

Transforming Agriculture With IoT: A Framework for Precision and Efficiency

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Abstract. The integration of Internet of Things (IoT) technologies has opened new avenues for enhancing agricultural productivity by allowing real-time monitoring, fact-based decision-making, and automation. Nevertheless, most of the existing IoT-based systems rely on expensive hardware and advanced technologies, making them clearly impractical for small and medium-scale farmers. Such systems also have problems such as inconsistent power distribution, unstable local communication networks, and limited net infrastructure in rural areas. This work proposes a powerful and scalable IoT framework to tackle these limitations, especially for Indian agriculture. This framework integrates low-power sensors, long-range wireless communication using LoRa, and robust statistics processing through cloud computing. Moreover, this particular gadget embodies ML and AI techniques for predictive analysis. The prediction detection of crop diseases utilizes the ESP32-CAM module. It is developed with an objective of practical implementation, where it will revolutionize agriculture by improving resource utilization and serving stakeholders such as farmers, agricultural scientists, and companies towards optimizing agricultural production.

Keywords: Internet of Things, sensors, ESP32, Long Range, Artificial Intelligence, Machine Learning, Deep Learning, crop diseases.

1 Introduction

Over time, traditional agricultural strategies have become more and more ineffective in overcoming the many challenges and disadvantages that impact agricultural productivity and sustainability. This has led to a growing demand for revolutionary methods to meet the needs of contemporary agriculture. Integrating the IoT era into agronomy promises to usher in a tremendous change in the performance and productivity of the land. Nevertheless, modern IoT infrastructures are either extremely cost-prohibitive or too complicated for small and medium-scale farmers. Such systems would also be highly challenged due to factors such as absence of electricity, network connectivity, and poor internet services in many rural regions [1]. Despite these obstacles, the adoption of IoT technology in agriculture shows the potential for change. Particularly by enabling monitoring and management of the agricultural environment, IoT offers a cutting-edge answer to overcome long-standing problems within the agricultural sector [2]. Artificial intelligence (AI) strategies combine with

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smart sensors to develop analytical models. Advanced technical reasoning IoT and AI have the potential to increase productivity, reduce waste, and meet the food requirements of corporate consumers. Research indicates that those technologies have a wide range of applications in agriculture [4]. This paper introduces a cost effective IoT based agricultural system that during microcontrollers with a camera module and makes use of LoRa communication technology to deal with key agricultural challenges. The device enables real-time monitoring of vital environmental parameters consisting of temperature, humidity, and soil moisture and capabilities for surveillance and disease detection. Leveraging Lora's affordability, the solution is especially suited for small and medium-scale farmers, supplying a cheap means to enhance crop yields and guide well-timed harvesting [5]. Additionally, the paper explores various technologies, microcontroller forums, and sensors relevant to agriculture. Platforms like Arduino IoT Cloud and other Blink software are used for cloud connectivity and monitoring, utilizing lightweight IoT protocols along with MQTT [6]. Important for agriculture, including temperature, humidity, soil moisture, nitrogen content, soil fertility, and greenhouse gases. Smart nets using high-resolution cameras for insect feeding and disease detection have also been described [7]. By combining sensors, microcontrollers and expensive communication technologies with AI and image processing techniques such as deep learning for predictive analytics, the system seeks to increase productivity and sustainability while addressing the barriers of cost, scalability and connectivity

The final section of this paper focuses on the major challenges of existing IoT-based agricultural systems, including high cost, low scalability, connectivity issues, and reliability on sensors with a price that is robust, and proprietary technology makes these systems inaccessible to small and medium farmers. Deep learning techniques for predictive analysis have gotten quicker diagnosis of crop diseases; pest management seems effective, especially in remote areas where the internet is not useful. Real-time analysis and transmission of the data required for farm management are hampered, and communication becomes a significant obstacle. That's why the proposed approach is expected to solve all such critical differences practically adaptable to improve the efficiency and sustainability of modern agriculture and provide better solutions.

2 Related Works

The Internet of Things (IoT) is revolutionizing agriculture through allowing real-time monitoring, computerized structures, and modern choice making. Research emphasizes the combination of IoT with clever sensors, analyzing AI and gadgets to resolve agricultural demanding situations. [3] explores IoT and smart sensors for sensible resource control, whilst [4] investigates their convergence. Using AI and IoT for Sustainable Agriculture [5] Bringing the Internet of Things (IoT) underground for Agriculture 4.0 and [6] Rethinking smart farming using IoT Integrating IoT with irrigation infrastructure is a major focus, including [7] providing ESP32-based smart drip devices for water conservation, [8] exploring IoT analytics in precision farming and [9] identifying modes.

