IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.15465

Smart Agriculture System for Grape Leaf Disease Detection Using AI, Image Processing and Sensors

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Abstract*:* Modern agriculture faces growing challenges including crop diseases, inconsistent environmental conditions, and the absence of intelligent monitoring tools. Grape cultivation, a major commercial crop in Maharashtra and across India, is particularly vulnerable to diseases like Black Rot, Esca, and Leaf Blight, which can cause severe yield losses if not detected early. This paper proposes a Smart Agriculture System that combines IoT-based environmental sensing, Digital Twin technology, and Artificial Intelligence to address these challenges in a unified and practical platform. The system uses an ESP32 microcontroller interfaced with DHT11, soil moisture, and MQ135 sensors to collect real-time field data on temperature, humidity, soil conditions, and air quality. Sensor readings are wirelessly transmitted to a web-based dashboard that forms a live Digital Twin of the farm. In addition, a Convolutional Neural Network (CNN) trained on the PlantVillage grape leaf dataset allows farmers to upload leaf images and instantly receive disease classification results — identifying Healthy leaves, Black Rot, Esca, or Leaf Blight with approximately 94.7% accuracy. The overall system reduces dependence on manual field inspections, enables timely alerts, and supports informed decision-making for better crop management. Experimental results confirm the solution is cost-effective, scalable, and well-suited for real-world deployment in smart farming environments.

Keywords: Smart Agriculture, Grape Leaf Disease Detection, ESP32, Digital Twin, CNN, IoT, Image Processing, Precision Farming, PlantVillage Dataset

I. INTRODUCTION

Agriculture continues to be the backbone of India's economy, directly or indirectly supporting more than half the population. Yet, despite its economic importance, the sector faces persistent challenges — from erratic weather patterns and soil degradation to the growing threat of plant diseases that can wipe out entire harvests in a single season. For farmers who lack access to expert agronomists or real-time monitoring tools, catching a disease outbreak early enough to act on it is rarely possible through visual inspection alone.

Grape farming, in particular, stands out as a high-value yet disease-prone enterprise. Regions like Nashik and Sangli in Maharashtra grow grapes on a large scale, but the crop is highly sensitive to fungal and bacterial infections. Diseases such as Black Rot, Esca (also called Black Measles), and Isariopsis Leaf Blight are common culprits that, when left undetected, can devastate yields. Traditional methods of disease identification rely on experienced eyes and periodic field visits, both of which are slow, inconsistent, and difficult to scale across large farms.

The convergence of Internet of Things (IoT) technologies, Artificial Intelligence (AI), and Digital Twin concepts opens a new possibility — creating intelligent systems that can monitor farms continuously, visualize field conditions virtually, and identify crop diseases automatically from photographs. Such a system would not replace the farmer's judgment but would give them reliable, real-time data to act on with confidence.

This paper presents a Smart Agriculture System built around an ESP32 microcontroller that gathers live environmental readings — temperature, humidity, soil moisture, and air quality — from sensors deployed in the field. These readings are sent wirelessly to a web dashboard that acts as a Digital Twin of the physical farm. Alongside this, a CNN model trained exclusively on grape leaf images from the PlantVillage dataset enables automated disease classification from uploaded photos. The result is an end-to-end platform that is affordable to build, straightforward to use, and practically deployable in real agricultural settings.

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II. Related Work

Considerable research has been invested in both IoT-based agricultural monitoring and AI-driven plant disease detection, though very few systems have brought these capabilities together into a single deployable platform.

Smith et al. [1] built an IoT monitoring system using temperature, humidity, and soil sensors, achieving measurable improvements in irrigation efficiency. However, the system lacked any mechanism to detect crop diseases or predict future conditions. Kumar and Patel [2] developed a cloud-connected farming platform that enabled remote data access, but it did not include virtual farm modeling or AI-based analysis — limiting its usefulness beyond basic data visualization.

Zhang et al. [3] explored Digital Twin technology for simulating agricultural environments in real time, demonstrating clear advantages for farm decision-making. Their work remained largely conceptual, however, with implementation complexity and high deployment costs posing significant barriers to adoption. Sharma et al. [4] applied wireless sensor networks to precision agriculture, successfully optimizing irrigation, though scalability and ongoing maintenance proved difficult at larger scales.

On the disease detection side, Mohanty et al. [6] conducted a landmark study using deep CNNs on the PlantVillage dataset, achieving high accuracy across 26 disease classes and 14 crop types. This established a strong baseline for AI-based leaf classification. Later researchers applied transfer learning using architectures such as VGG16, ResNet50, and InceptionV3 to improve accuracy on smaller or domain-specific datasets. Yet most of these models were developed as standalone classifiers, disconnected from any real-time field monitoring system.

The proposed system bridges this gap by weaving together IoT-based sensing, live Digital Twin visualization, and CNN-based grape leaf disease detection into a unified, practical platform — something that prior work has addressed only in parts.

