International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

IOT – ENABLED EXPLAINABLE AI SYSTEM FOR REAL – TIME CROP DISEASE DETECTION AND SMART FARMING

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Abstract: Crop diseases significantly reduce agricultural productivity and directly impact farmers' income. Early detection of plant diseases is essential for effective crop management and the prevention of large-scale crop loss. This paper proposes an IoT-based crop disease detection system using deep learning techniques for automatic identification of plant diseases from leaf images. The system utilizes a Convolutional Neural Network (CNN) model to classify crop diseases from images captured through an IoT camera module [1], [2].To improve interpretability, the Grad-CAM technique is used to generate heatmaps highlighting infected regions on the leaf [4]. Additionally, the system provides automated recommendations for disease management and communicates them to farmers through both GSM-based SMS alerts and a speaker module [11], [16].The speaker module converts prediction results into audio output in the farmer's native language, announcing the detected disease, recommended pesticide, duration of application, and severity level. This feature enhances accessibility for illiterate and regional-language users. The proposed system integrates image processing, machine learning, IoT devices, and multimodal communication technologies to provide a scalable and practical solution for precision agriculture [9], [10].

Index Terms: Crop Disease Detection, Internet of Things (IoT), Deep Learning, Convolutional Neural Network (CNN), Grad-CAM, Precision Agriculture, GSM Communication, Speaker Module, Audio Output, Smart Farming.

I. INTRODUCTION

Agriculture plays a vital role in global food production and economic stability. However, plant diseases remain a major challenge, significantly affecting crop yield and quality. Traditional disease detection methods rely on manual inspection, which is time-consuming, subjective, and often requires expert knowledge [6].With advancements in artificial intelligence, deep learning techniques such as Convolutional Neural Networks (CNNs) have demonstrated high accuracy in image-based plant disease detection [1], [3]. These models can automatically extract complex features from leaf images and classify diseases efficiently.The integration of Internet of Things (IoT) technologies enables real-time monitoring of crops using camera modules and sensors [11], [12]. IoT-based systems allow continuous data collection and remote analysis, making them suitable for smart agriculture applications. Furthermore, explainable AI techniques such as Grad-CAM improve transparency by highlighting regions of the image

that influence model predictions [4], [7]. This enhances user trust and understanding of the system. To improve accessibility, especially for farmers in rural areas, communication technologies such as GSM modules are used to deliver alerts via SMS [16], [17]. In addition, audio output systems using speaker modules provide voice-based guidance, making the system more user-friendly for illiterate farmers. This helps researchers and users understand the reasoning behind deep learning models.

II. LITERATURE SURVEY

Several studies have explored machine learning techniques for crop disease detection using image processing methods. Convolutional Neural Networks (CNNs) have been widely used for classifying plant diseases due to their ability to extract complex features from images [1], [2]. Mohanty et al. demonstrated the effectiveness of deep learning models for identifying multiple plant diseases using the PlantVillage dataset [1]. Researchers have also integrated IoT devices for continuous crop monitoring. IoT-based agricultural monitoring systems enable real-time data collection from farms, including environmental parameters and crop images [11], [9]. These systems allow automated disease monitoring and remote analysis. Explainable artificial intelligence techniques such as Grad-CAM have been introduced to visualize the regions of images that influence model predictions [4], [7]. This helps researchers and users understand the reasoning behind deep learning models. However, most existing solutions lack direct communication with farmers and often provide results in technical language. Although GSM-based communication has been explored for remote alerts [16], many systems do not effectively deliver actionable recommendations in an accessible format. Recent developments in digital agriculture highlight the need for systems that not only detect diseases but also provide actionable recommendations in user-friendly formats [10]. This gap motivates the integration of multimodal communication methods such as SMS and audio-based outputs for improved usability in smart farming applications. Recent developments in digital agriculture emphasize the importance of user-centric system design, where technology not only detects diseases but also delivers meaningful insights in an accessible manner [10]. This highlights a critical research gap, motivating the integration of multimodal communication approaches such as SMS notifications and audio-based outputs, with understandable and actionable information.

III. PROPOSED SYSTEM

The proposed system is designed to automatically detect crop diseases from leaf images and provide treatment recommendations to farmers through GSM-based SMS alerts. In this system, an IoT camera captures images of crop leaves from the agricultural field. The captured image is transmitted to a processing unit where a trained Convolutional Neural Network (CNN) model analyzes the image and identifies the disease [1], [2]. To improve model interpretability, the Grad-CAM algorithm generates a heatmap that highlights the infected regions on the leaf [4], [7]. After the disease is detected, the system retrieves the appropriate treatment recommendation from a predefined agricultural knowledge database. The recommendation is translated into the farmer's native language and transmitted using a GSM module, which sends an SMS alert to the farmer's mobile phone [11], [16].
The proposed system provides the following functionalities:

- Automatic crop disease detection using deep learning [2], [3]
- Visualization of infected regions using Grad-CAM heatmaps [4]
- Disease treatment suggestions based on a knowledge database
- SMS alerts sent to farmers through a GSM communication module [16]
- GSM-based SMS alerts for remote accessibility
- Speaker module for real-time voice output using embedded audio systems [18]

