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Original Article

AI-Driven Plant Disease Diagnosis with Conversational Chatbot Support for Precision Farming

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Abstract *- Agricultural productivity remains extremely vulnerable due to a lack of plant disease detection. This stage leads to a drastic disaster in crop productivity, which significantly affects food prosperity globally and affects farmers' ability to manage their agricultural systems. Early plant disease detection improves the agricultural management system, and providing the best practices in an applicable way leads to faster, sustainable farming practices. The proposed technique leverages AI Models to analyze plant leaf images and accurately describe the diseases affected, while a Natural Language Processing (NLP)-based chatbot delivers valid actionable insights and treatment recommendations to farmers for fast recovery of the plant in their own multilingual language. This technique provides high accuracy in maintaining the latency level. This framework offers chatbot assistance for farmers to guide the best agricultural practices, especially treating disease-affected plants, to promote their crop production. Additionally, the system provides the integration of a multilingual chatbot to help farmers in their native language.*

Keywords *- Plant Disease Detection, Precision Agriculture, Chatbot Integration, Deep Learning, Sustainable Farming.*

1. Introduction

1.1. Background and Motivation

Crop disease management is a critical challenge faced by every farmer in their agricultural management system. This leads to the destruction of yield production and food security worldwide. Early plant disease detection and treatment of the affected plants are critical to preventing them from causing very harmful, widespread plant damage.

Traditional plant disease management systems, which rely on manual inspection by agricultural experts, are not only time-consuming and costly but also not available for many rural farming communities. This makes the need to utilize the AI techniques for identifying the plant disease, mainly helps in extracting the image features from complex data, pattern recognition, and provides timely advisory action to be followed from the agricultural management assistant to farmers without waiting for an agricultural expert.

1.2. Challenges of Traditional Disease Detection

Plant disease detection and crop health management have depended on visual observations from farmers. Treating the plants after visually analyzing them is too late for taking action, which has a high impact on recovering them at an early stage. Although these methods work effectively in controlled environments, they have a number of significant shortcomings in practical farming contexts.

Farmers often identify diseases only after the plant has been affected by the disease, when visual symptoms appear on the plants, which is too late for diagnosing and treating the disease. These methods also have limitations like expert dependency, time-consuming and costly action needed, and the chance of human error is high.

1.3. Role of AI and Deep Learning Methods in Plant Disease Detection

Advanced AI technologies have provided new ways in which plant diseases can be easily detected and diagnosed at a very early stage. Unlike traditional approaches to machine learning, which require a great deal of hand-crafted feature image selection and identification, highly trained deep learning models extract image features and noise removal of images hierarchically and have the capability of classifying and analyzing the images with great accuracy, even if the lighting and background differ.

1.4. Why Combine Disease Detection with Conversational Chatbots

Once a crop disease is detected, farmers need clear, context-specific advice on diagnosing the process of plant disease treatment strategies. A standalone plant disease detection application is not sufficient because farmers may not have that kind of knowledge about appropriate organic or chemical treatments, Safe application methods and dosages, and preventive measures to avoid recurrence. Here, AI-powered conversational chatbots play a transformative role where they advise and recommend treatment strategies.

Integrated within the plant disease detection system, chatbots can deliver disease details and treatment recommendations instantly and frequently, support multilingual communication and break language barriers, provide guidance on organic solutions, reduce environmental harm, and offer step-by-step instructions for plant disease management. The integration of detection and advisory systems creates a closed-loop precision farming solution across the world, ensuring not just diagnosis but actionable interventions that empower farmers to make informed treatment decisions quickly.

1.5. Research Problem

Most of the research concentrates on either plant disease detection or organic treatment recommendation strategies, despite the advanced AI-based farming. This is the main problem addressed in this research. There is no widely adopted system that integrates both plant disease detection with an advanced interactive conversational chatbot with multilingual features in a single platform optimized for precision farming in real-time.

1.6. Research Objectives

This study aims to optimize, evaluate, and integrate an AI-based plant disease detection technique with a conversational chatbot, focusing on the following objectives:

- To design and implement an AI-trained model for detecting crop diseases from diseased plant images.
- Develop a Natural Language Processing (NLP)-based conversational chatbot to provide real-time treatment advice in multiple languages.
- This will be available to farmers in a web application for easy use and interaction.
- This System enhances the parameters such as accuracy, response time, and farmers' usability worldwide for their intended use.

1.7. Scope and Significance

The proposed system helps farmers to improve their farming practices, where they find the difficulties accessing modern agricultural expertise in smart farming, to improve the growth of agricultural resources through a user-friendly integrated chatbot. The cutting-edge AI algorithms methods integrated with a chatbot to promote the affordable agricultural activity by integrating low-cost mobile technology, thereby:

- Early plant disease detection reduces the yield loss and improves crop productivity.
- They recommend the advanced, eco-friendly farming practices through organic treatment recommendations.
- Elevating the high-level support for farmer with valid advisory recommendations in their own language.

2. Literature Review

Use of CNN-based architectures for training models, machine learning algorithms, and along with environmental parameters has been proven for increasing crop yield and disease prediction over deep learning methods (Attri et al. 2024). Smart farming and innovative precision farming rely on IoT sensors integrated with ML algorithms for identifying plant disease in a great potential way, clustered algorithms (Orchi et al. 2021).

