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Geo-Location Based Plant Disease Diagnosis with Treatment Recommendation Multilingual Chatbot

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Abstract

Plant diseases significantly affect agricultural productivity by reducing crop quality, decreasing yield, and causing economic losses to farmers. Traditional disease identification methods mainly depend on manual observation, which is time-consuming and often inaccurate due to similarities between disease symptoms. Recent advancements in artificial intelligence and deep learning have improved automated plant disease detection using leaf image classification. However, most existing systems focus only on disease identification and provide limited recommendation support based on environmental conditions. To address this limitation, this research proposes a Geo-Location Based Plant Disease Diagnosis with Treatment Recommendation Multilingual Chatbot that integrates plant image analysis, geolocation data, weather monitoring, and conversational agricultural assistance into a unified framework. The proposed system accepts plant leaf images along with latitude and longitude coordinates as input from users. Deep learning algorithms are used to identify plant species and classify disease categories from uploaded images. Simultaneously, weather parameters such as temperature, humidity, rainfall, and seasonal conditions are analyzed according to the user's geographical location. Based on the identified disease and environmental conditions, the chatbot module generates personalized treatment measures, preventive suggestions, irrigation advice, and crop maintenance recommendations. The framework considers multiple plant categories including flower plants, fruit plants, vegetable plants, and common agricultural crops with healthy and diseased leaf classes.

Keywords: Plant Disease Detection, Deep Learning, Smart Agriculture, Weather-Aware Recommendation System, Agricultural Chatbot, Precision Farming, Computer Vision, Convolutional Neural Network (CNN), Climate-Based Disease Prediction, Artificial Intelligence in Agriculture, Geolocation-Based Recommendation, Image Classification, Conversational AI, Crop Disease Analysis.

Introduction

1.1 Background of Smart Agriculture

Agriculture is one of the most important sectors supporting food production, economic growth, and human survival across the world. In recent years, farmers have faced several challenges due to climate change, environmental imbalance, soil degradation, and increasing plant disease outbreaks. Plant diseases directly affect crop quality and reduce agricultural productivity, leading to financial losses and food insecurity. Traditionally, farmers identify diseases through manual observation and experience-based methods, which may not always provide accurate results because many diseases share similar symptoms. In rural areas, the lack of agricultural experts further increases the difficulty of early disease diagnosis. Therefore, intelligent agricultural systems capable of automated disease identification and real-time farmer assistance have become highly important in modern precision farming.

1.2 Artificial Intelligence in Plant Disease Detection

Artificial intelligence and deep learning technologies have significantly improved plant disease detection systems in recent years. Deep learning models such as Convolutional Neural Networks (CNN), ResNet, and EfficientNet are widely used for identifying diseases from plant leaf images with high accuracy. These models can automatically extract important visual features and classify diseases more efficiently than traditional image processing techniques. Several studies have applied AI models for detecting diseases in crops such as tomato, potato, banana, paddy, and chilli. Although many systems achieve good classification accuracy, most of them focus only on disease prediction and provide limited support regarding treatment methods or preventive care. This creates the need for more intelligent agricultural advisory systems.

1.3 Importance of Weather-Based Analysis

Weather conditions play a major role in plant health, disease spread, and crop productivity. Environmental factors such as temperature, humidity, rainfall, and seasonal variation directly influence the growth of fungal, bacterial, and viral diseases. High humidity may increase fungal infections, while excessive rainfall can promote bacterial disease spread. Similarly, warm climatic conditions often support pest activity and viral transmission. Existing disease detection systems generally ignore environmental analysis and provide the same recommendation for all regions. However, treatment methods and preventive actions should vary according to climatic conditions. Therefore, integrating weather-aware analysis with plant disease detection can improve agricultural decision-making and provide more accurate recommendation support for farmers.