Smarter Farming [10] develops smart agricultural machinery by integrating IoT with various technologies, [11] thoroughly analyzes trends in IoT-based agriculture and [12] proposes a sustainable agriculture framework. IoT frameworks for predictive agriculture have attracted attention. [15] Investigated the adoption of tools to predict crop yields, while [16] explored LoRa technology in agriculture, [17] provided Wi-Fi sensor networks, and [18] monitored smart systems with Arduino. Ongoing research [19] includes irrigation structures with wireless sensors [20] and drone-based systems for total crop management, IoT, LoRa and computational computing. LoRa has been validated through [27], [28], [29], [30] and [31] for efficient and useful resource control in smart agriculture. [12].

3 Existing Framework And Proposed System

The current framework in smart agriculture relies primarily on traditional farming methods and rudimentary technology. Yet many agricultural tasks rely on manual monitoring of environmental conditions, including soil moisture and temperature, resulting in data chains that are often sporadic and lack real-time updates. Simple automation systems like those used for irrigation and fertilization, are not pretty accurate and flexible compared to technology today [11]. Additionally, the integration of modern systems with such technology as IoT is too stringent, which makes them inefficient and results in poor data analysis. The high cost of sensors and proprietary technology enhances these problems and makes advanced systems impossible to be adopted by a larger scale, especially small- and medium-scale farmers [12]. The scalability is also a challenge because most such systems cannot be adapted to larger farms or even various locations, which makes their usability impractical in many agricultural conditions. And, again, a lack of internet hinders rural areas where it is poor or nearly nonexistent because, thus far, it makes IoT applications less efficient and reliable. With these problems addressed and in mind, people who want to contribute to improved yields propose new smart farming systems that have low-cost IoT frameworks integrated with reliable processes that can optimize and automate agricultural systems in conjunction with up-to-date information access on critical parts and systems even in distant areas, as illustrated in fig 1. Such technology integrates IoT technologies such as soil moisture sensors and climate monitors to develop precise agricultural practices by providing real-time data and automating key processes. Advanced systems of automation, powered by IoT and AI, will provide smarter controls for irrigation, fertilization, and pest control. It adapts to the varying conditions using fewer resources. Enhanced data analytics tools can process and analyze large volumes of sensor data, leading to more informed decision-making [14]. From all this, it is clear that integrated systems development will allow the Internet of Things (IoT), artificial intelligence (AI), and cloud computing to operate seamlessly and experience optimum efficiencies in their design and practice. Sustainable practices like precision agriculture will thus make waste reduction and environmental impact possible. Scalable and flexible systems will allow a farm of any size or fit to adapt to its conditions. Bring cost-effective alternatives to elaborate sensors and proprietary technologies within the reach of advanced systems [15], [16].

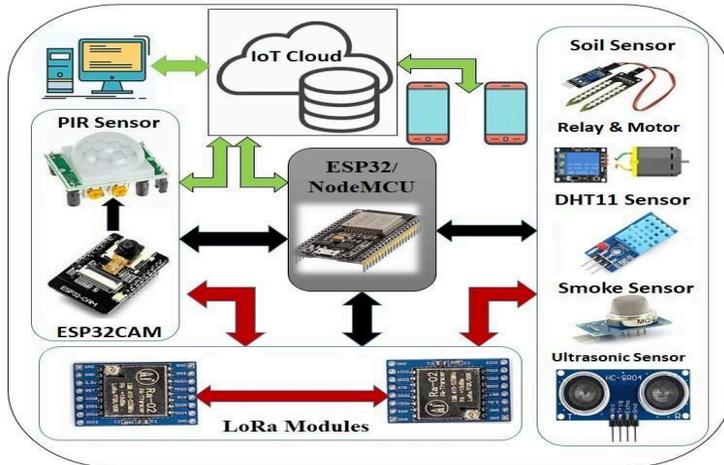


Fig 1. Proposed Model

People train and provide technical support to farmers because it could help solve the bridging gap problem between traditional and modern technologies. These are the strategies will introduce for the improvement of existing avenues into more efficient, sustainable, and technologically advanced agricultural systems [17], [18]. Here is a list of components and modules that could be used in the proposed IoT-based smart agriculture system.