Li et al. (2021) found that the efficacy of VGGNet and ML systems for identifying plant disease using various datasets from the cloud has elevated the recent advances in image classification using deep learning techniques, and has increased the accuracy analysis of plant disease. The Combination of AI and IOT for capturing real-time images using object-detecting sensors through a drone for smart farming analysis(Orchi et al., 2021). Ahmed and Yadav (2023) noted the recent advances in CNNs techniques and transfer learning for plant disease detection, to enhance performance and accuracy for resource-limited settings in agriculture.

Panchal et al. (2023) demonstrated the efficacy of ResNet deep learning systems for facilitating the analysis of plant disease. Sivakumar et al. (2025) designed agricultural chatbots powered by AI to improve the crop recommendation services for farmers in multiple languages, which enhances farmer engagement for their crop yields. Prasad and Thyagaraju (2024) facilitated the use of IoT with Machine Learning (ML) and Deep Learning (DL) for early detection of plant disease with their clustering algorithms. I was impressed by Upadhyay and Kumar's (2022) application of CNN-based models for paddy (rice) crop disease detection, where accuracy relies on a very high level, and the image classification method is very advanced and optimized. The AI-driven conversational chatbot for treatment recommendations integrated with real-time plant disease detection algorithms via IoT, proposed by Kothari et al. (2024), is for efficient farming and preventing plants in the early stages.

The AI applications in agriculture for identifying real-time images through sensors and support chatbots and virtual assistants play a vital role as they seem to be very powerful tools for agricultural management (Sivakumar et al, 2023). Therefore, cloud-integrated platforms were recommended for processing the image with extensive agricultural datasets for predictive analytics and early plant disease prevention (Sajitha et al, 2024). Hybrid deep learning models are applied for image classification and segment the leaf region to analyze the plant disease detection, windows minimize the computational methods and their requirements while still being a precise methodology. More recent research on image preprocessing for plant diseases has incorporated multimodal learning cloud frameworks, advancing the state of the art in AI for predictive accuracy with new fusion techniques with deep learning

(Kolluri et al, 2024). Research focusing on improving advanced techniques for chatbot integration with plant disease diagnosis and recommendations aimed to enhance farmer accessibility and to prevent the plants at a very early stage, and guiding them with the advisory systems (Ahmad et al., 2023). Further studies are implemented and explainable for the advanced AI frameworks to bridge the gap between trained model predictions (Huo et al., 2023). The review of Machine learning and deep learning techniques in AI for plant disease detection, published in 2025, uses techniques like CNN, GAN, and attention mechanisms for advanced real-time smart farming applications (Prasad Singh et al. 2025). The critical challenges in crop yield improvement, agricultural resource optimization, and early plant disease detection play a vital role in handling AI-powered solutions for integrated crop health monitoring and disease prevention in precision agriculture systems.

3. Proposed Methodology

The proposed system aims to assist regional farmers to maintain and evolve their agricultural practices with the help of artificial intelligence, which framework provides the real-time crop disease detection using Convolutional Neural Network models and supports a comprehensive solution through a chatbot using Natural Language Processing (NLP) responsive technologies. This system enhances the agricultural system and reduces food insecurity by leveraging deep learning techniques for crop disease detection and prosperity, which increases crop productivity, improving decision-making, and chatbot integration provides help to farmers with a user-friendly platform accessible globally.

3.1. Objectives of the Proposed System

The main intention of the proposed methodology is to provide a deep learning plant disease detection system integrated with a multilingual chatbot using advanced natural language processing techniques for precision farming and a well-maintained AI-driven agricultural management system globally.

3.2. System Architecture Overview

The architecture of the system comprises three layers (Figure 1):

- Input Layer
  - Farmers can either upload their diseased plant images directly using a mobile or web-based application or use real-time images captured from any IOT devices in the fields.
- Processing Layer: This layer performs:
  - Image preprocessing is used to eliminate noise, find the image size to a standard value, and normalize the image.
  - Image segmentation using cluster-based algorithms (e.g., K-means).
  - Convolutional Neural Networks (CNN) were used to identify crop diseases into predefined classified disease groups with high accuracy.
- Advisory Layer: This layer hosts an AI-powered chatbot, which:
  - Provides treatment advice using the natural language processing technique and JSON responsive structure, and includes a translation feature for multilingual language options.

3.3. Workflow of the Proposed Methodology

The proposed system describes the following sequential stages like once farmer uploaded the diseased images it undergoes the regular process using OpenCV and TensorFlow models for image preprocessing especially to standardizes the image size and eliminating background noise in the image after preprocessing the image using cluster algorithms the image process the segmentation by layer by layer which undergoes three layer segmentation to achieve the accuracy and maintain the latency value and finally the output image is validated with feature extraction technique using trained CNN model. The deep learning classification helps in diagnosing the disease and storing the data, like identifying the disease name, affected area, and maximizing the accuracy level, and storing the data in a cloud database. The chatbot took the reference output from the cloud and provided the reply response by recognizing the pattern using intent recognition, and the dialog manager acts as a bridge to deliver the reply. Using advanced translation techniques, multilingual language support is achieved in the chatbot.

3.4. Algorithmic Framework

The proposed approach follows these steps:

Step 1: Acquire image input from farmers or any real-time image-capturing devices.
Step 2: Preprocessing the image for noise removal and color normalization for image processing methodology.
Step 3: Perform image segmentation to isolate the ROI (Region of Interest).
Step 4: Extract significant features from the image bit by bit and feed them to the corresponding CNN models.
Step 5: Identify the plant disease and affected area with accuracy.
Step 6: Trigger chatbot response for the identified

3.5. Data Flow Between Modules

- Image Data → Processing Layer: Using the OpenCV library, the preprocessing, segmentation, and feature extraction of the images are achieved with high accuracy.
- Disease Classification → Advisory Layer: JSON response contains the personalized guidance structure for farmers.