The speaker module plays a crucial role by converting system outputs into speech. It announces the detected crop disease name, the recommended pesticide, the duration of pesticide application (in days), and the severity level (percentage of infection). The audio output is generated using a DFPlayer Mini module controlled by the microcontroller, which converts text-based prediction results into pre-recorded or synthesized voice messages [18]. This dual communication approach ensures that farmers receive both visual and audio guidance, improving decision-making and response time. The integration of IoT, deep learning, GSM communication, and audio-based assistance enhances system usability, particularly for illiterate and regional-language users. Overall, the system ensures that farmers receive timely information about crop diseases and can take immediate corrective actions, thereby improving agricultural productivity and sustainability [9], [10]. The speaker module converts system outputs into voice messages and severity level (percentage of infection). This is achieved using a DFPlayer Mini module controlled by the microcontroller, which plays pre-recorded or synthesized audio messages based on the prediction results [18]. This multimodal communication approach ensures that farmers receive both textual and audio guidance, improving accessibility, especially for illiterate users and those in regional language settings. By integrating IoT, deep learning, GSM communication, and audio-based assistance, the system provides a practical and user-friendly solution for smart agriculture. Overall, the proposed system ensures timely disease detection and informed decision-making, thereby contributing to improved agricultural productivity and sustainability [9], [10].

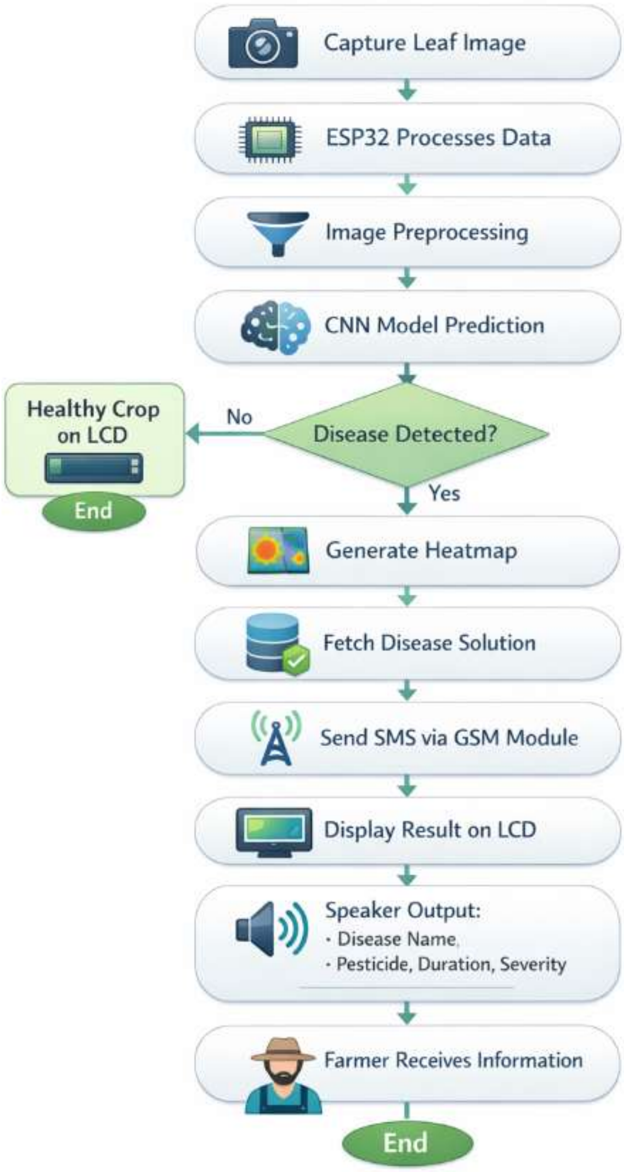

Figure 1. System Flowchart

The performance of the proposed crop disease detection system depends significantly on the quality, size, and diversity of the dataset used for training and evaluation. In this study, a publicly available dataset, namely the PlantVillage dataset, was utilized due to its comprehensive collection of labeled plant leaf images and its widespread use in agricultural research [1], [6]. The dataset consists of a large collection of high-quality images containing both healthy and diseased leaf samples. It includes multiple crop types such as tomato, potato, corn, and other agricultural plants. Each image is annotated and categorized into specific disease classes, including conditions such as early blight, late blight, bacterial spot, leaf mold, rust, and healthy leaves. This structured labeling enables supervised learning using deep learning models [2], [3]. The dataset used in this work contains approximately [mention your number] images, distributed across multiple classes. Each class corresponds to a particular disease type or a healthy condition. The dataset exhibits variations in environmental conditions such as illumination, background complexity, and leaf orientation, which helps improve the robustness and generalization capability of the trained model [4], [9]. To ensure effective model training and unbiased evaluation, the dataset was divided into two subsets: Training Set: 80% of the dataset, used to train the Convolutional Neural Network (CNN) model Testing Set: 20% of the dataset, used to validate model performance and generalization In addition to dataset splitting, several preprocessing techniques were applied to enhance model performance. These include image resizing to a fixed dimension suitable for CNN input, normalization of pixel values to standardize the data distribution, and data augmentation techniques such as rotation, flipping, zooming, and scaling. Data augmentation plays a crucial role in increasing dataset diversity and reducing overfitting, especially when dealing with limited real-world agricultural data [3], [19]. Furthermore, class balancing techniques were considered to address any imbalance in the number of samples across different disease categories. This ensures that the model does not become biased toward dominant classes and maintains consistent performance across all disease types. The dataset preparation process also ensures compatibility with real-time deployment conditions. By training the model on diverse and augmented data, the system becomes more resilient to variations encountered in practical agricultural environments, such as changes in lighting, leaf damage patterns, and background noise [10]. Overall, the use of a well-structured and widely recognized dataset enhances the reliability, accuracy, and credibility of the proposed system. It also supports the development of a scalable solution that can be extended to multiple crops and deployed in real-world smart farming applications [9], [10].