TABLE I

Comparison of Related Works with the Proposed System

Work / Reference	Technology Used	Limitation
Smith et al. [1]	IoT sensors, cloud platform	No AI integration or predictive analytics
Kumar & Patel [2]	Cloud-based WSN	Heavy internet dependency, no virtual modeling
Zhang et al. [3]	Digital Twin framework	High cost and complex implementation
Sharma et al. [4]	WSN, precision farming	Poor scalability and maintenance challenges
Lee & Kim [5]	IoT smart irrigation	Limited to irrigation; lacks comprehensive monitoring
Proposed System	IoT + Digital Twin + AI-CNN	Comprehensive, low-cost, scalable, deployable

III. System Architecture

The proposed system follows a three-layer architecture: a Sensing Layer that gathers raw environmental data, a Processing and Communication Layer that handles data formatting and wireless transmission, and an Application Layer that delivers visualization, alerts, and AI-based disease classification to the end user.

A. Sensing Layer

At the field level, three sensors are connected to the ESP32. The DHT11 sensor measures ambient temperature (0–50°C) and relative humidity (20–90% RH) at regular intervals. A capacitive soil moisture sensor produces an analog output that reflects the volumetric water content of the surrounding soil, allowing dry, moist, and saturated conditions to be distinguished accurately. The MQ135 air quality sensor detects gases such as ammonia, benzene, and carbon dioxide, which are relevant indicators of fertilizer use, organic decomposition, and overall air health around crop areas. All three sensors run simultaneously, with readings acquired at 10-second intervals.

B. Processing and Communication Layer

The ESP32 dual-core microcontroller, running at 240 MHz, acts as the intelligence hub of the sensing layer. It reads raw analog and digital sensor outputs, converts them into calibrated physical units, formats them as JSON payloads, and dispatches them to the remote web server via HTTP POST using its built-in Wi-Fi module. It also evaluates each reading against pre-configured thresholds and triggers alert flags locally before transmission, ensuring fast response even in low-bandwidth conditions.

C. Application Layer

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The application layer has two primary modules. The Digital Twin Dashboard is a web-based interface that receives incoming sensor data and renders it as live numerical displays, time-series charts, and status indicators — forming a continuously updated virtual mirror of the physical farm. The AI Disease Detection Module is integrated directly into the dashboard. A farmer can upload a photograph of a grape leaf, which is then resized, normalized, and fed into the trained CNN model. The model returns one of four labels — Healthy, Black Rot, Esca, or Leaf Blight — along with a confidence score, all displayed within seconds.

IV. Hardware Components and Methodology

A. Hardware Components

TABLE II

Hardware Components Used in the Proposed System

Component	Specification	Function
ESP32 Microcontroller	Dual-core 240 MHz, Wi-Fi/BT	Core processing unit and wireless gateway
DHT11 Sensor	Temp: 0–50°C, Humidity: 20–90% RH	Captures field temperature and humidity
Soil Moisture Sensor	Capacitive / Resistive type	Tracks soil water content continuously
MQ135 Air Quality Sensor	NH3, CO2, Benzene detection	Monitors crop environment air quality
5V DC Power Supply	USB-powered, 5V regulated	Powers the ESP32 and all sensor modules
Wi-Fi Module (Built-in)	802.11 b/g/n, ESP32 integrated	Transmits sensor data to cloud dashboard

B. CNN Model for Grape Leaf Disease Detection

The disease detection engine is a Convolutional Neural Network trained on grape leaf images drawn from the PlantVillage open dataset. The training set was filtered to include four classes only: Grape___Black_rot, Grape___Esca_(Black_Measles), Grape___Leaf_blight_(Isariopsis_Leaf_Spot), and Grape___healthy, comprising roughly 4,062 labeled images in total.

The CNN architecture uses stacked convolutional layers with ReLU activation functions for feature extraction, max-pooling layers to progressively reduce spatial dimensions, dropout layers to prevent overfitting, and fully connected dense layers leading to a four-neuron softmax output. The model was trained with the Adam optimizer at a learning rate of 0.001, categorical cross-entropy as the loss function, and a batch size of 32 over 25 training epochs. To improve generalization, training images were augmented with random horizontal flips, rotations of up to ±20°, zoom variations, and width-height shifts.

