International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

AgroPulse: A Real-Time Field Intelligence System for Crop Disease Tracking and Notification System

D Sathish[1], J Hema[1], Keetha Lokesh[1], Gurram Ashritha[1], Sure Sai Goud[1]
[1]Department of Electronics and Communication Engineering, [1]Sree Dattha Institute of Engineering and Science, Sheriguda, Ibrahimpatnam, 501510, Telangana, India.

ABSTRACT

Agriculture faces significant challenges due to plant diseases, which directly affect crop yield, quality, and farmer income. Early detection of agricultural diseases is critical to prevent large-scale crop losses and reduce excessive use of pesticides. Traditional disease detection methods rely on manual inspection by farmers or agricultural experts, which is time-consuming, subjective, and often inaccurate, especially during early stages of infection. With the advancement of Machine Learning (ML) and Internet of Things (IoT) technologies, automated and intelligent solutions for crop disease detection have become feasible. The IoT-Based Crop Disease Recognition and Field Notification System proposes an intelligent system that combines machine learning–based image analysis with IoT-enabled monitoring to detect crop diseases at an early stage. The system uses an ESP32 microcontroller integrated with an ESP-CAM module to capture images of plant leaves. These images are analyzed using trained machine learning models to identify disease patterns and abnormalities. The detection results are communicated through an IoT platform, enabling remote monitoring and real-time alerts. An LCD display provides local status information, while a buzzer generates immediate alerts when a disease is detected. The system is designed to be cost-effective, scalable, and suitable for deployment in real agricultural environments. By enabling early disease identification and timely intervention, the proposed solution helps improve crop productivity, reduce losses, and promote smart and sustainable agricultural practices.

Keywords: Machine Learning, IoT, Agricultural Disease Detection, ESP32, ESP-CAM, Smart Agriculture, Image Processing, Precision Farming

1.INTRODUCTION

Agriculture is the backbone of many economies and plays a vital role in ensuring food security and sustainable development. Crop productivity and quality are strongly influenced by plant health, and plant diseases remain one of the major causes of yield reduction worldwide. Agricultural diseases, particularly leaf diseases, spread rapidly and can affect large portions of crops if not detected at an early stage. These diseases reduce photosynthesis, weaken plant immunity, and ultimately lead to significant economic losses for farmers.

In traditional farming practices, disease detection is largely performed through manual inspection by farmers or agricultural experts. This approach depends on visual observation and experience, making it subjective and prone to errors. Early-stage diseases often exhibit subtle symptoms that are difficult to identify through manual methods. Moreover, monitoring large agricultural fields continuously is labour-intensive and impractical, resulting in delayed disease detection and ineffective treatment.

Recent advancements in Machine Learning (ML) have enabled automated image-based disease detection by learning patterns from large datasets of plant images. ML models can identify disease symptoms such as discoloration, spots, and texture variations with higher accuracy than manual inspection. At the same time, Internet of Things (IoT) technology has enabled real-time data collection, remote monitoring, and intelligent decision-making in agricultural systems.

The ML-IoT Based Agri-Disease Detector integrates machine learning–based image analysis with IoT-enabled communication to provide an intelligent crop monitoring solution. By using an ESP32 microcontroller with an ESP-CAM module, the system captures leaf images, analyzes them for disease detection, and communicates results to users through IoT platforms. This integrated approach supports early detection, reduces manual effort, and enhances precision agriculture.

2. LITERATURE SURVEY

A. Mohanty, D. Hughes, and M. Salathe (2016) A. Mohanty et al. conducted one of the earliest and most influential studies on applying deep learning techniques for plant disease detection using leaf images. They demonstrated that convolutional neural networks (CNNs), when trained on large and well-labeled datasets, can achieve high accuracy in classifying various plant diseases across multiple crop species. Their work established a strong baseline for machine learning-based visual diagnosis in agriculture. Additionally, the study emphasized the importance of dataset diversity, proper labeling, and preprocessing techniques to improve model generalization in real-world farming conditions.