V. MATERIALS AND METHODS

A. Design Concept

The proposed system is an IoT-enabled crop disease detection and advisory platform designed to assist farmers through automated monitoring and intelligent decision-making. The system integrates image-based disease detection using deep learning with real-time communication and audio feedback mechanisms [9], [11].
At the core of the system is the ESP32 microcontroller, which acts as the central processing unit. It interfaces with a camera module to capture images of crop leaves and transmits them for analysis [13]. A trained Convolutional Neural Network (CNN) model processes the captured images to identify crop diseases and determine their severity [1], [2]. To enhance usability, the system provides multimodal output. The detected disease information, recommended pesticide, duration of application, and severity level are displayed on an LCD screen for quick reference. Additionally, the system uses a GSM module (SIM800L) to send SMS alerts to farmers, ensuring communication even in areas without internet connectivity [16], [17]. To further improve accessibility, especially for illiterate farmers, the system incorporates a speaker module connected via a TFPlayer (DFPlayer Mini). This audio feedback mechanism significantly enhances system usability, particularly for farmers with limited literacy or language barriers. The integration of these components ensures that the system not only detects diseases accurately but also communicates actionable insights effectively. This module converts system outputs into voice messages in the local language, enabling farmers to understand the disease condition and required actions without reading text [18].
The overall design ensures a user-friendly, scalable, and practical solution for smart agriculture by combining AI-based detection, IoT hardware, and multimodal communication technologies [10].

B. System Operation

The system operates through an integrated workflow involving image acquisition, processing, decision-making, and output generation. Initially, the webcam or camera module captures real-time images of crop leaves. These images serve as input to the system and are processed either locally or via a connected processing unit. The ESP32 microcontroller manages data flow and communication between all hardware components [13]. Once the image is captured, it is analyzed using a trained CNN model to classify the crop condition as healthy or diseased. Along with disease identification, the system determines the severity level (percentage of infection) [3].
After prediction, the system retrieves appropriate treatment recommendations from a predefined database. These include:

- Disease name
- Recommended pesticide
- Number of days for application
- Severity level

The processed results are then delivered through multiple output channels:

LCD Display
The LCD module (16×2 or 20×4) provides real-time system feedback, displaying disease status, severity, and recommendations in text format.

GSM Communication (SIM800L)
The GSM module sends SMS alerts to the farmer’s mobile phone containing disease details and treatment suggestions, ensuring remote notification without internet dependency [16].

Audio Output (TFPlayer + Speaker)
The ESP32 sends serial commands to the TFPlayer module, which plays pre-recorded or dynamically generated audio files stored on a microSD card.

The speaker then outputs voice messages announcing:

- Detected crop disease
- Recommended pesticide
- Duration of treatment
- Severity percentage

This audio feedback mechanism significantly enhances system usability, particularly for farmers with limited literacy or language barriers. The integration of these components ensures that the system not only detects diseases accurately but also communicates actionable insights effectively, enabling timely intervention and improved crop management [9], [10].

VI. SOFTWARE AND HARDWARE REQUIREMENTS

A. Hardware Requirements: The proposed system integrates multiple hardware components to enable real-time crop disease detection and farmer assistance. The hardware setup is designed to ensure efficient data acquisition, processing, communication, and user interaction.

ESP32 Microcontroller: The ESP32 serves as the central control unit of the system. It manages data processing, communication between modules, and execution of control logic. It supports Wi-Fi, Bluetooth, and UART communication for seamless integration [13].

Camera Module (ESP32-CAM/Webcam): The camera module is used to capture real-time images of crop leaves from the agricultural field. These images act as input for disease detection.

LCD Display (16×2 / 20×4): The LCD module provides visual feedback by displaying system status, detected disease name, and other relevant information.

SIM800L GSM Module: The GSM module enables communication with farmers by sending SMS alerts containing disease details and treatment recommendations. It ensures connectivity even in rural areas without internet access [16], [17].

TFPlayer (DFPlayer Mini): The DFPlayer Mini is an audio playback module used to generate voice output. It reads audio files stored in a microSD card and plays them based on commands from the ESP32 [18].