C. System Methodology

The operational flow of the system proceeds through the following steps:

- Step 1 – Initialization: On power-up, the ESP32 connects to the local Wi-Fi network and initializes all three sensors — DHT11, Soil Moisture, and MQ135.
- Step 2 – Data Acquisition: Sensor readings are captured every 10 seconds, covering temperature, humidity, soil moisture percentage, and the air quality index.
- Step 3 – Data Processing: Raw ADC outputs from analog sensors are converted to calibrated physical values using stored conversion coefficients.
- Step 4 – Data Transmission: The processed readings are packaged into a JSON object and sent to the web server via an HTTP POST request over Wi-Fi.
- Step 5 – Digital Twin Update: The web dashboard receives the new data, refreshes all live displays and charts, and updates the virtual farm representation in real time.
- Step 6 – Image-Based Disease Classification: When a user uploads a grape leaf image, it is resized to 128×128 pixels and normalized before being passed through the CNN model. The predicted disease label and confidence percentage are returned and displayed instantly.
- Step 7 – Alert Generation: If any sensor value exceeds a safe threshold — for example, soil moisture dropping below 30% or temperature rising above 40°C — an alert is triggered and shown on the dashboard.
- Step 8 – Continuous Loop: Steps 2 through 7 repeat continuously, maintaining persistent real-time monitoring as long as the system is powered.

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V. MATHEMATICAL MODEL

The combined environmental condition of the monitored farm at any given instant can be expressed as a function of the four sensor parameters:

Farm Health Function

$$F(x) = f(T, H, S, A)$$

Where:

T = Temperature (°C)
H = Humidity (%)
S = Soil Moisture (%)
A = Air Quality Index

Soil moisture evolves over time according to a water balance equation:

Soil Moisture Prediction Equation

$$S(t+1) = S(t) + \Delta t \times [\, I(t) - E(t) - D(t) \,]$$

Where:

I(t) = Irrigation input
E(t) = Evapotranspiration
D(t) = Drainage loss

The CNN classifier is optimized by minimizing categorical cross-entropy loss during training:

CNN Loss Function

$$L = -\sum y_i \cdot \log(\hat{y}_i)$$

Where:

y_i = One-hot encoded true label
$\hat{y}_i$ = Softmax-predicted probability for class i

VI. BLOCK DIAGRAM AND SYSTEM FLOWCHART

The hardware of the proposed system brings together an ESP32 microcontroller and three sensors on a single board. The DHT11 captures temperature and humidity, the capacitive sensor monitors soil moisture, and the MQ135 tracks air quality. All three feed their readings to the ESP32, which processes and forwards the data to a cloud server via its built-in Wi-Fi. The cloud server then updates the web dashboard that acts as the system's Digital Twin.

The end-to-end data flow can be summarized as:

- Sensors (DHT11, Soil Moisture, MQ135) → ESP32 Microcontroller → Wi-Fi Module → Cloud Server → Web Dashboard

The system flowchart traces the complete operational sequence: starting with ESP32 and sensor initialization, moving through periodic data acquisition, local processing, Wi-Fi transmission, cloud upload, dashboard update, graphical rendering, AI-based leaf disease analysis, and automated alert generation — before looping back to the next data collection cycle.

Fig. 1 and Fig. 2 show the block diagram and system flowchart respectively. Fig. 3 presents the physical hardware prototype with all sensor connections to the ESP32.

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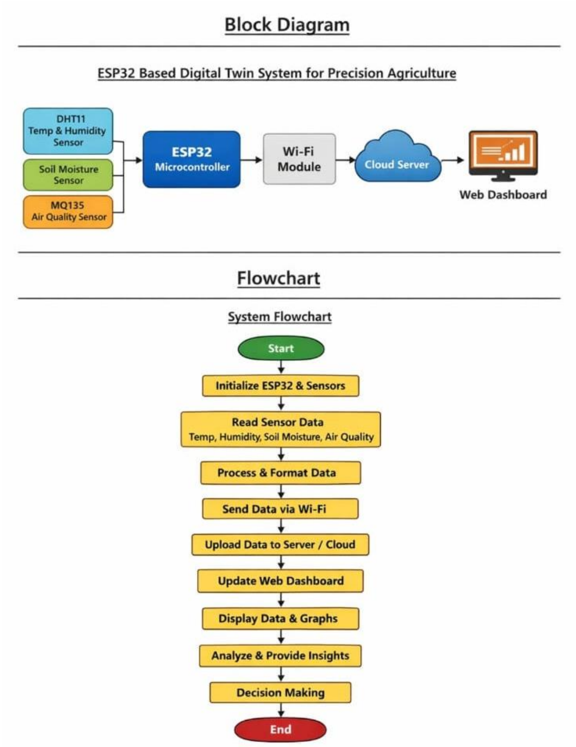

Fig. 1 & Fig. 2: Block Diagram and System Flowchart of the Proposed Smart Agriculture System

