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Ai-Enabled Embedded System for Plant Disease Detection and Precision Pesticide

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Abstract:

Agricultural productivity is heavily influenced by the timely detection of plant disease and efficient pesticide application. Traditional methods rely on manual inspection and broad-spectrum spraying, which are labour-intensive and environmentally unsustainable. The existing system often lacks real-time responsiveness, precision targeting and integration between AI and embedded hardware. To overcome these limitations, we proposed an AI-enabled embedded system that detects plant diseases and applies pesticides with high accuracy and minimal waste. Our system uses a RetinexNet for illumination enhancement and DnCNN for noise reduction, implemented in Python. The disease classification results are transmitted via serial communication to an ESP32 controller programmed in Embedded C. The controller activates a relay-driven pesticide pump, displaying disease type on a 16×2 12C LCD and triggers an alert sound. The power is supplied via a regulated 12V battery system, ensuring field deployability. The experimental results show improved detection accuracy and a significant reduction in pesticide usage, demonstrating the system's potential for scalable eco eco-friendly smart farming.

Keywords: Plant disease detection, Embedded system, Precision agriculture, Pesticide spraying, RetinexNet, DnCNN, Deep Learning, Serial Communication, IoT in farming.

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

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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].

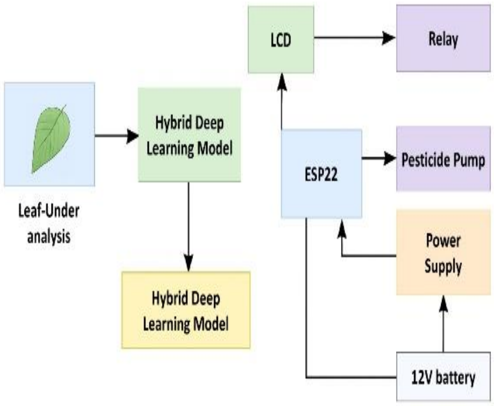

Figure 1: AI-enabled embedded system for plant disease detection

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, labour-intensive and prone to human error. The pesticide application is often indiscriminate, leading to environmental harm and, 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 shown in Figure 1.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 Survey

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 fertilizer spreading raises considerations about intervention specificity, avoiding over towards AI-enabled embedded systems for plant growth and health management.

3. Related Works

Recent developments in plant disease detection have utilized convolutional neural networks (CNN) for image-based classification, achieving modest accuracy under laboratory conditions Figure 2. The models, such as RetinexNet and DnCNN, have since added advanced preprocessing functionality, illuminance corrections and noise removal, which significantly enhanced detection efficiency in dynamic field conditions. Concurrently with these advancements, IoT-enabled agriculture systems have moved to incorporate sensor networks, edge computing and cloud integration for real-time monitoring Table 1. However, most current frameworks do not have embedded actuation capabilities, being purely passive data collectors. This disconnect causes interventions to be late and prohibits scalability.

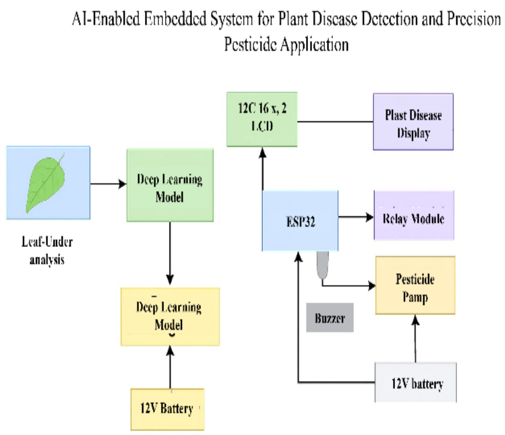

Figure 2: Plant disease detection and pesticide application

The reliability in the field is an issue caused by unstable power supply, environmental noise, and hardware fragility. These shortcomings highlight the necessity of low low-power, reliability-based AI system that integrates correct detection with instance, localized response, something this work seeks to solve.