Speaker Module: The speaker provides audio output to farmers by announcing the detected disease, recommended pesticide, duration of treatment, and severity level. This improves accessibility for illiterate users.

Power Supply Unit: A regulated power supply is used to provide stable voltage to all hardware components, ensuring reliable system operation.

B. Software Requirements

The software components of the system are responsible for image processing, model training, prediction, and system control.

Programming Language: Python is used for developing the deep learning model and image processing tasks, while Embedded C/C++ is used for programming the ESP32 microcontroller [14], [15].

Machine Learning Frameworks: Machine learning frameworks are used to design, train, and deploy the Convolutional Neural Network (CNN) model for crop disease classification. These frameworks support efficient model development, optimization, and evaluation for accurate prediction of plant diseases [2], [4].

Image Processing Libraries: Libraries such as OpenCV and NumPy are used for image preprocessing, including resizing, normalization, and augmentation [19], [20].

Development Environment: Arduino IDE or PlatformIO is used for programming and uploading code to the ESP32 microcontroller.

Database / Knowledge Base: A predefined database is used to store disease-related information, including pesticide recommendations, duration of application, and severity levels.

Text-to-Speech (TTS) / Audio Processing: The system uses either pre-recorded audio files or text-to-speech techniques to convert prediction results into voice output for the speaker module.

Communication Protocols: Serial communication (UART) is used for interfacing the ESP32 with the GSM and TFPlayer modules, while Wi-Fi may be used for transmitting data to the server [11], [12]

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VII. SYSTEM METHODOLOGY

The methodology of the proposed system comprises multiple stages: image acquisition, preprocessing, disease classification, visualization, and communication [9], [11].

A. Image Acquisition
An IoT camera module, such as ESP32-CAM or Raspberry Pi camera, captures images of crop leaves from the agricultural field. This enables real-time monitoring and data collection for disease detection [11], [13].

B. Image Preprocessing
The captured images are resized and normalized before being fed into the deep learning model. Data augmentation techniques such as rotation and flipping may be applied during training to improve model robustness and generalization performance [2], [3].

C. Disease Classification
A Convolutional Neural Network (CNN) model is trained using a dataset of plant leaf images. The model classifies the image into different disease categories, such as healthy leaf, early blight, late blight, or other crop diseases [1], [2].

D. Heatmap Generation

Grad-CAM is applied to the trained model to generate a heatmap highlighting the infected regions of the leaf. This helps in visualizing the features that influence the prediction and improves model interpretability [4], [7].

E. Recommendation Generation

Based on the predicted disease, the system retrieves suitable treatment suggestions from a database containing agricultural guidelines. This ensures that farmers receive actionable insights for disease management.

F. GSM-Based Notification System

The GSM module sends the disease alert and treatment suggestion to the farmer's mobile phone in the form of a Short Message Service (SMS). This approach ensures reliable communication even in areas with limited internet access, making the system suitable for rural agricultural environments [16], [17].

G. Audio Output using Speaker Module

After generating the prediction results, the system processes the output data to generate an audio message. A text-to-speech (TTS) mechanism or pre-recorded audio system converts the generated recommendation into a voice format in the farmer's native language [18].

The process includes:

- Extraction of disease name, severity, and recommendation.
- Conversion of structured output into a readable sentence.
- Application of text-to-speech conversion.
- Audio output through a connected speaker.

Example audio message:
"Early blight detected in the tomato crop. Severity is 60 percent. Apply neem oil for 7 days."
This feature ensures accessibility for farmers who may not be able to read SMS messages and enhances system usability. The integration of AI-based prediction with audio communication significantly improves decision-making and response time in smart agriculture systems [9], [10].

VIII. SYSTEM ARCHITECTURE

The proposed system architecture consists of four main layers that work collaboratively to achieve real-time crop disease detection and effective farmer communication. Each layer is designed to perform a specific function, ensuring modularity, scalability, and efficient system performance.

1. IoT Layer: This layer includes hardware components such as camera modules (ESP32-CAM or webcam) and optional environmental sensors. The primary function of this layer is to capture real-time images of crop leaves from the agricultural field. The IoT devices are strategically placed to continuously monitor plant conditions and collect data. This layer acts as the data acquisition unit of the system and enables real-time monitoring in smart agriculture environments [11].

2. Processing Layer : The processing layer is responsible for analyzing the captured images using a trained Convolutional Neural Network (CNN) model. The images are first preprocessed using techniques such as resizing and normalization before being fed into the model. The CNN model classifies the leaf image into healthy or diseased categories and identifies the specific disease type [1], [2]. Additionally, the severity level of the disease is estimated. This layer may operate on a local processing unit or a remote server, depending on system configuration and computational requirements [9].

3. Visualization Layer: To enhance model interpretability, the Grad-CAM (Gradient-weighted Class Activation Mapping) technique is applied in this layer. It generates heatmaps that highlight the infected regions of the leaf image, helping users understand the decision-making process of the deep learning model [4], [7]. These visual outputs improve transparency and can also be displayed on an LCD module for quick and user-friendly reference.