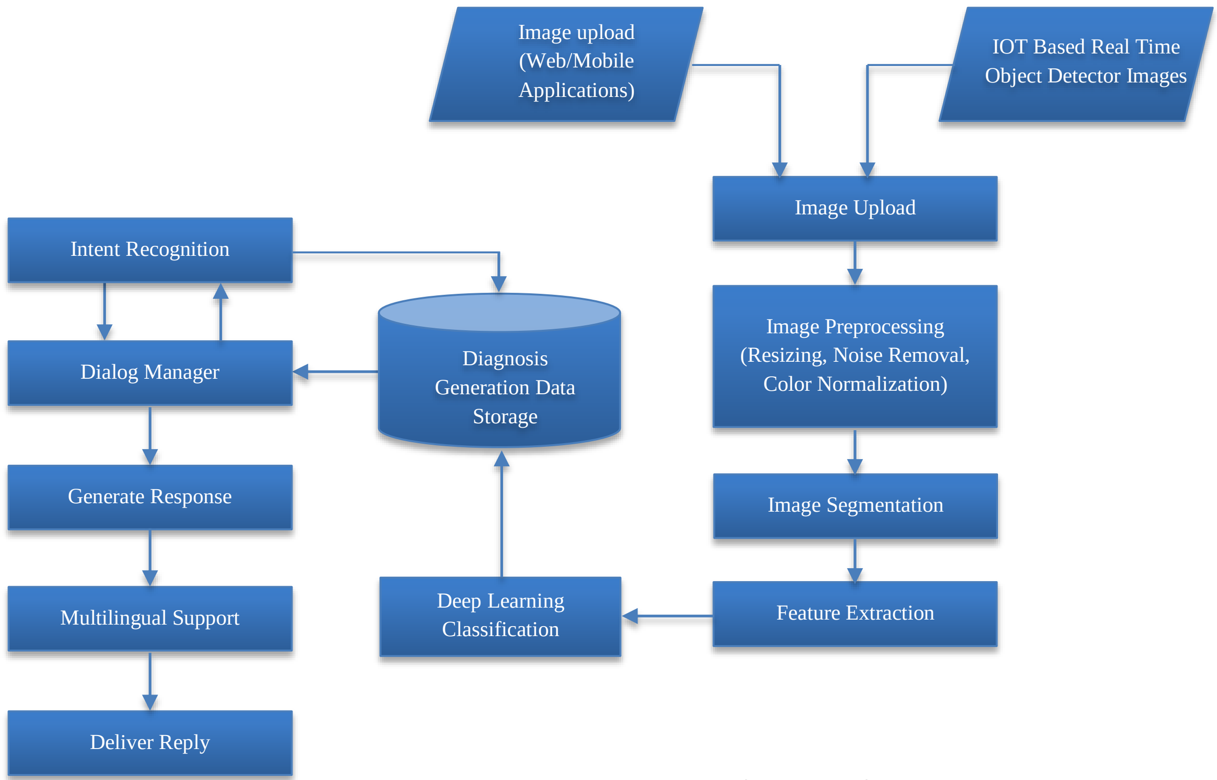

Fig. 1 Proposed AI-powered system architecture for precision farming

3.6. Advantages of the Proposed Methodology

- An AI chatbot offers valid advice and timely treatment for farmers to improve their plant health management.
- Large-scale field monitoring provides the scalability for precision farming.
- Accuracy and handling of the CNN models reduce the complexity in scanning the segmented leaf textures according to the environmental variations.
- Adaptive advisory treatments and precautions result in robustness of the systems.

4. Experimental Setup & Implementation

4.1. Introduction

Nowadays, to enhance smart farming, AI technology plays a vital role, especially when it comes to plant disease detection, which significantly helps farmers to increase plant productivity and restrict crop yield loss.

The proposed system uses Machine learning and image preprocessing techniques for identifying and diagnosing plant disease from crop images. This can be achieved by using MATLAB GUI, which is helpful for identifying the crop disease at a very early stage.

A conversational chatbot is also integrated with one that generates a quick response to treat the crops. This implementation has several stages, like image acquisition, image preprocessing, image segmentation, feature extraction, and classification.

4.2. System Workflow

The Steps followed in the workflow:

- Image Acquisition: Farmers can directly upload their own images in any mobile/web application, or we can capture the images through some real-time IOT devices. Preprocessing: Elevate the image through techniques like resizing the uploaded image, removal of noise, contrast image adjustment, and color normalization, which are applied to the uploaded image, and will get the segmented images.
- Segmentation: After preprocessing, the image is segmented bit by bit to diagnose the diseased regions of the uploaded leaf image, which are segmented using clustering algorithms.
- Image Feature Extraction: The Gray Level Co-occurrence Matrix (GLCM) and associated metrics are used to extract image features for statistical and texture-based features, especially for the segmented image region.
- After Analysis, diseased plants are categorized into groups like tomato mosaic virus, bacterial spot, early blight, septoria leaf spot, and healthy.
- Integration with Chatbot: The Results are analyzed and transferred to a web-based intent identification for plant disease advisory recommendations in the early identification of plant disease.

4.3. Image Preprocessing

The Quality of the uploaded image is preprocessed to enhance the image, improve segmentation, and increase classification accuracy. The Image is a typical dimension of 256 × 256 pixels. Contrast enhancement of the image is implemented by using the imadjust() function to optimize and improve visual clarity to the next level, while conversion to the Lab color space relies on accurate color-based segmentation of the image.