Category	**Model**	**Strengths**	**Limitations**
Disease detection models	Baseline CNN	Fast inference	Noisy conditions
Disease detection models	RetinexNet	Effective illumination correction	Requires a preprocessing pipeline
Disease detection models	DnCNN	Robust denoising for image clarity	Not a classifier
Disease detection models	retinex Net +hybrid	High accuracy	Computationally heavier
IOT agriculture system	Sensor-based monitoring	Soil moisture and temperature	Passive system
IOT agriculture system	Cloud-integrated dashboards	Centralized analytics	Power dependency
IOT agriculture system	Drone-based spraying	Remote access	Lacks fine-grained targeting

Identified gaps	Nill	Nill	Lack of embedded actuation
Identified gaps	Nill	Nill	High power consumption

Table 1: Comparative overview of existing approaches

4. System Overview

The proposed system is a real-time Artificial intelligence embedded solution designed to detect plant disease and apply pesticides with precision. To integrate image-based disease classification with automated spraying and reduce manual labour and chemical use. The hardware setup, such as ESP32-CAM for capturing leaf images, ESP32 microcontroller for control logic, relay module to operate the pesticide pump, 16×2 12C LCD for disease display and buzzer for alert generation. The power is supplied and a regulated 12V battery system. On the software side, the hybrid deep learning model, such as retinexNet for brightness enhancement and DnCNN for noise reduction, was implemented in Python. The model processes real-time leaf images and transmits the classification result to the ESP32 via serial communication. The tightly coupled hardware and software are represented in the following Figure 3, enabling responsive, field-to-deployable disease detection and targeted pesticide application, making it suitable for smart farming environments.

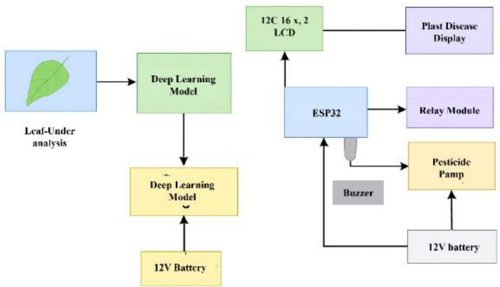

Figure 3: Precision pesticide application

V. HARDWARE DESIGN

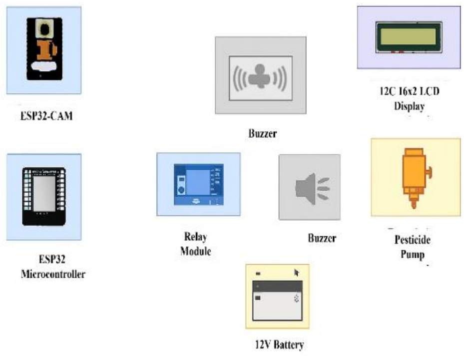

Figure 4: Hardware design for plant disease detection

The proposed system integrates multiple embedded components to enable real-time plant disease detection and target pesticide application. The ESP32 Microcontroller acts as the central control unit. It receives disease classification data and serial communication and manages output actions such as display, alert, and pump activation. The program is written in C for efficient real-time control. ESP32-CAM denotes the capture of real-time images of plant leaves. It serves as the input node for the deep learning model and enables on-site image acquisition with low power consumption and wireless capability. The relay module and pesticide pump indicate that the relay module acts as an electronic switch and allowing the ESP32 to control the 12V pesticide pump indirectly. This ensures safe and reliable activation of the spraying mechanism only when disease is detected. 12C 16×2 LCD displays to detect the disease type for the user, Figure 4. The 12C interface simplifies wiring and reduces GPIO usage to making it ideal for compact embedded designs. The Buzzer alert system generates an audible signal when a disease is detected and provides immediate feedback to field operators. The power supply of a 12V battery with voltage regulation of 12V battery powers the system. The voltage regulator converts 12V to 5V for the ESP32 and other low-voltage components to ensure stable operation in field conditions.

5. Software Design

The software design combines deep learning-based image processing and embedded control logic to facilitate real-time detection of plant disease and automated spraying of pesticides. The Python-based deep learning model, such as a pipeline for disease detection, is carried out in Python with a hybrid model consisting of RetinexNet and DnCNN. The model analyses leaf images taken by the ESP32-CAM and detects disease type with high accuracy based on its performance. RetinexNet for brightness and contrast enhancement of drawing from the Retinex theory, RetinexNet separates images into reflectance and illumination. It enhances low-light leaf images through increased contrast and brightness while maintaining natural texture. DnCNN for Noise reduction are DnCNN is a deep neural network trained to remove Gaussian noise and real-world noise. It fine-tunes enhanced images from RetinexNet for clean input during disease classification. Figure 5. The serial communication protocol are upon classification, the disease tag is sent from the Python environment to the ESP32 microcontroller through wired serial communication. This guarantees data exchange between software and hardware to be reliable and low-latency. The embedded C logic for ESP32 control and ESP32 is developed in embedded C to read incoming disease data, display it on 12C LCD, turn on the buzzer alert and switch on the relay module for pesticide spraying. The logic provides timely and deterministic behaviour in field conditions.