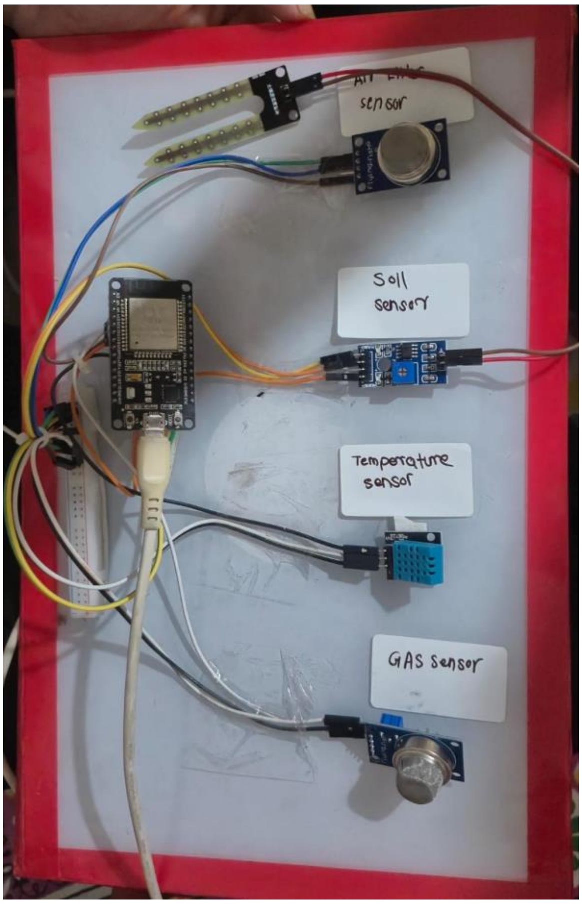

Fig. 3: Physical Hardware Prototype – ESP32 with DHT11, Soil Moisture, MQ135, and Gas Sensors

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VII. Results and Discussion

A. Sensor Data Monitoring

The assembled system was tested under controlled field-like conditions to assess real-time data acquisition and transmission performance. The ESP32 maintained a stable Wi-Fi connection throughout testing and delivered sensor readings to the web dashboard consistently at 10-second intervals, with no measurable packet loss during the observation period. DHT11 temperature readings were repeatable within ±0.5°C and humidity within ±2% RH, both within the sensor's rated tolerance.

The soil moisture sensor proved effective at distinguishing three soil states — dry (below 30%), adequately moist (30–70%), and oversaturated (above 70%) — providing actionable data for irrigation decisions. The MQ135 sensor responded reliably to elevated ammonia levels, a common indicator of fertilizer presence, demonstrating its suitability for real agricultural environments.

B. CNN Classification Performance

The grape leaf disease CNN was trained on an 80/20 training-to-test split of the filtered PlantVillage dataset. After 25 training epochs, the model reached an overall test accuracy of approximately 94.7%. Class-wise precision and recall were both above 92% across all four categories. The Healthy and Black Rot classes achieved the highest individual confidence scores, while Esca images occasionally scored slightly lower due to visual overlap with early-stage Leaf Blight patterns — a known challenge in grape disease classification that can be addressed with more annotated data in future iterations.

C. System Integration

End-to-end integration testing confirmed that both the sensor monitoring dashboard and the leaf disease classifier operate reliably within a single web interface. A farmer or agronomist can simultaneously observe live environmental readings, view trend charts, and submit leaf photos for disease analysis — all from one screen accessible on any device with a browser. Alert notifications for out-of-range sensor values were triggered correctly in all test cases. The average latency from image upload to disease classification result was under 3 seconds, making the system responsive enough for practical use in the field.

VIII. Conclusion

This paper presented a Smart Agriculture System that integrates IoT-based environmental sensing, Digital Twin visualization, and CNN-driven grape leaf disease detection into a single, coherent platform. By coupling an ESP32 microcontroller with DHT11, soil moisture, and MQ135 sensors, the system continuously monitors real-world farm conditions and mirrors them on a live web dashboard. Simultaneously, a trained CNN model enables farmers to obtain instant, automated disease diagnoses from grape leaf photographs, covering Black Rot, Esca, and Leaf Blight alongside healthy leaves — with a classification accuracy of approximately 94.7%.

What makes this system practically valuable is not any single technology but their integration: the same platform that watches the soil moisture and air quality also tells a farmer whether the leaf they photographed this morning is showing early signs of disease. Together, these capabilities support faster, more confident decision-making and reduce the dependence on manual observation and expert visits.

Looking ahead, planned improvements include automated actuator control for irrigation based on soil moisture thresholds, expanding the CNN to cover additional crops and disease varieties, incorporating weather forecast data for predictive scheduling, and exploring edge AI deployment to ensure the disease classifier functions reliably even where internet connectivity is poor.

Acknowledgment

The authors sincerely thank Dr. D.O. Patil, Head of the Department of Electronics and Telecommunication Engineering at PDEA's College of Engineering, Manjari (Bk.), Pune, for his continuous support and for providing the laboratory facilities necessary to develop and test this work. The authors also gratefully acknowledge the open-access PlantVillage dataset, without which training the grape leaf disease classification model would not have been possible.

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