Key Steps Include:

- Image resizing
- Contrast enhancement
- Color normalization (RGB → L*a*b)

MATLAB Snippet:

```
Image = imread('leaf.jpg');
Image = imresize(Image, [256,256]);
Image_adjusted = imadjust(Image, stretchlim(Image));
cform = makecform('srgb2lab'); lab_img = applycform(Image_adjusted, cform);
```

4.4. Image Segmentation

After the preprocessing of the image, the user selects the cluster containing the diseased region part, which is then used for further implementation of the disease diagnosis. Image Segmentation elevates the diseased region alone from the healthy parts of the leaf. The implementation applies K-means clustering on the Lab* color channels, segmenting the plant diseased image parts into three clusters.

MATLAB Snippet:

```
image_uploaded = double(lab_img(:,:,2:3));
rowsVal = size(image_uploaded,1);
colsVal = size(image_uploaded,2);
image_uploaded = reshape(image_uploaded, rowsVal*colsVal, 2);
img_cluster_idx = kmeans(image_uploaded, 3, ‘distance’, ‘sqEuclidean’, ‘Replicates’,3);
pixel_Value = reshape(img_cluster_idx, rowsVal, colsVal);
```

4.5. Feature Extraction

After Segmentation of the diseased region, the algorithm captures the texture and statistical features using Gray Level Co-occurrence Matrix (GLCM) and basic statistical functions. This feature is crucial in diagnosing the different types of diseases.

MATLAB Snippet:

```
Seg_glcms = graycomatrix(segmented_img);
stats = graycoprops(Seg_glcms,'Contrast Correlation Energy Homogeneity');
Img_Contrast = stats.Contrast;
Mean = mean2(segmented_img);
EntropyVal = entropy(segmented_img);
```

4.6. Disease Classification

The extracted image feature vector is implemented in a Hybrid Classifier, which has undergone processing for both Support Vector Machine (SVM) and custom rules.

The classifier is trained using a dataset (Training_Data.mat) and suggests the diagnosis for each disease class, such as:

- Bacterial Spot
- Septoria Leaf Spot
- Early Blight
- Tomato Mosaic Virus
- Healthy Leaf

4.7. Accuracy and Performance

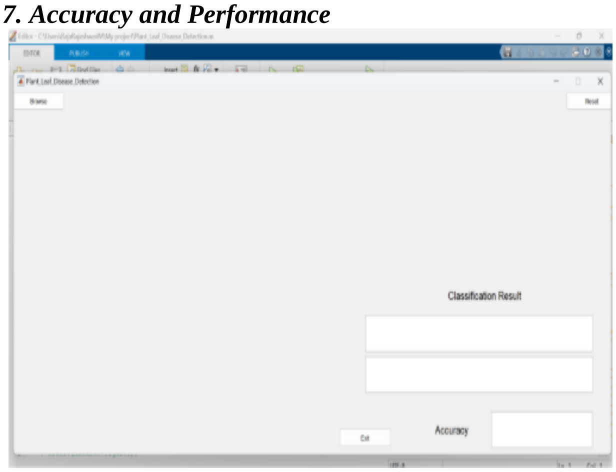

Fig. 2 Initial image upload option screen

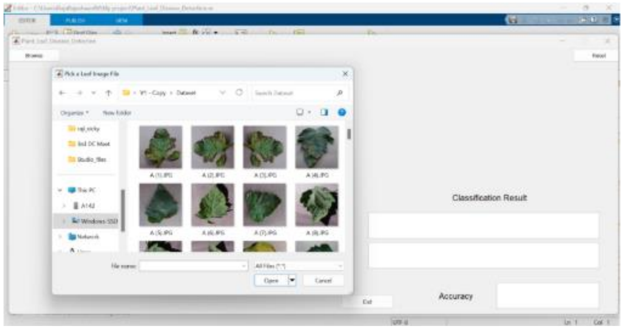

Fig. 3 Browse image screen

Figure 2 describes the initial screen where users can upload their own plant image for the diagnosis process, and this screen will be used in MATLAB local host port, where a built-in user-friendly system is available for farmers' ease of use in real-time applications.

Figure 3 enables them to upload the image in the web application interface.

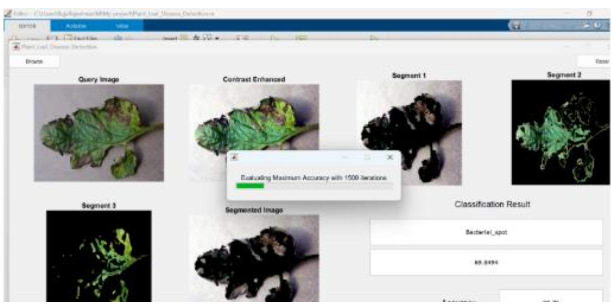

Fig. 4 Analyzing image Screen

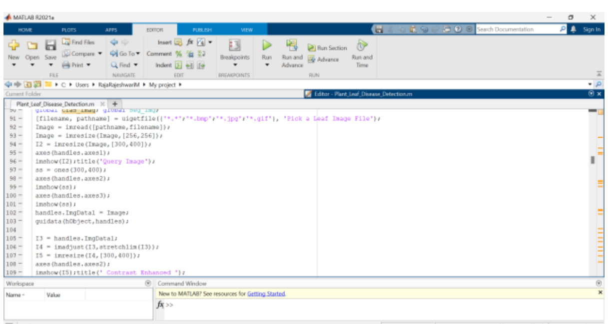

Fig. 5 Python code in MATLAB Simulation

The trained model for plant disease diagnosis is tested for 1500 iterations, achieving a valid maximum accuracy of approximately 99.76% in MATLAB simulation, where Figure 4 shows the analysis process in MATLAB application. Accuracy calculation is based on classifications taken for the total samples of trained plant diseases.