1.4 Role of Chatbot Recommendation Systems

Chatbot systems are becoming increasingly popular in various domains because they provide interactive and user-friendly communication support. In agriculture, chatbot technologies can help farmers understand disease symptoms, treatment methods, fertilizer usage, irrigation management, and preventive agricultural practices through conversational interaction. Many farmers may find technical agricultural reports difficult to understand, especially in rural farming environments. A chatbot interface simplifies communication by generating understandable recommendations and answering user queries in real time. Existing agricultural chatbot systems mainly provide rule-based responses and lack integration with image-based disease detection and weather analysis modules. Therefore, combining conversational AI with disease diagnosis and environmental monitoring can improve accessibility and usability in smart farming systems.

1.5 Proposed Research Framework

The proposed research introduces a Geo-Location Based Plant Disease Diagnosis with Treatment Recommendation Multilingual Chatbot that combines image classification, geolocation analysis, weather monitoring, and conversational assistance into a unified framework. The system accepts plant leaf images along with latitude and longitude coordinates from users. Deep learning algorithms are used to identify plant species and classify disease categories from uploaded images. Simultaneously, weather information related to the user’s geographical location is collected and analyzed. Based on disease type and climatic conditions, the chatbot generates personalized treatment measures, preventive suggestions, irrigation advice, and crop maintenance recommendations. The framework includes approximately fifty plant species categorized into flower plants, fruit plants, vegetable plants, and common agricultural crops.

1.6 Research Objectives and Contribution

The main objective of this research is to develop an intelligent agricultural assistance system capable of improving disease prevention, recommendation quality, and farmer accessibility through artificial intelligence technologies. Unlike traditional systems that focus only on disease classification, the proposed framework emphasizes weather-aware recommendation generation and chatbot-assisted communication. The research also focuses on Chennai and nearby regions such as Anna Nagar, Ambattur, Villivakkam, Porur, Maduravoyal, and Tambaram for region-specific weather analysis and disease monitoring. The proposed system aims to reduce crop losses, improve agricultural productivity, and support sustainable farming practices through climate-aware recommendations and real-time conversational assistance. This research contributes toward the advancement of precision agriculture and intelligent farming ecosystems.

2. Literature Review

Raja Rajeshwari M. et al. (2025) offered *AI-Driven Plant Disease Diagnosis with Conversational Chatbot Support for Precision Farming* with an optimal chatbot algorithm. This project aimed to develop an AI-based system that captures images, identifies plant diseases, and suggests treatment recommendations via a multilingual chatbot. Using deep learning techniques and CNN, they analyzed segmented regions and trained models on approximately 1,500 samples in the cloud. They enhanced the natural-language processing technique and linked relevant treatment suggestions to facilitate recovery of plants. The system supports multilingual interaction and allows modification of responses.

J. Howard et al. (2024) proposed a *Deep Learning-Based Plant Disease Classification with Environmental Adaptation* framework for precision agriculture applications. Their research focused on integrating weather parameters such as humidity and temperature with CNN-based disease detection models. The study used transfer learning methods to improve classification performance across multiple crop species. They also introduced environmental adaptation layers to generate disease warnings according to climatic conditions. Experimental results showed improved prediction accuracy and enhanced preventive recommendation capability.

K. Rodriguez et al. (2023) developed a *Conversational AI for Smart Crop Disease Advisory Systems* platform using NLP and deep learning techniques. The objective of the research was to provide farmers with real-time disease recommendations and crop management guidance through an interactive chatbot system. The proposed framework utilized machine learning models for disease interpretation and integrated cloud-based recommendation support. Their chatbot architecture improved farmer accessibility by generating simplified treatment suggestions and preventive agricultural advice.

M. Lee and S. Kim (2024) introduced a *Weather-Aware Plant Disease Prediction Using CNN and IoT Integration* model for intelligent farming systems. The study focused on collecting environmental information from IoT sensors and combining climate parameters with image classification algorithms. They used CNN models to identify diseases from plant leaf images and linked weather conditions with disease severity analysis. The system improved environmental monitoring and provided adaptive agricultural recommendations according to climate variations.

