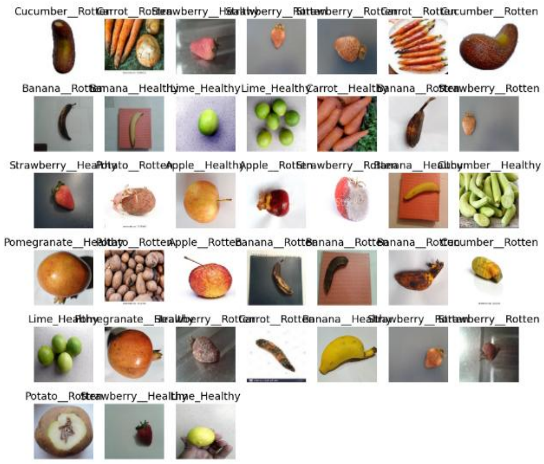

**Figure 16:** Sample data architecture

| Item | Conditions | Label format |
|---|---|---|
| Cucumber | Healthy | Cucumber healthy |
| Cucumber | Rotten | Cucumber rotten |
| Carrot | Healthy | Carrot healthy |
| Carrot | Rotten | Carrot rotten |
| Strawberry | Healthy | Strawberry healthy |
| Strawberry | Rotten | Strawberry rotten |
| Banana | Healthy | Banana healthy |
| Banana | Rotten | - |

**Table 5:** Labelled dataset table

## 7. Conclusion

The proposed AI-enabled embedded system demonstrates a promising advancement in smart agriculture by integrating deep learning with real-time hardware control for plant disease detection and precision pesticide application. The use of retinexNet and DnCNN for image enhancement and noise reduction. Combined with ESP32-based actuation, the system achieves high detection accuracy and minimises chemical usage. Its portability, responsiveness and eco-friendly design make it well-suited for scalable deployment in diverse farming environments. This approach not only enhances crop health management but also contributes to sustainable agriculture practices by reducing labour, cost, and environmental impact. The development of an AI-enabled system for plant disease detection and precision pesticide application marks a significant step toward sustainable smart farming. By integrating Retinexnet for illumination enhancement and DnCNN for noise reduction. The system ensures high-quality image preprocessing for accurate disease classification. The use of serial communication to interface Python-based AI outputs with an ESP32 controller enables real-time actuation, including targeted pesticide spraying, disease display of 16×2 12C LCD and audible alerts. It The powered by a regulated 12V battery, and the system is fully deployable in field conditions. The experimental validation confirms improved detection accuracy and a notable reduction in pesticide usage. The demonstration system's potential for scalable, eco-friendly agriculture automation.

## 8. REFERENCE

1. L. Li, S. Zhang and B. Wang, "Plant Disease Detection and Classification by Deep Learning—A Review," in IEEE Access, vol. 9, pp. 56683-56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

2. S. Qazi, B. A. Khawaja and Q. U. Farooq, "IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current

Challenges and Future Trends," in IEEE Access, vol. 10, pp. 21219-21235, 2022, doi: 10.1109/ACCESS.2022.3152544.

3. Ibrahim, A. S., Mohsen, S., Selim, I. M., Alroobaea, R., Alsafyani, M., Baqasah, A. M., & Eassa, M. (2025). AI-IoT-based smart agriculture pivot for plant disease detection and treatment. Scientific Reports, 15(1), 1-16. https://doi.org/10.1038/s41598-025-98454-6

4 Nyakuri, J. P., Nkundineza, C., Gatera, O., Nkurikiyeyezu, K., & Mwitende, G. (2025). AI and IoT-powered edge device optimised for crop pest and disease detection. Scientific Reports, 15(1), 1-14. https://doi.org/10.1038/s41598-025-06452-5

5 X. Xue, V. Thakur, H. Dhumras, R. H. Jhaveri and T. R. Gadekallu, "Real-Time Pest Detection Using ResNet-50 and Vision Transformer: An IoT-Enabled Mobile Application for Smart Agriculture," in IEEE Transactions on Consumer Electronics, doi: 10.1109/TCE.2025.3599533.

6 R. Indumathi, N. Saagari, V. Thejuswini, and R. Swarnareka, "Leaf Disease Detection and Fertiliser Suggestion," 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2019, pp. 1-7, doi: 10.1109/ICSCAN.2019.8878781.

7 S. V. Militante, B. D. Gerardo and N. V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE), Yunlin, Taiwan, 2019, pp. 579-582, doi: 10.1109/ECICE47484.2019.8942686.

8 W. Shafik, A. Tufail, A. Namoun, L. C. De Silva and R. A. A. H. M. Apong, "A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends," in IEEE Access, vol. 11, pp. 59174-59203, 2023, doi: 10.1109/ACCESS.2023.3284760.

9 P. Jiang, Y. Chen, B. Liu, D. He and C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," in IEEE Access, vol. 7, pp. 59069-59080, 2019, doi: 10.1109/ACCESS.2019.2914929.

10 G. Shrestha, Deepsikha, M. Das and N. Dey, "Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON), Kolkata, India, 2020, pp. 109-113, doi: 10.1109/ASPCON49795.2020.9276722.

11 L. S. Puspha Annabel, T. Annapoorani and P. Deepalakshmi, "Machine Learning for Plant Leaf Disease Detection and Classification – A Review," 2019 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2019, pp. 0538-0542, doi: 10.1109/ICCSP.2019.8698004.

12 Tang, Y., Chen, C., Leite, A. C., & Xiong, Y. (2023). Editorial: Precision control technology and application in agricultural pest and disease control. Frontiers in Plant Science, 14, 1163839. https://doi.org/10.3389/fpls.2023.1163839

13 Mahlein, Anne-Katrin. "Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping." Plant disease 100.2 (2016): 241-251, 18 Jan 2016https://doi.org/10.1094/PDIS-03-15-0340-FE

14 Rajagopal, M. K., & MS, B. M. (2023). Artificial Intelligence -based drone for early disease detection and precision pesticide management in cashew farming. ArXiv. https://arxiv.org/abs/2303.08556

15 Chin, R., Catal, C.., & Kassahun, A. Plant disease detection using drones in precision agriculture. Precision Agric 24, 1663–1682 (2023). https://doi.org/10.1007/s11119-023-10014-y

16 Mahlein, AK., Oerke, EC., Steiner, U. et al. Recent advances in sensing plant diseases for precision crop protection. Eur J Plant Pathol 133, 197–209 (2012). https://doi.org/10.1007/s10658-011-9878-z

17 P. Kulkarni, A. Karwande, T. Kolhe, S. Kamble et al., "Plant Disease Detection Using Image Processing and Machine Learning," 2021.