4.8. Integration with Chatbot

After analyzing the image and classifying the plant disease, the result is forwarded to a web-based chatbot module that provides valid recommendations for treating the diseased plants. The chatbot recommends prevention methods to safeguard the plant from further infection. The chatbot is designed with multilingual support to ease the farmers' understanding in their own convenient language for precision farming. Figure 5 explores the Python code adopted with MATLAB simulation.

5. Results and Performance Evaluation

This describes implementation results for plant disease detection with MATLAB Simulation integrated with a conversational chatbot through real-time plant images. The plant disease detection models were trained over 1500 cloud-based datasets with a high accuracy of 99.76%. The chatbot responses were made to deliver organic treatments and support to enhance the advanced agricultural practices.

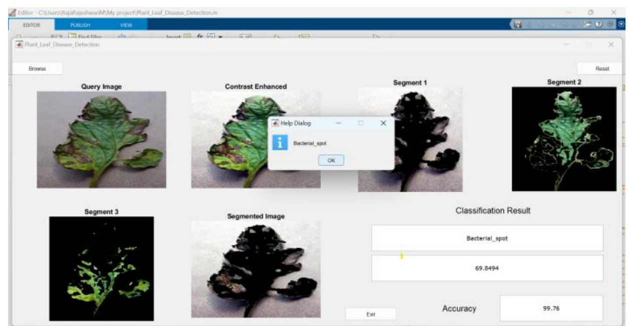

Fig. 6 Conversation chatbot interface

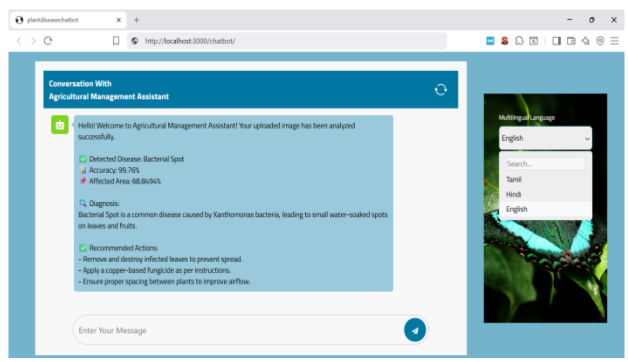

Fig. 7 Tomato leaf affected with MATLAB-Simulation Output

Figure 6 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from the MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants at the early stage, with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

Figure 7 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
    - Identified Disease: Bacterial Spot
    - Accuracy: 99.76%
    - Affected Area: 69.8494
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

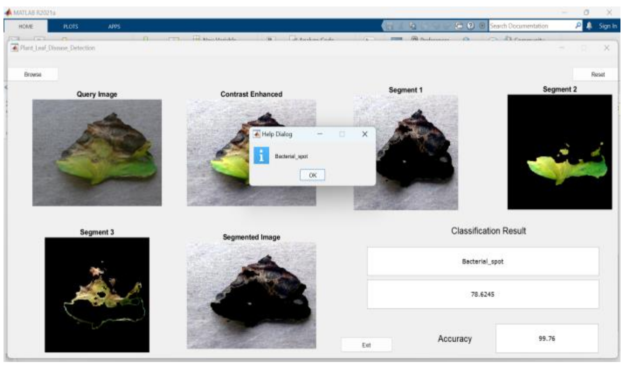

Fig. 8 Potato leaf affected with MATLAB-simulation output

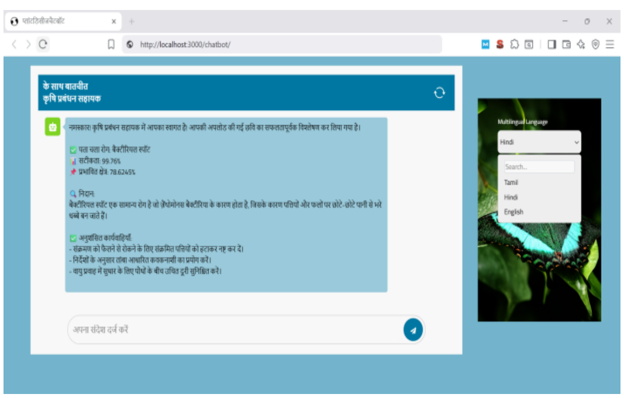

Fig. 9 Conversation Chatbot Interface

Figure 8 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
    - Identified Disease: Bacterial Spot
    - Accuracy: 99.76%
    - Affected Area: 78.6245
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 9 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants at the early stage, with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