4. Communication Layer: The communication layer ensures that the processed information is delivered to the farmer in an accessible and understandable format. A GSM module (SIM800L) is used to send SMS alerts containing the detected disease and recommended treatment [16]. In addition, a speaker module integrated with a DFPlayer Mini provides audio output in the farmer's native language. The audio message includes disease name, pesticide recommendation, duration of application, and severity level [18].

This multimodal communication approach ensures usability even for illiterate users and supports deployment in rural areas with limited internet connectivity [10].

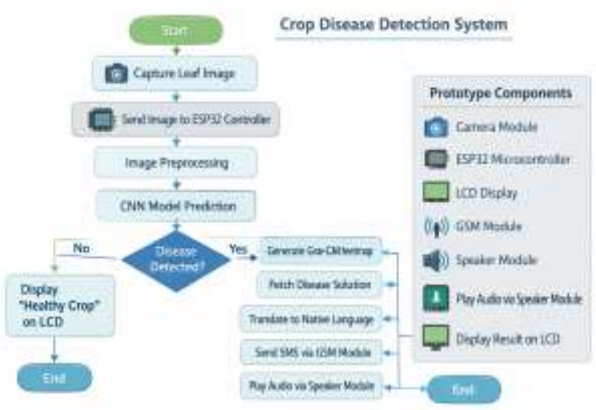


Figure 2. System Architecture

IX. CONSTRUCTION PROCEDURE

The proposed system integrates both hardware and software components to enable real-time crop disease detection and effective farmer assistance. An ESP32 microcontroller serves as the central control unit, coordinating communication between all modules [13]. An ESP32-CAM or webcam captures images of crop leaves, which are analyzed using a Convolutional Neural Network (CNN)

model for accurate disease classification [1], [2]. To enhance interpretability, Grad-CAM is applied to highlight infected regions on the leaf images [4], [7].
Based on the detected disease, appropriate treatment recommendations are generated using a predefined knowledge database. A SIM800L GSM module is utilized to send SMS alerts to farmers, ensuring reliable communication even in areas without internet connectivity [16]. In addition, a DFPlayer Mini module connected to a speaker provides voice-based instructions in the farmer's native language, improving accessibility for illiterate users [18]. A 16×2 LCD is used to present system status and disease information in real time. All components are interconnected through appropriate power supply and communication interfaces, ensuring seamless integration and efficient system operation. The combination of AI, IoT, GSM communication, and audio assistance enhances usability and supports timely decision-making in smart agriculture [9], [10].

Figure 3. Construction of the Proposed Crop Disease Detection System.