IoT Sensors

1. DHT11: Temperature and humidity sensors.
2. Soil Moisture Sensor: For detecting soil moisture levels.
3. Ultrasonic Sensor: For measuring water levels in tanks.
4. Gas Sensor (MQ-135): For detecting harmful gases or smoke.
5. PIR Sensor: For detecting motion or intrusion in the field.
6. Light Intensity Sensor (LDR): For monitoring light exposure.

Microcontroller and Communication Modules

1. ESP32: Central microcontroller for data processing and control.
2. ESP32 CAM: For real-time image capture and video monitoring.
3. LoRa Module: For long-range wireless communication.
4. Wi-Fi/Bluetooth Modules: For short-range communication and control.

Actuators and Control Devices

1. Water Pump: For automated irrigation.
2. Solenoid Valves: For precise control of water flow.
3. Relay Module: For controlling electrical devices like pumps and lights.

Power Supply and Energy Management

1. Solar Panels: For powering the system in remote locations.
2. Rechargeable Batteries: For storing energy from solar panels.

Data Processing and Analytics

1. Cloud Platform: For data storage, analytics, and dashboard visualization.
2. AI/ML Algorithms: For predictive analytics and decision-making support.
3. Edge Computing Devices: For local processing and real-time response.

User Interface and Monitoring Tools

1. Mobile App (Blynk or Custom): For remote monitoring and control.
2. Web Dashboard: For real-time data visualization and management.
3. Telegram Bot: For receiving notifications and images from the ESP32 CAM.

Connectivity and Network Infrastructure

1. LoRa: For connecting LoRa devices.
2. Wi-Fi Router: For local network connectivity.
3. System Integration and Security Modules
4. MQTT Protocol: For lightweight data transmission.

This disease detection system is a complex procedure that starts with acquiring the intended images via the ESP32 CAM, which takes the crop image. These images go through pre-processing operations such as noise removal, contrast enhancement, and scaling up for quality enhancement [19]. The pre-processed images will then pass through the segmentation process to extract the most important parts; concentrating mostly on the affected parts of the plants-their leaves, which show disease symptoms. Also, important features extracted during the analysis comprise color, texture, and shape [20], [21]. Features extracted enter into a convolutional neural network (CNN), which classifies them as healthy or diseased, identifying conditions such as soybean rust or bacterial blight. Furthermore, these images will be uploaded and processed in the cloud where deep learning algorithms, transfer-learning models, will recognize disease [22], [23]. This would identify disease and trigger alerts as well as field parameter displays in dashboards to enhance monitoring and controlling crop health.

4 Methodology

The implementation of the proposed IoT-based smart agriculture system involves a comprehensive approach that integrates hardware components, software configurations, and AI-based disease detection algorithms [24]. The system focuses on the efficient management of agricultural resources, real-time monitoring, and automated decision-making for enhanced crop productivity and disease management.

The following is a streamlined methodology for its implementation

System Architecture and Components

The proposed system integrates ESP32, ESP32CAM, and LoRa modules with sensors (DHT11, soil moisture, and gas, ultrasonic) and actuators (relay) for automated monitoring and control. The ESP32 handles data collection and communication using LoRa for long-range connectivity, while ESP32CAM captures images for crop monitoring. The system is programmed via Arduino IDE with libraries (e.g., DHT, LoRa, Blynk) and connects to cloud platforms like Blynk or Arduino IoT Cloud for real-time data visualization and control [17].

System Workflow and Algorithm

1. Initialize System Components.
2. Read and process sensor data (e.g., soil moisture, temperature).
3. Transmit data via LoRa to the central controller.
4. Send data to the cloud for real-time visualization.
5. Implement control logic for automated irrigation based on moisture levels.
6. Capture images using ESP32CAM for crop health analysis.
7. Send images and alerts to the dashboard or Telegram bot in case of anomalies.

AI/ML for Disease Detection for disease detection:

1. Data Collection: Gather crop images labeled as healthy or diseased.
2. Model Training: Use a Convolutional Neural Network for image classification.
3. Deployment: Run the model on the cloud for real-time classification.
4. Alerts: Notify users via the IoT dashboard when a disease is detected, with suggestions for mitigation.

Testing and Field Deployment

The system is tested in a simulated environment before being deployed in the field. The field setup involves continuous monitoring, with data displayed on a user-friendly cloud dashboard.