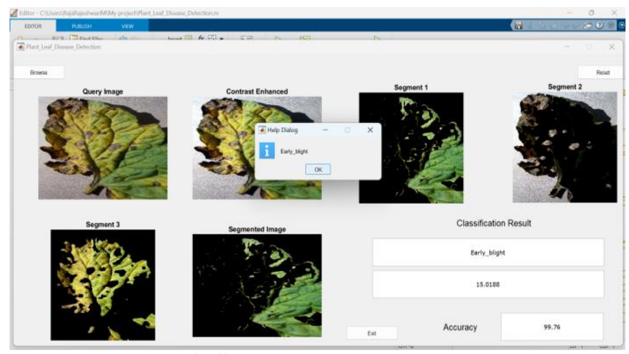

Fig. 10 Basil leaf affected with MATLAB-simulation output

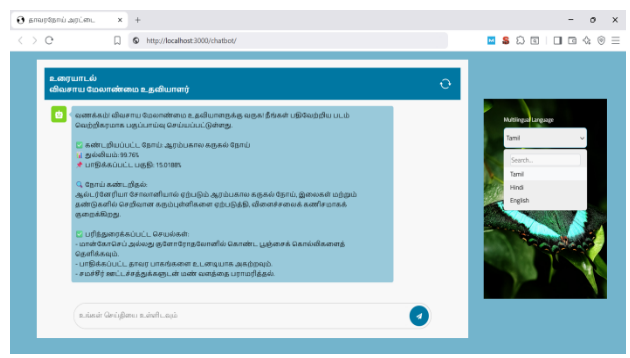

Fig. 11 Conversation Chatbot Interface

Figure 10 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
    - Identified Disease: Early Blight
    - Accuracy: 99.76%
    - Affected Area: 15.0188
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 11 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from the MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

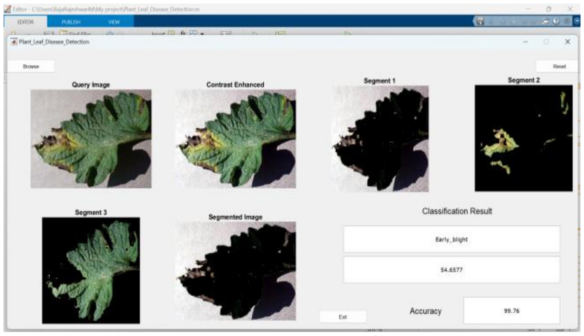

Fig. 12 Chatbot Interface

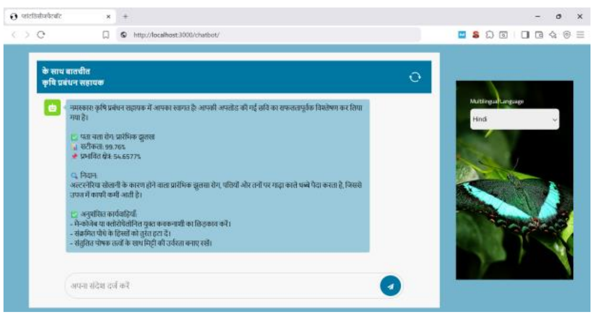

Fig. 13 Hibiscus leaf affected MATLAB-simulation output

Figure 12 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants at the early stage, with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

Figure 13 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
  - Identified Disease: Early Blight
  - Accuracy: 99.76%
  - Affected Area: 54.6577
- After receiving the plant disease detection, it will open a web application in a browser for Chatbot Support.

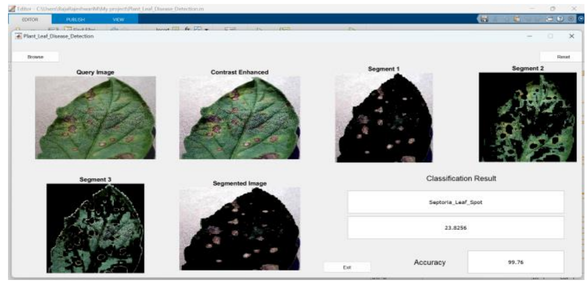

Fig. 14 Marigold leaf affected with MATLAB-simulation output

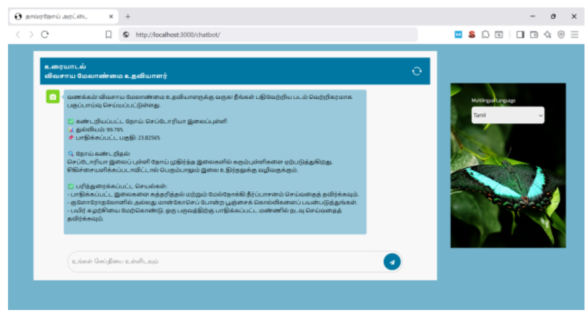

Fig. 15 Conversation Chatbot

Figure 14 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
  - Identified Disease: Septoria Leaf Spot
  - Accuracy: 99.76%
  - Affected Area: 23.8256
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 15 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

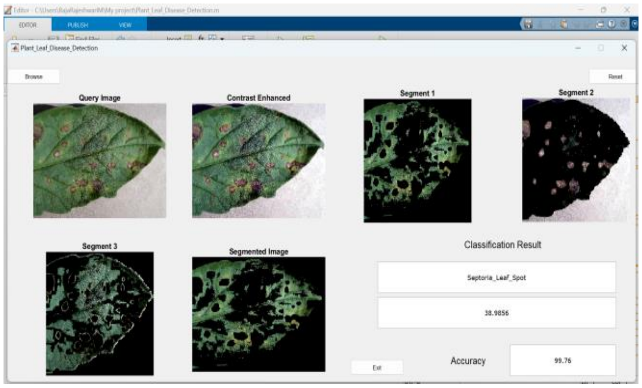

Fig. 16 Bell Pepper leaf affected with MATLAB-simulation output

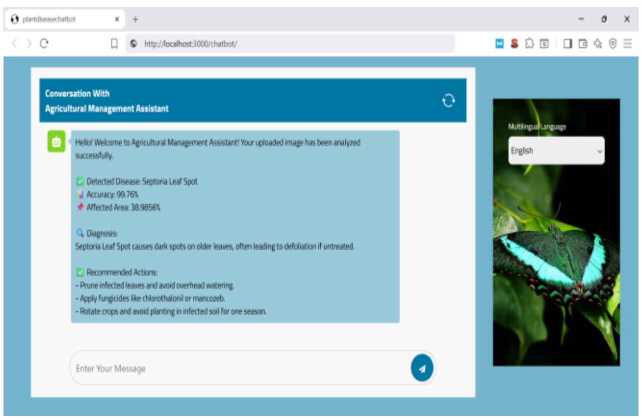

Fig. 17 Conversation Chatbot Interface

Figure 16 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
    - Identified Disease: Septoria Leaf Spot
    - Accuracy: 99.76%
    - Affected Area: 38.9856
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 17 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early, with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