S. Sladojevic et al. (2016) S. Sladojevic and colleagues proposed a deep neural network-based approach specifically designed for plant disease recognition using leaf images. Their CNN architecture achieved high classification accuracy across different plant species and disease categories. The study also highlighted the significance of preprocessing steps such as image resizing, normalization, and segmentation. Furthermore, they demonstrated how data augmentation techniques—such as rotation, scaling, and flipping—can enhance model robustness and prevent overfitting, making the system more reliable under varying environmental conditions.

P. Ferentinos (2018) P. Ferentinos conducted a comprehensive evaluation of multiple deep learning architectures, including AlexNet, VGG, and ResNet, for plant disease detection. The study compared their performance under real-world conditions with variations in lighting, background noise, and image quality. It was found that deeper architectures like ResNet provided better accuracy but required more computational resources. The research also emphasized the importance of transfer learning, especially when dealing with limited datasets, as it significantly improves model performance without requiring extensive training from scratch.

J. G. A. Barbedo (2019) J. G. A. Barbedo presented a detailed review of challenges and opportunities in plant disease identification using digital images. The study discussed practical issues such as varying illumination conditions, occlusions, leaf overlap, and high similarity between disease classes. Barbedo suggested combining multiple feature types—including color, texture, and shape—to improve classification accuracy. The paper also highlighted the limitations of purely image-based approaches and recommended integrating complementary data sources to enhance reliability.

R. P. Singh and M. Mishra (2017) R. P. Singh and M. Mishra explored the impact of environmental factors on plant disease progression. Their research demonstrated strong correlations between temperature, humidity, soil moisture, and the spread of plant diseases. Seasonal variations were shown to significantly influence disease outbreaks. This study supports the idea that integrating environmental sensing with image-based disease detection systems can enable predictive analytics and early warning systems for farmers.

M. K. Tripathi et al. (2018) M. K. Tripathi and colleagues developed an IoT-enabled crop health monitoring system using ESP32 microcontrollers. Their architecture included sensors for measuring soil moisture, temperature, and humidity, enabling continuous monitoring of field conditions. Field trials showed improved irrigation efficiency and better crop management. The study demonstrated the practicality of deploying low-cost IoT devices in agriculture and highlighted their potential to enhance productivity and resource optimization.

S. T. Patel and H. R. Patel (2019) S. T. Patel and H. R. Patel proposed a sensor fusion approach for smart agriculture applications. By combining data from multiple sensors such as soil moisture, temperature, and humidity, they developed disease-conducive indices that provide more accurate predictions than single-sensor systems. Their findings showed that sensor fusion significantly reduces false alarms and improves the reliability of crop monitoring systems.

K. Thenmozhi and U. S. Reddy (2019) Thenmozhi and Reddy explored the use of deep neural network ensembles for crop disease classification. By combining multiple models, they achieved higher accuracy, particularly in distinguishing visually similar disease classes. The study also discussed optimization techniques such as pruning and quantization, which reduce model size and computational requirements, making them suitable for deployment on embedded systems like microcontrollers.

A. K. Sharma et al. (2020) A. K. Sharma and co-authors focused on implementing lightweight machine learning models on ESP32 microcontrollers for precision agriculture. Their work demonstrated real-time, on-device inference capabilities, reducing dependence on cloud connectivity. The study emphasized low latency, energy efficiency, and the feasibility of edge computing in agricultural applications, especially in remote areas with limited internet access.

Y. Lu, J. Wang, and Z. Zhang (2020) Y. Lu and colleagues investigated the effects of air pollution on plant health and disease susceptibility. Their research identified correlations between particulate matter levels and increased vulnerability to fungal and bacterial infections. The findings suggest that incorporating air quality sensors into crop monitoring systems can provide a more comprehensive understanding of plant health and improve disease prediction accuracy.