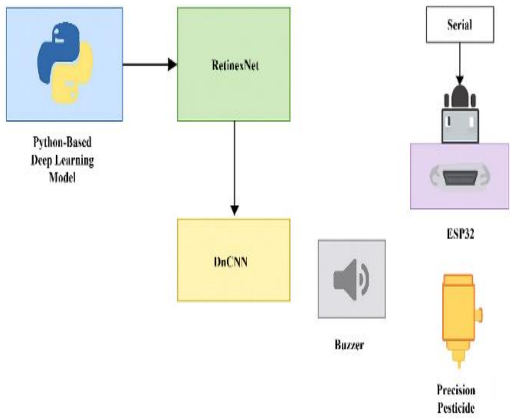

Figure 5: Software design for plant disease detection

6. Methodology

The suggested system has a systematic step-by-step approach to identify plant disease and sprays pesticides with precision. The suggested system works sequentially to detect the disease with accuracy and spray pesticides accurately.

A. Leaf image capture

During the first phase of the system process and the ESP32-CAM module is responsible for taking real-time photos of the plant leaves in the actual field condition. This low-power and compact camera module suits embedded applications well, allowing on-site image capture without the need for an external device. The images taken are the major input for disease diagnosis, offering visual information that indicates the present state of the plant's health. Automating the image capture process, the system enables frequent and consistent monitoring, providing the basis for timely and accurate disease detection through deep learning algorithms.

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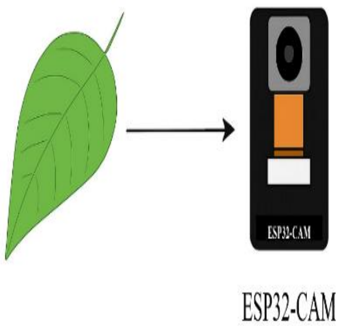

Figure 6: Leaf image capture

B. Disease classification

Once the leaf image is acquired by the ESP-32CAM and it is filtered using a Python-based hybrid deep model for strong disease classification Figure 7. The initial step utilises RetinexNet and which adjusts the image's contrast and brightness by distinguishing between illumination and reflectance, highlighting faint disease patterns even with low light intensity. The output of the enhanced image is then used as input for DnCNN and a deep convolutional neural network designed to remove the noise that was added during enhancement and due to environmental causes. The pre-processing is done in two steps to guarantee that the classifier has clean and high-quality input. The model then compares the processed image with trained data to effectively determine the kind of plant disease and create a label that is sents to effectively determine the kind of plant disease and create a label that is sent to the embedded controller for subsequent action.

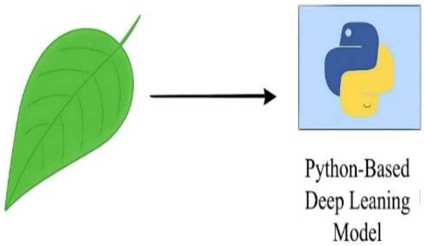

Figure 7: Disease classification

C. Data transmission to the controller

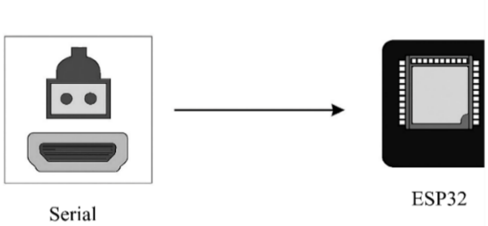

Figure 8: Data transmission to the controller

Once the deep learning model categorises the plant disease and its outcome is sent to the ESP32 microcontroller over a serial communication protocol. Here, the process files are in the gap between software analysis and hardware execution. Figure 8. The serial communication facilitates a quick, low-latency data transfer, so that the ESP32 can obtain the disease label in real time. The reliability and simplicity of this protocol are best suited for use in embedded systems, particularly in field applications where reliability is paramount. The ESP32 responds with a classification result by triggering the corresponding response and indicating the disease type, sending alerts and actuating the pesticide pump as required.