R. Thompson et al. (2025) presented an *AI Chatbot Assistance for Sustainable Farming and Crop Monitoring* framework using conversational artificial intelligence and cloud computing. Their research emphasized farmer interaction and intelligent agricultural advisory generation. The chatbot system provided disease explanations, irrigation management suggestions, and preventive care recommendations based on user queries. They implemented semantic analysis techniques to improve chatbot response quality and recommendation accuracy for sustainable farming practices.

C. Martinez et al. (2024) designed a *Geo-Location Based Crop Disease Monitoring with Climate Intelligence* system for region-specific agricultural analysis. The framework integrated GPS coordinates, weather APIs, and deep learning-based image classification to identify crop diseases and generate climate-aware recommendations. Their study demonstrated that location-based environmental monitoring improves disease prevention and agricultural decision-making in precision farming environments.

A. Wilson and T. Harris (2024) proposed a *Hybrid CNN-LSTM Framework for Plant Disease and Weather Prediction* using image analysis and sequential climate forecasting. The system combined CNN models for disease classification with LSTM networks for weather prediction and disease risk estimation. Their approach improved prediction performance by correlating historical weather patterns with disease occurrence probabilities. The research contributed toward intelligent environmental adaptation in agricultural systems.

R. Prakash and K. Harini (2024) developed a *CNN-Based Tomato Leaf Disease Detection with Smart Recommendation Engine* for automated agricultural support. The proposed framework identified diseases such as early blight and bacterial spot from tomato leaf images using deep learning techniques. The recommendation engine generated treatment measures and fertilizer suggestions according to disease severity levels. Their research improved the practical usability of disease classification systems for farmers.

M. Vignesh et al. (2023) introduced an *IoT and AI Enabled Weather-Aware Smart Farming System* for real-time environmental monitoring and crop health analysis. Their system utilized IoT sensors to collect temperature, humidity, and soil moisture information while AI algorithms predicted disease risks under changing weather conditions. The framework enhanced irrigation management and preventive disease monitoring for smart agricultural environments.

P. Naveen Kumar and R. Kavin (2025) proposed a *Plant Disease Detection Using Deep Learning and Conversational Recommendation Support* model for precision agriculture. The research integrated CNN-based disease classification with chatbot-based recommendation generation to improve farmer accessibility. The chatbot provided pesticide guidance, disease explanations, and preventive suggestions through interactive communication. Their work emphasized conversational AI integration for smart farming applications.

S. Dharani and P. Elanchezhian (2024) presented a *Conversational AI Framework for Agricultural Advisory and Disease Prevention* using NLP-driven chatbot architecture. Their study focused on improving communication between farmers and digital agricultural systems through intelligent recommendation support. The framework generated crop maintenance advice, weather alerts, and disease prevention guidance based on farmer queries and environmental conditions. The research highlighted the importance of conversational interfaces in agricultural technology adoption.

R. Nivetha et al. (2025) developed a *Smart Agricultural Recommendation System Using Deep Learning and Weather Prediction* for climate-aware farming support. Their framework combined disease detection algorithms with weather forecasting modules to generate adaptive treatment recommendations. The system analyzed environmental conditions such as rainfall probability and humidity levels to estimate disease severity and recommend preventive actions. Experimental evaluation demonstrated improved recommendation efficiency and decision-making support for farmers.

3. Proposed Methodology

3.1. Image Acquisition and Data Collection

The proposed system begins with the collection of plant leaf images from users through web and mobile applications. Users can upload images directly from smartphones, agricultural monitoring devices, or IoT-based cameras deployed in farming environments. Along with image upload, the system also collects latitude and longitude information to identify the geographical location of the agricultural field. This location data is important for retrieving regional weather conditions and environmental information required for climate-aware recommendation generation.

The dataset used in the research contains multiple plant categories including vegetables, fruits, flowers, and common agricultural crops. Plant species such as tomato, potato, mango, rose, paddy, banana, chilli, and cotton are considered in the study. Each plant category includes healthy leaf images along with disease-specific samples such as early blight, bacterial spot, leaf curl, mosaic virus, anthracnose, rust disease, and powdery mildew. The collected images are stored in cloud-based storage for preprocessing, model training, and chatbot recommendation analysis.