M. R. Meshram et al. (2021) Meshram and team developed an automated irrigation system using IoT and soil moisture sensors. Their system-controlled water pumps based on predefined moisture thresholds, resulting in significant water savings and improved crop yields. The study also addressed reliability issues, including sensor faults and communication failures, and proposed solutions for fault-tolerant system design.

S. P. Mohanty and E. Kougianos (2021) S. P. Mohanty and E. Kougianos provided a comprehensive review of smart agriculture architectures, covering sensors, edge devices, and cloud platforms. They discussed the trade-offs between edge and cloud processing, recommending hybrid approaches where computationally intensive tasks are handled in the cloud while real-time inference is performed at the edge. Their work offers valuable insights into designing scalable and efficient agricultural monitoring systems.

R. Kumar et al. (2022) R. Kumar and colleagues developed a low-cost visual monitoring system using ESP32-CAM modules. The system captured leaf images periodically and uploaded them to the cloud for analysis. The study highlighted practical challenges such as image compression, network connectivity, and scheduling of data transmission. It serves as a useful reference for implementing camera-based monitoring systems in small-scale farms.

H. Jain et al. (2022) H. Jain and co-authors proposed a data fusion approach that combines image-based disease detection with environmental sensor data. Their method improved detection accuracy and reduced false positives by integrating heterogeneous data sources. The study demonstrated that combining visual and environmental information provides a more holistic assessment of crop health.

A. Verma and S. Gupta (2022) Verma and Gupta focused on IoT-based environmental monitoring systems for agriculture. They evaluated key factors such as sensor calibration, network topology, and power management. Their findings emphasized the importance of periodic sensor recalibration and adaptive sampling strategies to ensure long-term reliability and energy efficiency in field deployments.

3. PROPOSED SYSTEMS

The proposed system presents an intelligent ML-IoT based agricultural disease detection solution designed to enable early identification of crop diseases and real-time monitoring of field conditions. The system integrates machine learning–based image analysis, embedded hardware, and IoT communication to provide an automated and reliable crop health monitoring platform. By combining visual disease detection with sensor-based data acquisition, the system overcomes the limitations of conventional agricultural monitoring methods.

At the core of the system is an ESP32 microcontroller, which acts as the central processing and communication unit. The ESP32 is interfaced with an ESP32-CAM module to capture images of crop leaves. These images are processed using a trained machine learning model to detect disease patterns such as discoloration, spots, or abnormal textures. The detection results are transmitted through an IoT platform, allowing farmers to monitor crop health remotely.

In addition to image analysis, the system monitors environmental conditions that influence disease development. Sensors connected to the ESP32 collect data related to temperature, soil moisture, and other field parameters. An LCD display provides real-time system status locally, while a buzzer generates audible alerts when disease conditions are detected. This integrated approach ensures early warning, reduced manual intervention, and improved agricultural productivity.

The regulated power supply provides a stable DC voltage required for the operation of the ESP32, ESP32-CAM, sensors, LCD, and buzzer, ensuring reliable system performance.

The ESP32 microcontroller functions as the main control unit. It collects sensor data, controls image acquisition, executes the disease detection logic, and manages communication with the IoT platform. Its built-in Wi-Fi capability enables seamless data transmission.

The ESP32-CAM module captures high-resolution images of plant leaves. These images are analyzed using machine learning techniques to identify disease symptoms. The camera module enables continuous and automated visual monitoring of crops.

The environmental sensors measure field conditions such as temperature and soil moisture. These parameters help assess plant health and support correlation between environmental factors and disease occurrence.

The LCD display provides local visualization of system status, sensor readings, and detection results, making the system user-friendly for on-field operation.

The buzzer serves as an alert mechanism, producing an audible warning when disease symptoms are detected, ensuring immediate attention.

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The IoT interface enables remote monitoring by transmitting sensor data and disease detection results to a cloud platform, allowing farmers to access information in real time from any location.