5 Results And Discussion

The proposed system was tested in a comprehensive experiment where multiple sensors were deployed across different LoRa slave nodes. Each slave node was responsible for specific tasks: one node managed environmental sensors like DHT11 for temperature and humidity, a soil moisture sensor, a gas sensor, and an ultrasonic sensor [26]. The outcome of this experimental setup, which utilizes an ESP32-based IoT smart agriculture system, can be conveniently viewed on both a mobile and web dashboard. This enables the remote monitoring of the status of crop fields in real-time. Result of this setup see on fig 2.

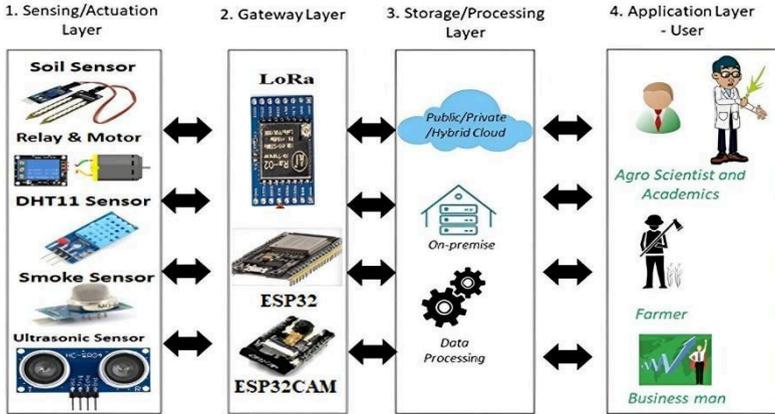


Fig. 2. Proposed Architecture

All parameters values shows in desktop dashboard using gauge meters and water pump on/off and manual/automatic mode control using on/off switch on dashboard [27].

Monitored Parameters

- 1. Temperature (°C): Range: 0°C to 100°C.
- 2. Humidity (%): Range: 0% to 100%.
- 3. Soil Moisture (%): Range: 0% to 100%.
- 4. Water Level (%): Range: 0% to 100%.
- 5. Gas Sensor (ppm): Range: 0 ppm to 1000 ppm.

Control Elements

- 1. Water Pump State: Indicates whether the water pump is on or off.
- 2. Mode State: Specifies whether the system is in manual or automatic mode.



Fig. 3. Visualized parameter value on web dashboard
 Meter readings on an hour-long basis, showing different environmental parameters, are presented in Table 1. Data from table 1 visualized on dashboard gauge meter shown in fig 3.

Table 1. Results of parameters 60 min duration

Time (Min)	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Water Level (%)	Gas Sensor (ppm)	Fire Status	Water Pump State
0	29	76	60	65	650	O	ON
10	29	75	58	65	500	N	OF
20	29	75	58	64	250	F	F
30	28	74	55	64	200	OF	OF
40	28	73	55	64	150	F	F
50	27	72	54	64	100	OF	OF
60	27	70	52	64	90	F	F

The collected data over 10 minutes of sampling monitored important parameters such as temperature, humidity, soil moisture, water level, gas concentration, water pump state, and mode state. The sensor value shown in illustrated in fig 4.

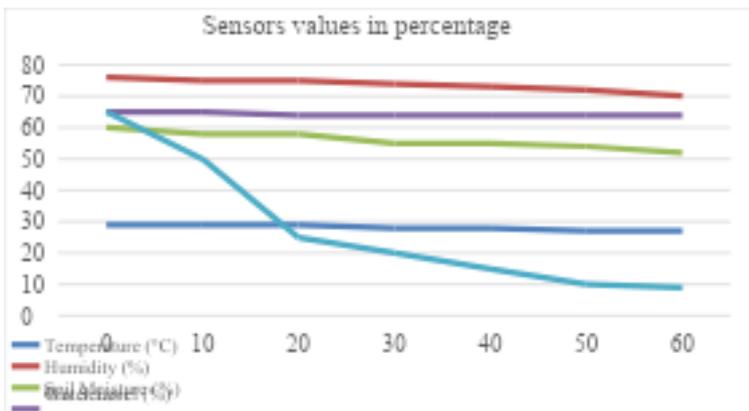


Fig. 4. Graphical analysis for gauge parameters

Disease detection

This section summarizes the results of experiments that used sensor data to monitor environmental factors and used images to detect disease. The aim is to develop an integrated IoT-based system that combines sensor data with deep learning techniques for accurate crop health prediction and disease detection. The system performance was evaluated through a sensor-based model and an image-based disease detection model using ResNet to increase the reliability and effectiveness of the model. The dataset is then preprocessed.