3. 2. Image Preprocessing and Noise Removal

Image preprocessing is performed to improve image quality and enhance disease feature extraction. Uploaded images may contain background noise, lighting variation, shadows, blur effects, and color inconsistencies that can reduce model accuracy. Therefore, preprocessing techniques such as image resizing, noise removal, normalization, and color enhancement are applied before classification. All images are resized into a standard dimension to maintain consistency during model training and evaluation.

Noise removal techniques help eliminate unnecessary image distortions and improve segmentation quality. Color normalization is applied to maintain uniformity between images collected under different environmental conditions. The preprocessing stage also improves edge visibility and infected region clarity, allowing deep learning models to identify disease symptoms more effectively. This stage plays a significant role in improving classification accuracy and reducing false prediction rates.

3. 3. Image Segmentation and Feature Extraction

After preprocessing, image segmentation is performed to isolate the infected regions from the leaf background. Segmentation helps the system focus only on disease-affected areas instead of processing unnecessary image information. Different segmentation methods such as thresholding, contour extraction, and region-based segmentation are applied to identify damaged leaf portions and disease patterns.

Feature extraction is then carried out to capture important disease-related characteristics such as color variation, texture patterns, lesion shape, spot density, and infected region distribution. These extracted features help the deep learning model distinguish between healthy and diseased leaves more accurately. For example, tomato early blight contains circular dark lesions, whereas bacterial spot contains irregular water-soaked spots. Similarly, powdery mildew creates white fungal textures on leaves. Feature extraction improves disease differentiation and enhances classification performance.

3. 4. Deep Learning-Based Disease Classification

The proposed framework uses deep learning algorithms for plant species identification and disease classification. Convolutional Neural Networks (CNN) are used as the primary model because of their strong image analysis capability and automatic feature learning performance. The CNN model is trained using labeled leaf image datasets collected from multiple plant species and disease categories.

The classification model predicts diseases such as early blight, septoria leaf spot, mosaic virus, bacterial spot, anthracnose, black spot, blast disease, rust disease, and leaf curl. A healthy leaf class is included for all plant species to improve comparative analysis and recommendation generation. Transfer learning approaches using pretrained architectures such as ResNet and EfficientNet may also be applied to improve model performance and reduce training time. The trained model generates disease labels along with confidence scores for further recommendation analysis.