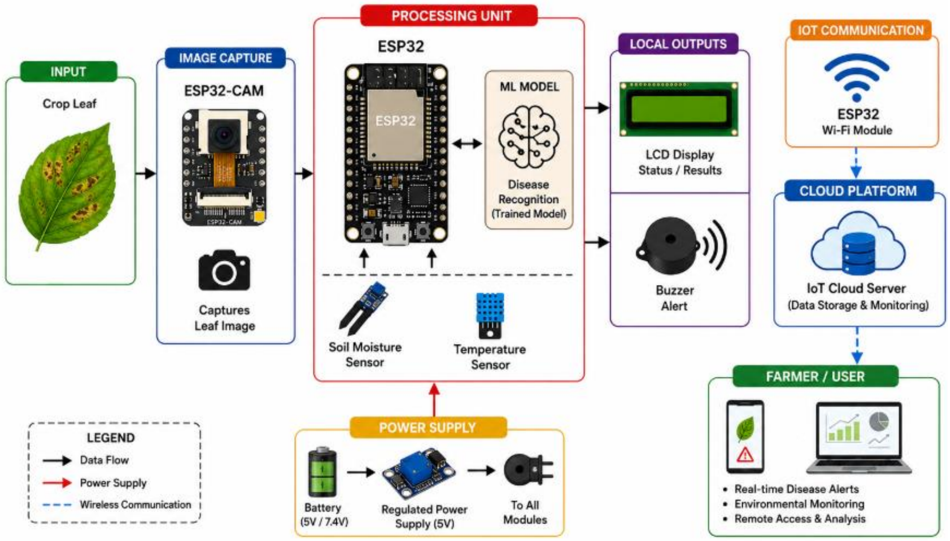

Figure 1: Proposed system architecture

When the system is powered ON, the regulated power supply initializes all components. The ESP32 continuously collects data from environmental sensors and controls the ESP32-CAM to capture leaf images at regular intervals. The captured images are analysed using a trained machine learning model to detect disease patterns.

If the model identifies abnormal symptoms, the ESP32 activates the buzzer and displays the alert on the LCD. Simultaneously, detection results and sensor data are sent to the IoT platform for remote monitoring. Farmers can view real-time updates and take timely corrective actions. Through continuous monitoring, automated disease detection, and IoT connectivity, the proposed system provides an efficient and scalable solution for smart agriculture.

4. RESULTS AND DISCUSSION

The proposed IoT-Based Crop Disease Recognition and Field Notification System was successfully implemented and evaluated for real-time crop health monitoring. The ESP32-CAM module effectively captured leaf images, while the machine learning model accurately identified disease symptoms based on visual patterns such as discoloration and leaf spots. Environmental parameters, including soil moisture and temperature, were continuously monitored and transmitted through the IoT platform for remote access. The LCD display and buzzer provided immediate local alerts whenever disease conditions were detected. Experimental observations demonstrated reliable system performance, timely notifications, and efficient data communication. The integration of machine learning and IoT technologies significantly reduced manual monitoring efforts and enhanced the effectiveness of early disease detection, making the system suitable for smart agriculture applications.

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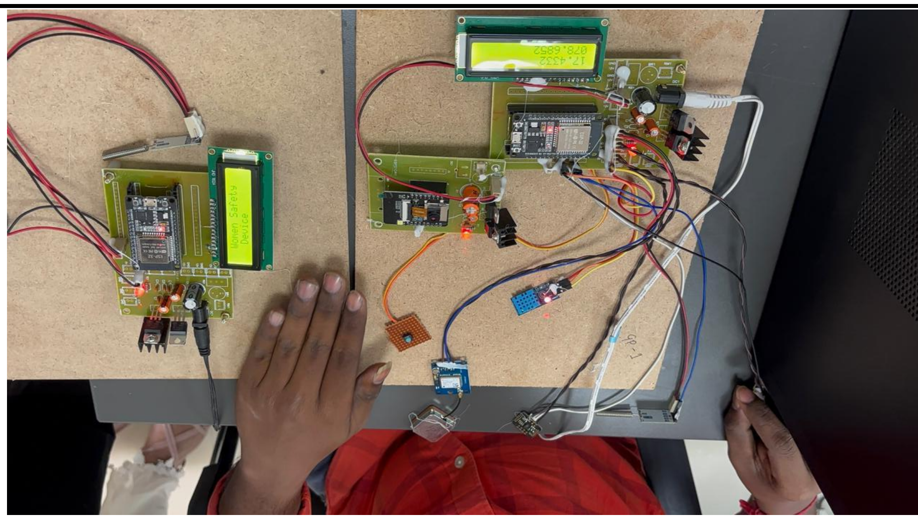