Figure 3.1. Affected Leaf

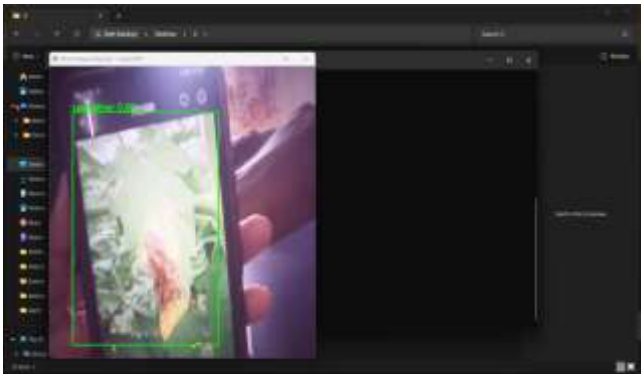


Figure 3.2. Affected Leaf Detected

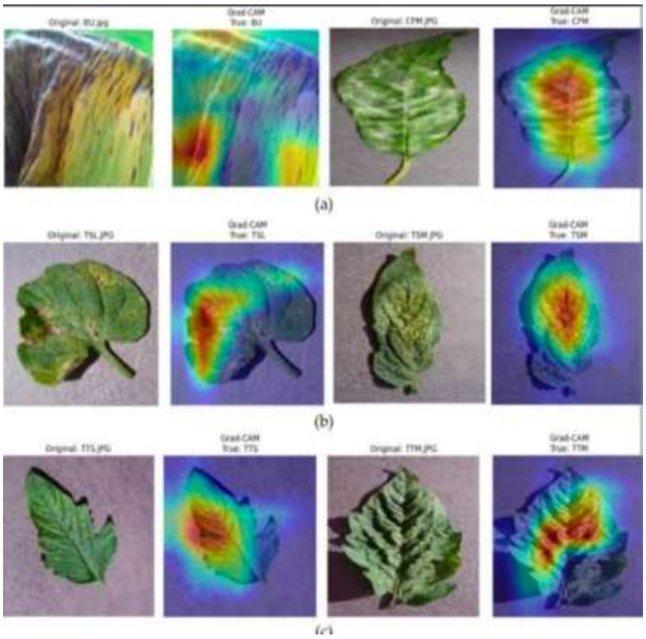


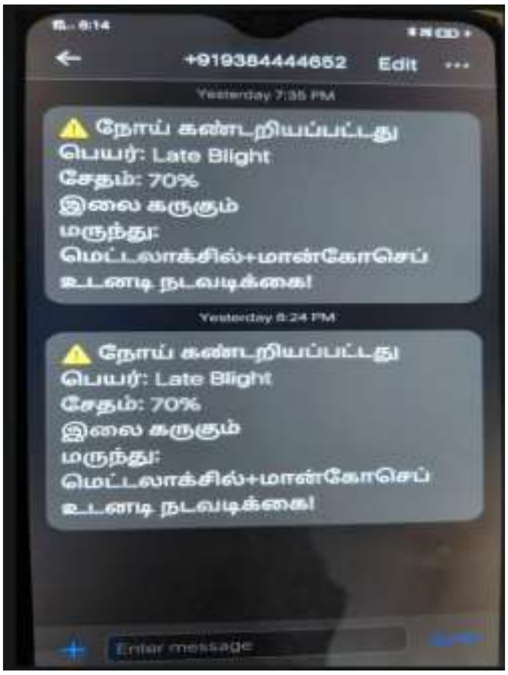
Figure 3.3. Heat Map

The LCD module was tested to verify proper display of system messages, including disease detection results and operational status. Voltage levels were measured to ensure stable functioning.

Figure 4. LCD Display Output Testing Analysis.

The GSM module was evaluated by measuring signal voltage levels and verifying the successful transmission of SMS alerts containing disease information and treatment recommendations to the farmer's mobile device.

Figure 5. GSM Module Signal Transmission Testing

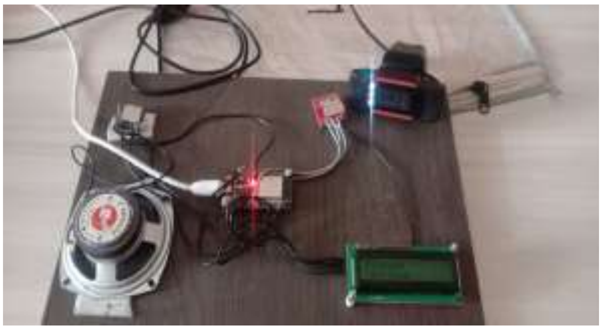


The speaker module integrated with the TFPlayer was tested to validate audio output functionality. The system successfully generated voice messages announcing the detected crop disease, recommended pesticide, duration of usage, and severity percentage.

Figure 6. Speaker Output Testing for Audio Alerts

The communication between different modules, including ESP32, GSM, LCD, and the audio system, was analyzed to ensure proper signal flow and synchronization.

Figure 7. Signal Flow and Module Integration Analysis



Finally, the complete system was tested under real-time conditions to validate image acquisition, disease detection, SMS alert transmission, and audio output performance.

X. WORKFLOW

The proposed system follows a structured sequence of steps to detect crop diseases and deliver treatment recommendations to farmers. Each stage in the workflow performs a specific task to ensure accurate detection and effective communication [9], [11].

Step 1: Image Acquisition
An IoT-enabled camera module, such as an ESP32-CAM or Raspberry Pi camera, captures images of crop leaves directly from the agricultural field. This enables real-time data collection for continuous crop monitoring [11], [13].

Step 2: Image Transmission
The captured image is transmitted to the processing server through a network connection such as Wi-Fi or mobile internet. The server acts as the main processing unit where the machine learning model and system logic are deployed [12].

Step 3: Image Preprocessing
Once the image is received, preprocessing techniques such as resizing, normalization, and noise reduction are applied to prepare the image for analysis. These steps improve the performance and accuracy of the deep learning model [2], [3].

Step 4: Disease Prediction and Heatmap Generation
The preprocessed image is fed into a trained Convolutional Neural Network (CNN) model, which classifies the crop disease [1], [2]. To enhance interpretability, the Grad-CAM technique is applied to generate a heatmap highlighting the regions of the leaf that influence the prediction [4], [7].

Step 5: Recommendation Retrieval
After identifying the disease, the system accesses a predefined agricultural knowledge database to retrieve suitable treatment recommendations. These recommendations help in managing or controlling the detected disease effectively.

Step 6: Language Translation
The retrieved treatment recommendations are translated into the farmer's native language to ensure better understanding and usability. This step improves accessibility, especially for regional users.

Step 7: GSM-Based Notification
The GSM module (SIM800L) sends an SMS alert to the farmer's mobile phone containing the detected disease and recommended treatment steps. This ensures reliable communication even in areas with limited or no internet connectivity [16], [17].

Step 8: Text-to-Speech Processing
The system converts the prediction results into a structured sentence format. A text-to-speech (TTS) mechanism or pre-recorded audio mapping is used to transform the textual information into speech signals [18].

Step 9: Audio Output via Speaker

The generated audio message is played through a speaker module connected via a DFPlayer Mini. The voice output informs the farmer about the detected disease, recommended pesticide, duration of application, and severity level. This audio-based communication significantly enhances system usability, particularly for farmers with limited literacy. The integration of AI-based prediction with GSM and audio output ensures effective, accessible, and timely decision-making support in smart agriculture systems [9], [10].