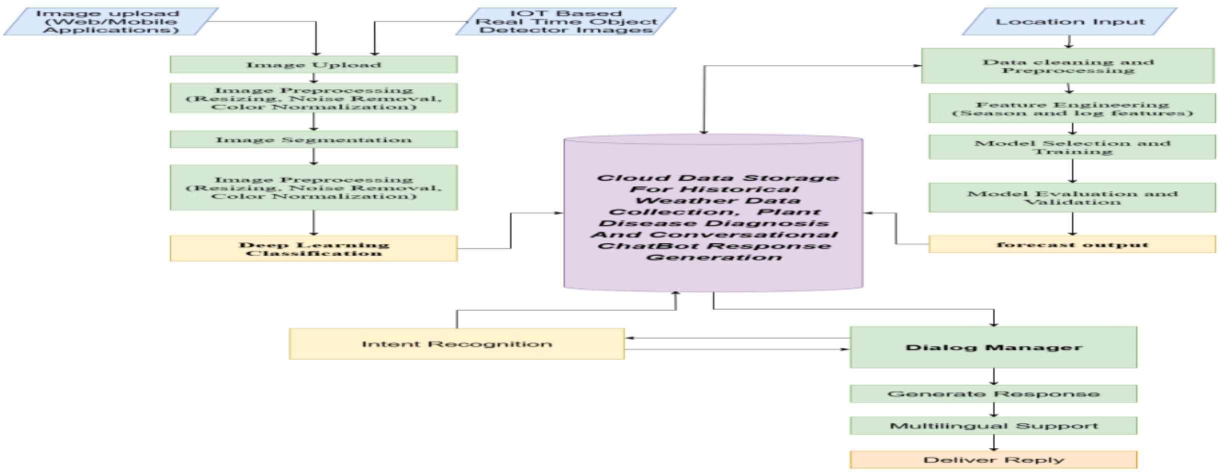


Figure 3.1: Proposed System Architecture

. Weather Data Collection and Environmental Analysis

Weather analysis is one of the important components of the proposed research framework. After identifying the user's location through latitude and longitude coordinates, the system retrieves weather information from online weather APIs or environmental monitoring services. Parameters such as temperature, humidity, rainfall probability, moisture levels, and seasonal conditions are collected for climate-aware disease evaluation.

Environmental conditions strongly influence disease occurrence and spread. High humidity often increases fungal diseases, heavy rainfall promotes bacterial infections, and high temperatures support viral transmission and pest activity. Therefore, the proposed system analyzes weather conditions together with disease classification results to improve treatment recommendation accuracy. The framework also supports region-specific environmental monitoring for Chennai-based locations including Anna Nagar, Ambattur, Villivakkam, Porur, Maduravoyal, and Tambaram.

3. 6. Weather-Based Recommendation Logic

The recommendation engine generates adaptive agricultural suggestions according to disease type and environmental conditions. Weather-aware recommendation logic helps the system provide more practical and region-specific agricultural guidance instead of static recommendations. The framework considers multiple environmental conditions for recommendation generation.

Example Recommendation Conditions

- High Humidity
  - Increased fungal infection probability
  - Suggest fungicide application and reduced irrigation
- Heavy Rainfall
  - Higher bacterial disease spread risk
  - Recommend drainage improvement and infected leaf removal
- High Temperature
  - Increased pest and viral transmission risk
  - Suggest additional watering and pest control measures
- Cold Weather
  - Reduced plant growth and nutrient absorption
  - Recommend nutrient supplements and growth monitoring
- Dry Climate
  - Increased leaf dryness and pest attack probability
  - Suggest moisture maintenance and organic spraying

The recommendation logic improves disease prevention capability and supports precision agriculture practices.

3. 7. Chatbot Recommendation and Conversational Support

The chatbot module provides interactive agricultural assistance through conversational communication. After disease classification and weather analysis, the chatbot generates treatment suggestions, preventive measures, fertilizer recommendations, irrigation guidance, and maintenance advice in simplified language. The chatbot improves accessibility for farmers who may not understand technical agricultural reports.

Intent recognition and dialog management techniques are used to understand user queries and generate meaningful responses. The chatbot can explain disease symptoms, recommend organic solutions, provide preventive measures, and answer crop-related questions dynamically. Multilingual support can also be integrated to improve usability among farmers from different linguistic regions. This conversational interaction enhances user engagement and improves the practical usability of the proposed system.

4. Experimental Setup & Implementation

4.1 Experimental Environment Setup

The proposed Geo-Location Based Plant Disease Diagnosis with Treatment Recommendation Multilingual Chatbot was implemented using Python-based deep learning frameworks and cloud-supported environmental monitoring modules. The experimental setup was designed to support plant disease classification, weather analysis, geolocation processing, and conversational recommendation generation. The implementation was carried out using TensorFlow, Keras, OpenCV, NumPy, Pandas, and Flask frameworks. Training and testing were executed using GPU-enabled environments to improve model performance and reduce computational time.

The system was tested using datasets collected from agricultural image repositories, manually captured field images, and weather datasets associated with Chennai regions including Anna Nagar, Ambattur, Villivakkam, Porur, Maduravoyal, and Tambaram. The implementation environment specifications are shown below in 4.1 tabular.