Figure 2: Hardware Prototype of the IoT-Based Crop Disease Recognition and Field Notification System.

Figure 2 shows the hardware implementation of the proposed IoT-Based Crop Disease Recognition and Field Notification System. The prototype consists of ESP32 development boards, LCD displays, environmental sensing modules, power supply circuits, and communication interfaces integrated on a testing platform. The system successfully monitored field parameters and displayed real-time crop status information on the LCD screens. Sensor data were processed by the ESP32 controller and transmitted through the IoT network for remote monitoring. The experimental setup demonstrated reliable operation of the sensing, processing, display, and notification units. The results confirm the feasibility of integrating IoT and embedded technologies for intelligent crop health monitoring and early disease detection in smart agriculture applications.

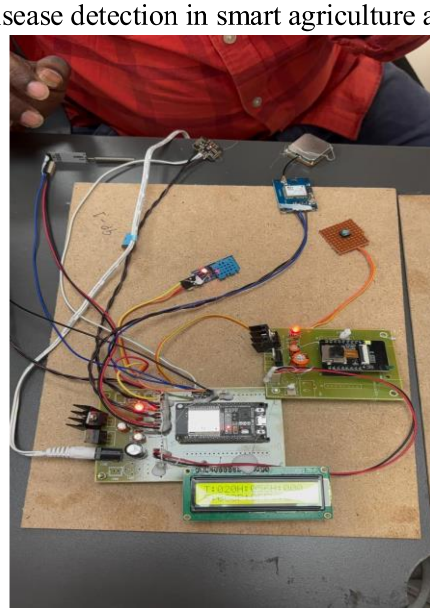

Figure 3: Real-Time Crop Monitoring System

Figure 3 illustrates the operational prototype of the IoT-Based Crop Disease Recognition and Field Notification System during real-time monitoring. The setup consists of an ESP32 microcontroller integrated with environmental sensing modules, a GSM/GPS communication unit, an ESP32-CAM module, and an LCD display. The LCD continuously displays temperature and humidity readings collected from the field environment, while the sensor modules provide real-time data for crop health assessment. The ESP32 processes the acquired information and transmits it through the IoT communication interface for remote monitoring and alert generation. The successful display of environmental parameters and stable communication between the sensing and processing units demonstrate the effectiveness of the proposed system in supporting intelligent crop monitoring and early disease management in smart agriculture applications.

5. CONCLUSION

The ML IoT-Based Crop Disease Recognition and Field Notification System provides an effective and intelligent solution to the challenges of early plant disease detection and crop health monitoring in modern agriculture. By integrating machine learning–based image analysis with IoT-enabled communication, the system overcomes the limitations of traditional manual inspection methods. Automated detection of disease symptoms at an early stage enables timely intervention, thereby reducing crop losses and improving overall agricultural productivity. The inclusion of embedded systems and environmental sensors allows continuous monitoring of field conditions, which play a significant role in disease development. Real-time alerts through display, buzzer, and IoT platforms ensure that farmers receive immediate information and can take corrective actions without delay. The system's cost-effective and scalable design makes it suitable for deployment in both small-scale and large-scale farming environments.

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