D. Display and alert

As soon as the ESP32 microcontroller acquires the disease classification output and it automatically triggers two important feedback circuits. The first is that the identified disease type is shown on a 16×2 12C LCD and giving the field operator a readable and interpretable output. The 12C interface facilitates easy wiring and saves GPIO pins, making it perfect for small embedded systems. At the same time, a buzzer is triggered to provide an audible notification so that operators can be immediately alerted even if they are not visually monitoring the display. Through the dual feedback system, usability and responsiveness are improved and allowing for fast intervention and reducing crop damage in Figure 9.

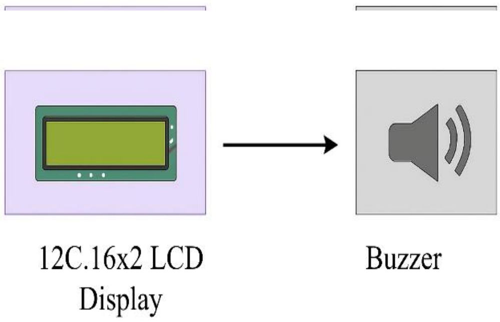

Figure 9: Display and alert architecture

E. Relay activation and pesticide spraying

To elaborate future in the relay module serves as an important go-between the low voltage of the ESP32 microcontroller and the high voltage pesticide pump. The ESP32 is not capable of driving the 12V pump directly because of voltage and current restrictions. The relay acts as an electrically isolated switch. Upon receiving a control signal from the ESP32 and the relay switches on the circuit. To enable current from the 12V battery to be passed to the pump. This design is both safe and modular, and the pump will only turn on if the disease is known to be present, avoiding excessive chemical use. This selective spraying serves both to apply pesticide and to minimise environmental pollution and costs of operation. Moreover over the modular configuration of the relay system facilitates effortless replacement and expansion of multiple actuators, and the pumps can be used for large field deployment. Through the combination of disease detection with automated actuation, the system concert passive monitoring into active intervention and is therefore a viable solution for precision agriculture Figure 10.

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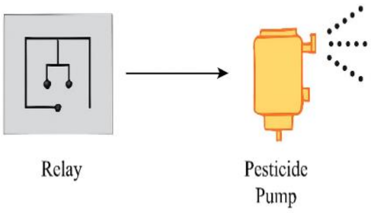

Figure 10: Relay activation and pesticide spraying

7. Development Setup

For easy field incorporation, the system was installed with a modular design, ESP32-CAM modules placed at canopy level for maximum leaf imaging and pump-actuated relays positioned alongside crop rows for immediate chemical infusion. Figure 11 shows a deployment setup of ESP32-CAM units that were deployed at canopy height with spray pumps aligned along crop rows. The powered by a regulated 12V battery, and the system maintained stable performance despite fluctuating sunlight, humidity and wind. The power was provided through a voltage-regulated 12V battery with onboard voltage adjustment, allowing continuous operation throughout multiday experiments. With varying sunlight, humidity, and wind and the system exhibited consistent performance, confirming its robustness under open field environments. This plug-and-play design enables fast expansion across remote farms with little infrastructure.

8. Results

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.

A. 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 12. 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.

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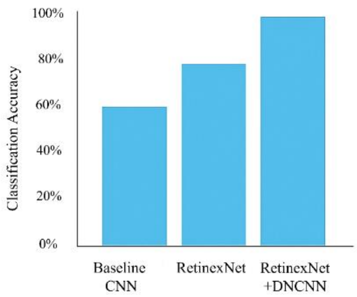

Figure 11: Accuracy of disease detection

B. 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 13. 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.

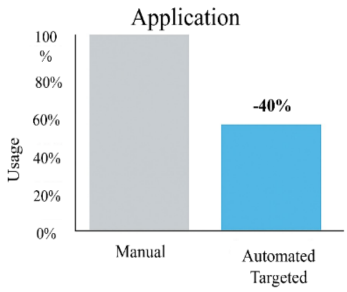

Figure 12: Efficiency of pesticide application

C. 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.

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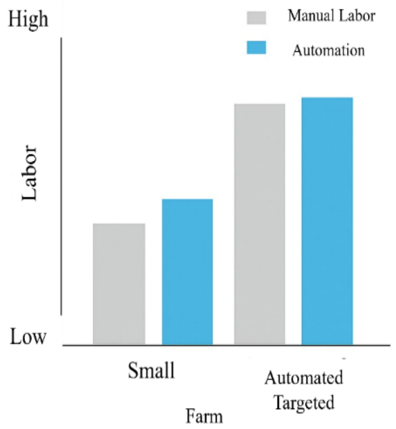

Figure 13: Comparison with manual methods

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D. 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 15. 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.