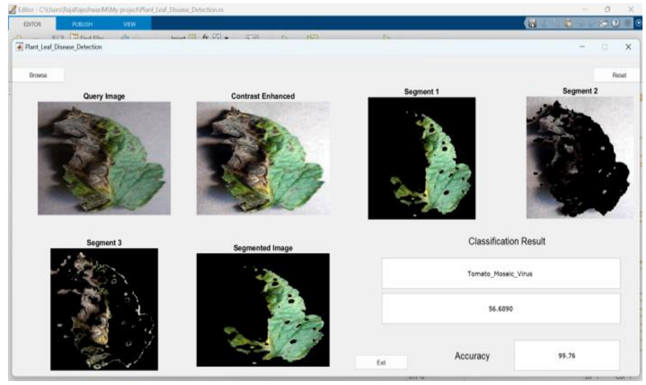

Fig. 18 Chilli Pepper leaf affected with MATLAB-simulation output

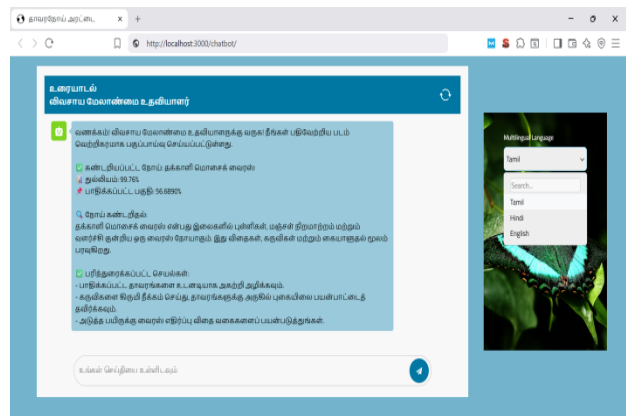

Fig. 19 Conversation Chatbot Interface

Figure 18 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
    - Identified Disease: Tomato Mosaic Virus
    - Accuracy: 99.76%
    - Affected Area: 56.6890
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 19 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from the MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

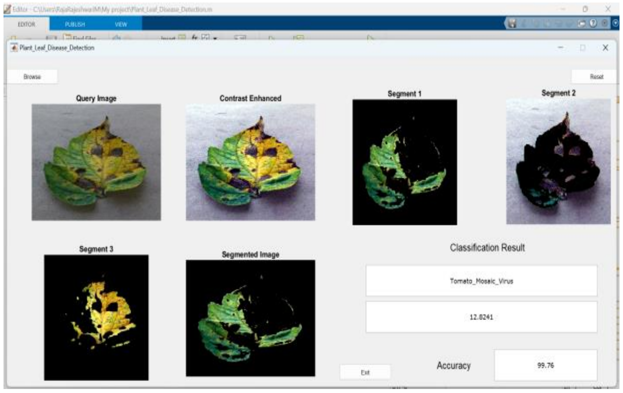

Fig. 20 Sunflower leaf affected with MATLAB-simulation output

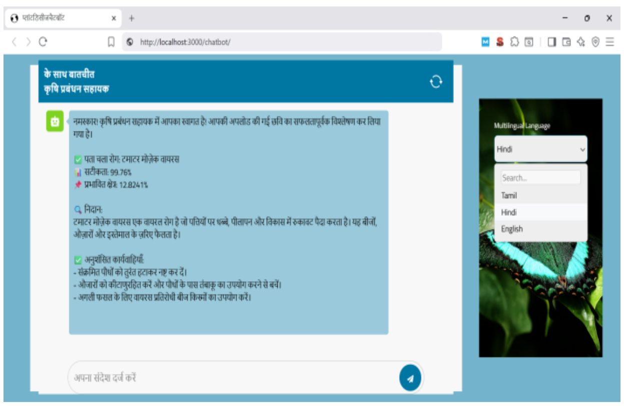

Fig. 21 Conversation Chatbot Interface

Figure 20 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
  - Identified Disease: Tomato Mosaic Virus
  - Accuracy: 99.76%
  - Affected Area: 12.8241
- After receiving the plant disease detection, it will open a web application in a browser for Chatbot Support.