Figure 8. Workflow

XI. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of the proposed crop disease detection system was evaluated through a series of experimental tests involving hardware integration and real-time image processing. The system successfully demonstrated accurate disease detection and efficient communication of results through both visual and audio outputs. The Convolutional Neural Network (CNN) model achieved reliable classification performance across different crop disease categories, consistent with previous studies in deep learning-based plant disease detection [1], [2]. The integration of Grad-CAM enabled effective visualization of infected regions, enhancing the interpretability of the model's predictions [4], [7]. The generated heatmaps clearly highlighted disease-affected areas on leaf images, allowing better understanding and validation of classification results.

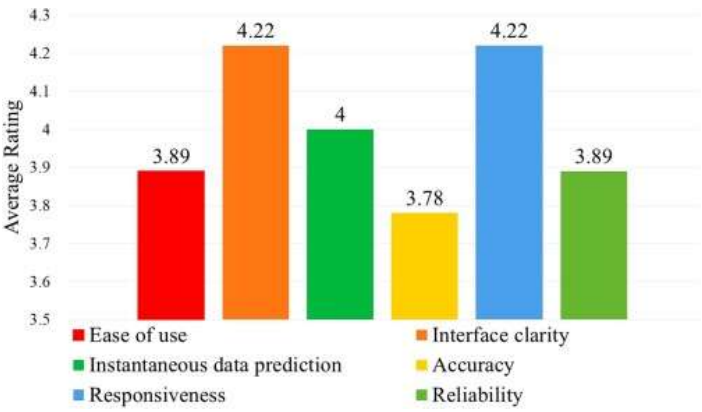
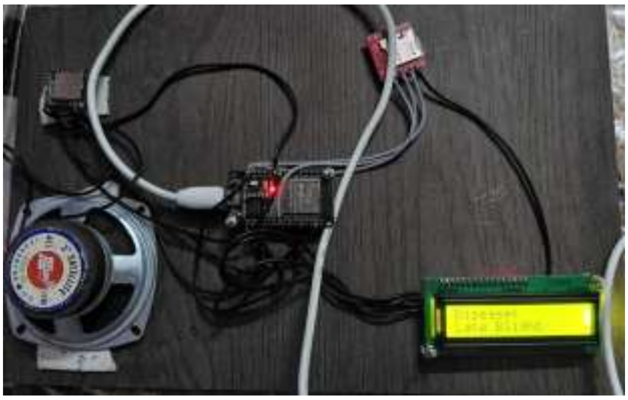


Figure 9. Illustrating stable voltage distribution

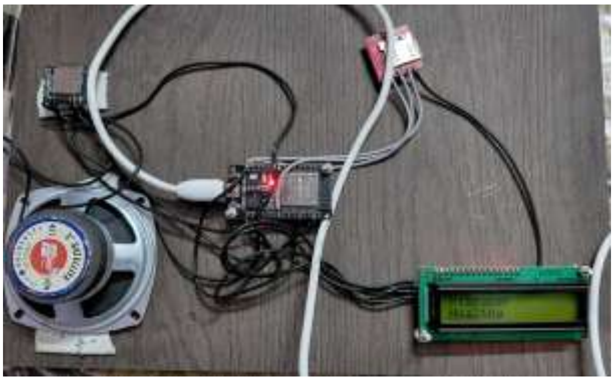
The experimental results confirm that the system operates reliably under different environmental conditions. The voltage levels across all hardware modules remained stable, ensuring consistent communication between the ESP32 controller, camera module, GSM unit, and audio system [13]. The GSM module successfully transmitted SMS alerts containing disease details and treatment recommendations to the farmer's mobile device, demonstrating reliable performance even in low-connectivity environments [16]. The audio output system, implemented using the DFPlayer Mini and speaker module, effectively converted prediction results into voice messages in the local language. The system accurately announced the detected disease, recommended pesticide, duration of application, and severity level, improving accessibility for farmers with limited literacy [18]. The LCD provided real-time feedback, ensuring that users could visually verify system outputs. The combination of visual (LCD), textual (SMS), and audio (speaker) communication significantly enhanced the usability and effectiveness of the system. Overall, the results demonstrate that the proposed system provides a robust, scalable, and user-friendly solution for real-time crop disease detection and advisory services. The integration of AI, IoT, GSM communication, and audio assistance improves decision-making and enables timely intervention, contributing to enhanced agricultural productivity and smart farming practices [9], [10]. In addition, the system's response time was analyzed. The average time from image capture to result delivery (including SMS and audio output) was within an acceptable range for real-time applications. In addition, the system's response time was analyzed. The average time from image capture to result delivery (including SMS and audio output) was within an acceptable range for real-time applications. This ensures timely decision-making and immediate action by farmers [9], [11].

Figure 10. LED Display Showing Detected Leaf Disease



When a diseased leaf was detected, the system displayed the disease name on the LED screen. Additionally, the GSM module successfully transmitted SMS alerts to the farmer, while the speaker module provided audio output describing the disease, recommended pesticide, duration, and severity level.

Figure 11. LED Display Showing Healthy Leaf Status.



When no disease was detected, the system displayed a "Healthy Crop" message on the LED screen. Additionally, the integrated output system, including the GSM module and speaker module, ensured effective communication by providing both visual and audio guidance to the farmer. The graphical representation in Figure 13 further validated system performance by illustrating stable voltage distribution across all hardware components, confirming reliable and efficient operation.