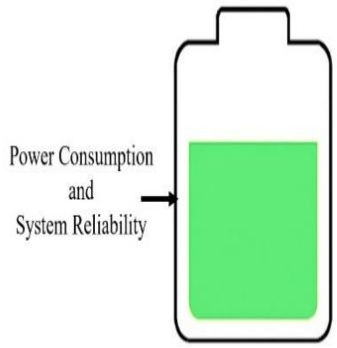

Figure 14: Power consumption and system reliability

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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 2**. 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 16. 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 2: 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 15: 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.

$$\text{Precision}=\frac{True\ positives}{True\ positives+False\ positives} \quad (1)$$

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 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.

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

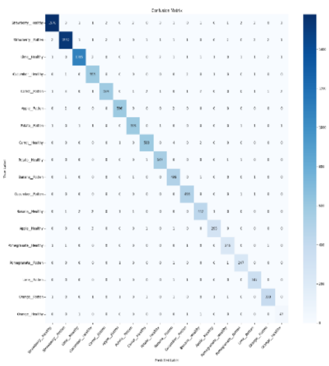

Figure 16: Confusion matrix

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

Table 3: 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 17. 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 3. Low off-diagonal values indicate extremely low misclassifications further consolidating the strength of the model in differenting further consolidating the strength of the model in differentiating healthy from spoiled produce across various classes.

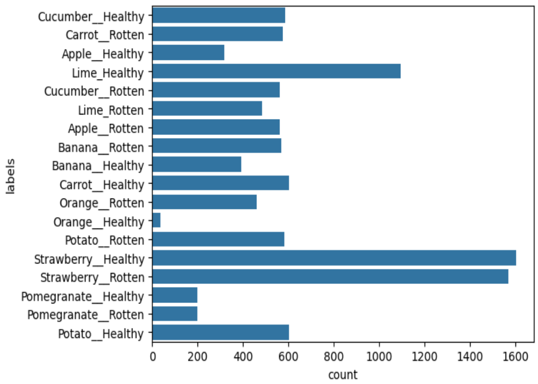

Figure 17: data and counts

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 4: Sample count by class

The above Figure 18 and Table 4 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 visualization, 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.

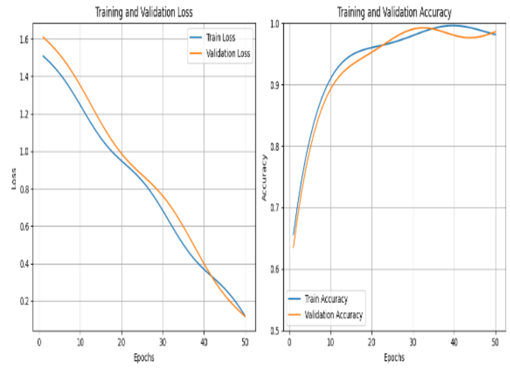

Figure 18: Loss and accuracy model

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 5: Model training metrics

The above Figure 19 and Table 5 show that the two line plots represent the training trajectory of a machine learning model across 50 epochs. The left plot indicates a gradual 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 generalization. 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.

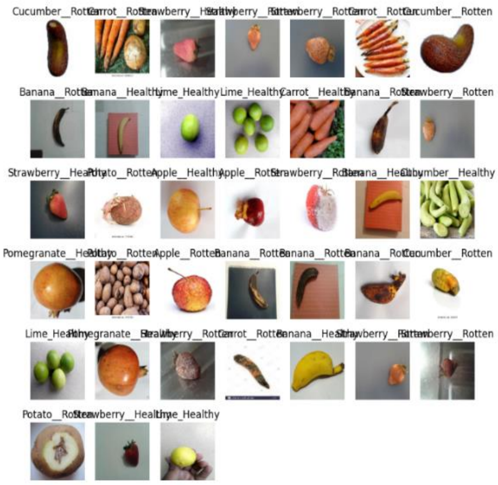

Figure 19: Sample data architecture

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 6: Labelled dataset table

9. 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.

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