Figure 21 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

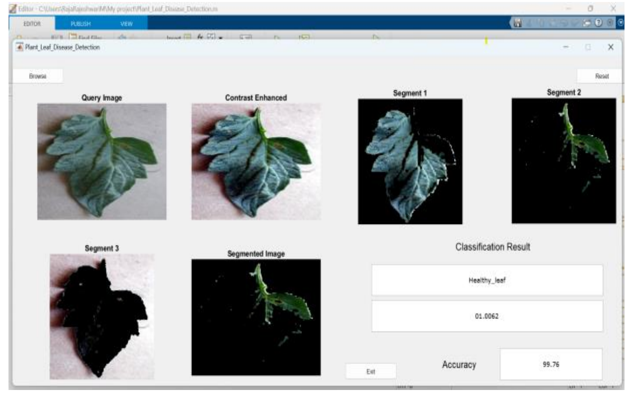

Fig. 22 Thyme leaf affected with MATLAB-simulation output

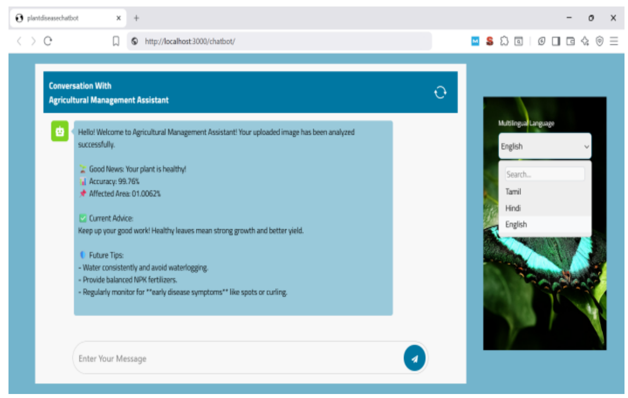

Fig. 23 Conversation Chatbot Interface

Figure 22 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
  - Identified Disease : Healthy Leaf(No Disease)
  - Accuracy: 99.76%
  - Affected Area: 01.0062
- After receiving the plant disease detection, it will open a web application in a browser for Chatbot Support.

Figure 23 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants early with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

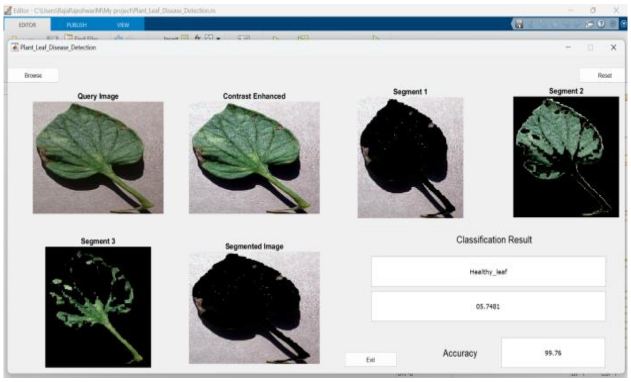

Fig. 24 Rose leaf affected with MATLAB-Simulation Output

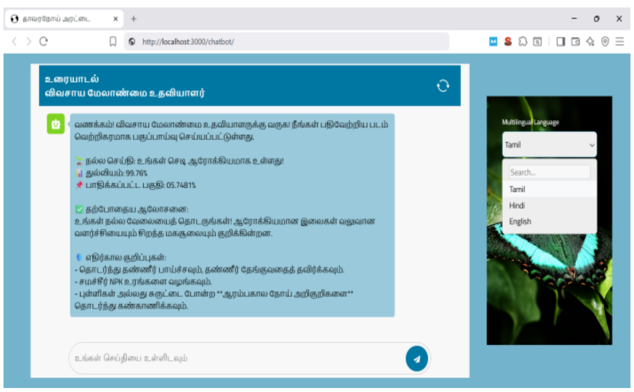

Fig. 25 Conversation Chatbot Interface

Figure 24 describes the output of plant disease detection using MATLAB Simulation. Once the Input image is received, the system performs the following steps,

- Image preprocessing (Contrast Image) and segmentation (Segment 1, Segment 2, Segment 3) to identify the affected areas of the uploaded image.
- After 1500 iterations of the trained models from the dataset in the cloud,
  - Identified Disease : Healthy Leaf(No Disease)
  - Accuracy: 99.76%
  - Affected Area: 05.7481
- After receiving the plant disease detection, it will open a web application for Chatbot Support in a browser.

Figure 25 displays the Agricultural Management Assistant chatbot running on a web browser at http://localhost:3000/chatbot/. The chatbot:

- Offer an Advisory diagnosis for the affected Plant disease using the output from MATLAB Simulation.
- Supports with actionable recommendations to treat the affected plants at the early stage, with diagnostic descriptions and advanced organic treatment measures.
- It provides multi-language support for farmer interactions (English, Tamil, Hindi), enhancing the ease of use and accessibility for regional farmers to access the application wisely.

6. Conclusion and Future Scope

6.1. Conclusion

The Importance of Artificial Intelligence is never addressed in Agricultural management systems, though we have the provision of using the revolutionized agricultural practices. Here, we have discussed in depth how to utilize them to identify plant diseases and recommend timely solutions to prevent plant diseases and increase yield productivity. The platform provides a wise integration of plant disease detection and chatbot in the same appliances, which results in a massive increase in crop production and enhances the supreme crop health management. This proposed system will result in maintaining the crops with proper health conditions and recommending practical solutions for farmers to overcome the challenges they face in agricultural fields.

6.2. Future Scope

Future studies can optimize the chatbot response with more regional language support with the help of Natural Language Processing, and we can also work on providing a voice assistant for an easier way of communicating with farmers. We can also capture the images using real-time IOT devices to reduce the manual uploading of image features. Additionally, to increase the predictive capability, we can integrate soil health monitoring by integrating modules for irrigation scheduling and humidity sensors to enhance more features for farmers and increase high-level precision farming techniques.

As technology adoption in agriculture grows day by day, the application can also integrate with weather prediction, which can evolve into a comprehensive smart farming ecosystem and also tackle the challenges faced by farmers due to climate change. In climate-smart farming techniques, we can achieve massive plant production for the agricultural management system and large yield productivity. Thus, the system opted for a fundamental AI-Powered Agricultural Management Chatbot for precision farming and for diagnosing plant diseases for farmer assistance.

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