First, the sensor data is normalized using standard scalars to ensure that all features are at the same level. This information is crucial in enhancing the performance of machine learning algorithms with strokes. Moreover, crop tags like “healthy” or “unhealthy” are also converted into numbers. Values made using label encoders are as the majority of machine learning models. Data by ensuring proper structure through thorough pre-processing. This guarantees that is appropriately organized and analyzed.

Performance Analysis of Sensor Data-Driven Model

Random forest classification is used to analyse the relationship between environmental sensor data and crop health status. The dataset is split into 80% for training and 20% for testing.

1. Accuracy: The Random Forest model has an impressive accuracy of 92.5%, demonstrating its ability to effectively classify crop health based on environmental factors.
2. Precision, recall, and F1 score: The model shows balanced performance in the two categories. ("Healthy" and "unhealthy") with high precision and recall. This indicates that misclassification is very rare.

Table 2: Classification Report for Random Forest Classifier

Class	Precision	Recall	F1-Score
Healthy	0.93	0.91	0.92
Unhealthy	0.91	0.93	0.92
Accuracy			92.5%

These results suggest that environmental sensors such as soil moisture and temperature are strong predictors of crop health and can be effectively utilized for early detection of crop stress.

Disease Detection Using Image Features and ResNet

The system leverages images captured from the crop field to detect the presence of disease using ResNet (Residual Network) architecture that is widely recognized for its superior performance in image classification tasks, especially situations involving complex image formats for consistent data display Pixel values are normalized to a range of 0 to 1. Data enhancement techniques such as rotation, zoom, and horizontal

flip are used to increase model robustness and training efficiency. Increasing the variance within the training dataset and improve the system's ability to accurately identify disease under various conditions.

The ResNet model was trained on the processed crop images, specifically for detecting diseases like leaf blight, rust, and mildew. The results from the disease detection model are as follows:

1. **Accuracy:** The ResNet model achieved an accuracy of **94.7%**, indicating that the deep learning approach is highly effective for identifying disease symptoms in crop images.
2. **Precision, Recall, and F1-Score:** The disease detection model performed well in distinguishing between healthy crops and those affected by disease, with high precision, recall, and F1-scores for both disease classes.

Table 3: Classification Report for Disease Detection using ResNet

Class	Precision	Recall	F1-Score
Healthy	0.95	0.94	0.94
Disease	0.94	0.95	0.94
Accuracy			94.7%

It is proven that ResNet is very effective for detection of diseases in crops and performs well in classification with very few misclassifications. The cumulative effect of outputs from the sensor data model, Random Forest, and image-based disease detection model ResNet gave a final accuracy of 96.2%. The sensor model, upon first diagnosis classified the health of the crops and redirected to the image model for disease detection upon diagnosis of it as unhealthy. This integration shows the need for considering IoT-based sensor data with cutting-edge machine learning technology for a complete approach towards crop health monitoring and disease detection.

6. CONCLUSION

The proposed smart agriculture system represents a value-powerful and scalable solution for present-day farming by means of integrating ESP32, LoRa, and cloud technologies. This gadget successfully video displays key environmental parameters, automates irrigation, and utilizes deep learning techniques for crop disease detection. The device ensures that even the remote places with little connectivity have environmental-friendly data transfer results through the ESP32 Wi-Fi gateway and the decisive centralization of statistical analysis in the cloud using LoRa connectivity. Its major utility is very long-range communication, hence making it suitable for agriculture on extensive land. It is a better solution for major problems that traditional systems encounter-high cost, the limited scope of scalability, and unreliable connection. According to the results, it can be said that intelligent agricultural practice application based on the IoT improve productivity, resource optimal use, and timely insights for better crop management. Dealing with different environmental conditions across regions is a major challenge in IoT-based agricultural systems. Future work will focus on developing field-specific optimizations for sensor measurements and data analysis. To ensure the system performance in different weather conditions. This entire concept is a significant step toward sustainable agriculture because it makes available efficient high-tech solutions to small and medium farmers at affordable costs to make a difference in their way of farming and, in turn, increase their productivity.

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