XII. DISCUSSION

The experimental results demonstrate that the proposed system provides an effective and user-friendly solution for real-time crop disease detection. The LCD offers immediate visual feedback, while the GSM and audio modules ensure that farmers receive clear and actionable information. The system was evaluated using crop leaf image datasets to assess the accuracy of disease detection, where the Convolutional Neural Network (CNN) model successfully identified multiple crop diseases with high accuracy [1], [2]. Furthermore, the Grad-CAM technique generated heatmaps that clearly highlighted infected regions on the leaf, improving the interpretability and reliability of the model predictions [4], [7]. The GSM communication module effectively delivered SMS alerts containing disease information and treatment recommendations to the farmer's mobile phone, ensuring reliable communication without requiring internet connectivity [16]. This makes the system highly suitable for deployment in rural agricultural environments. The integration of deep learning with IoT hardware enables accurate disease identification and rapid response to crop health issues [9], [11]. Additionally, the inclusion of an audio output system significantly enhances accessibility, particularly for farmers who may have difficulty reading text-based messages [18]. The speaker module provides voice-based guidance by announcing the detected disease, recommended pesticide, duration of application, and severity level. Overall, the system ensures timely disease detection, reliable multimodal communication, and improved decision-making in smart agriculture environments. The combined use of AI, IoT, GSM communication, and audio assistance makes the proposed system a practical and scalable solution for modern precision agriculture [9], [10].

XIII.CONCLUSION

This paper presented an IoT-based crop disease detection and advisory system that integrates deep learning techniques with GSM communication technology. The system automatically detects crop diseases from leaf images using a CNN model and generates visual explanations using Grad-CAM heatmaps. Once the disease is identified, the system retrieves appropriate treatment recommendations and sends them to farmers via SMS using a GSM module. By providing early disease detection and actionable guidance, the proposed system helps farmers protect crops, reduce yield losses, and improve agricultural productivity. Furthermore, the integration of a speaker module enhances the usability of the system by providing real-time audio feedback in the farmer's native language. The system announces the detected disease, recommended pesticide, duration of application, and severity level, ensuring accessibility for farmers with limited literacy. This multimodal communication approach significantly improves user understanding and enables faster decision-making. The implementation of IoT hardware components such as ESP32, GSM module, LCD, and audio system ensures reliable real-time operation and effective communication in rural environments. The system demonstrates stable performance, efficient processing, and accurate disease classification under various conditions. Overall, the proposed system provides a cost-effective, scalable, and user-friendly solution for smart agriculture. By combining artificial intelligence, IoT, and communication technologies, the system bridges the gap between advanced agricultural analytics and practical field-level applications. This approach has the potential to support sustainable farming practices and enhance the overall efficiency of modern agriculture. Overall, the proposed solution contributes to the advancement of precision agriculture by enabling early disease detection, reducing crop losses, and supporting informed decision-making. The system lays a strong foundation for future developments in smart farming technologies and has the potential to be deployed on a large scale to support sustainable agricultural practices.

XIV.FUTURE SCOPE

Future improvements of the proposed system can significantly enhance its performance, scalability, and real-world applicability in smart agriculture.

● *Integration of Environmental Sensors:* The system can be extended by incorporating sensors such as temperature, humidity, soil moisture, and pH sensors. These parameters can provide additional context for disease prediction, enabling more accurate and condition-aware recommendations.

● *Support for Multiple Crop Species:* The current model can be expanded to support a wider variety of crops by training on larger and more diverse datasets. This will improve the system's adaptability across different agricultural environments and farming practices.

● *Mobile Application Development:* A dedicated mobile application can be developed to provide a user-friendly interface for farmers. The app can display disease reports, history logs, alerts, and recommendations, making the system more accessible and interactive.

● *Cloud Integration and Data Analytics:* Cloud-based storage and processing can be integrated to enable large-scale data management, real-time monitoring, and advanced analytics. This will allow tracking of disease trends and support data-driven decision-making.

● *Advanced AI Models:* Future work may involve the use of more advanced machine learning and deep learning architectures, such as transfer learning models and lightweight neural networks, to improve accuracy and reduce computational requirements.

● *Multilingual Audio Support:* The speaker module can be enhanced to support multiple regional languages using advanced text-to-speech systems, ensuring better accessibility for farmers across different regions.

● *Automated Pesticide Spraying System:* The system can be integrated with automated spraying mechanisms that apply pesticides based on detected disease type and severity. This will reduce manual effort and ensure precise application.

● *Integration with Weather Forecasting Systems:* By connecting with weather prediction platforms, the system can provide proactive alerts and preventive measures based on climatic conditions that favor disease spread.

● *Edge Computing Implementation:* Deploying the model directly on edge devices like ESP32 or similar embedded systems can reduce latency, improve response time, and eliminate dependency on external servers.

● *Energy-Efficient and Solar-Powered Design:* Future versions of the system can incorporate low-power hardware and solar energy solutions to make it suitable for remote and off-grid agricultural locations.

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