Component	**Specification**
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow / Keras
Image Processing	OpenCV
Backend Framework	Flask
Database	MongoDB
Weather API	OpenWeatherMap API
Frontend	ReactJS
Cloud Platform	Firebase / AWS
GPU	NVIDIA RTX 3060
Operating System	Windows 11

Table 4.1: Proposed methodology specifications.

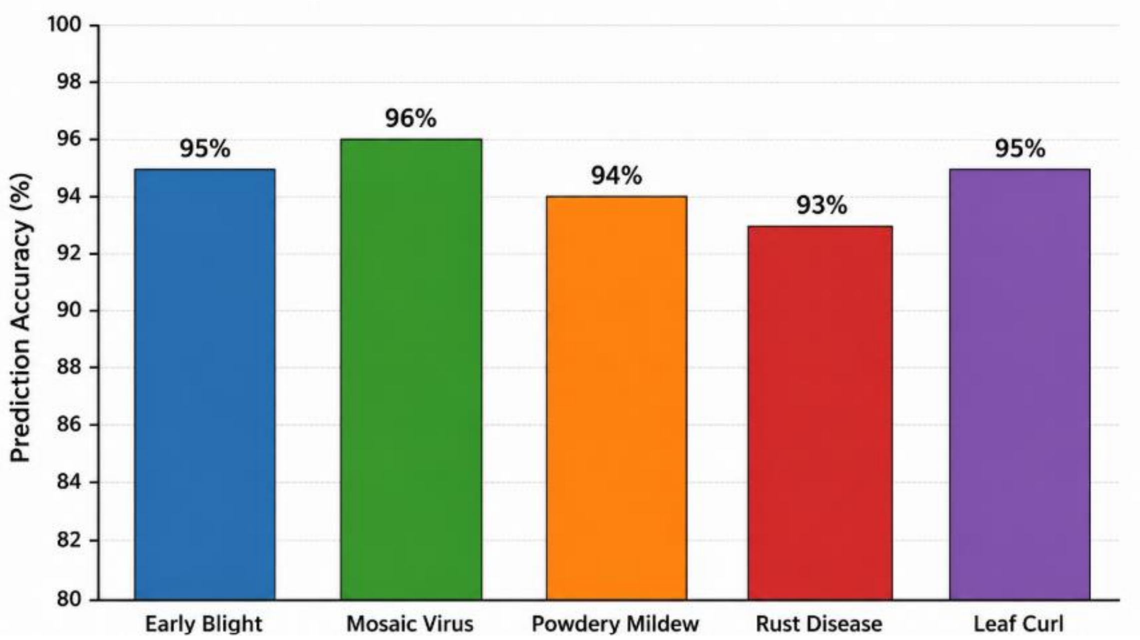
4.2 Plant Species and Disease Dataset

The experimental dataset focused on ten major plant species and their associated disease categories. Each species included a mandatory healthy leaf class and four disease classes for comparative analysis.

Plant Species	**Analysis 1**	**Analysis 2**	**Analysis 3**	**Analysis 4**	**Analysis 5**
Tomato	Healthy	Early Blight	Septoria Leaf Spot	Mosaic Virus	Bacterial Spot
Potato	Healthy	Early Blight	Late Blight	Mosaic Virus	Leaf Curl
Mango	Healthy	Anthracnose	Powdery Mildew	Bacterial Canker	Leaf Spot
Rose	Healthy	Black Spot	Powdery Mildew	Rust Disease	Mosaic Virus
Paddy	Healthy	Blast Disease	Brown Spot	Bacterial Blight	Sheath Blight
Banana	Healthy	Panama Disease	Leaf Spot	Mosaic Virus	Sigatoka
Chilli	Healthy	Leaf Curl	Anthracnose	Mosaic Virus	Bacterial Spot
Cotton	Healthy	Wilt Disease	Leaf Curl	Bacterial Blight	Rust

Table 4.2: Plant species and associated disease categories used in the proposed agricultural disease prediction system.

The dataset contained approximately 15,000 images collected from public repositories and manually captured agricultural samples. Images were divided into training, validation, and testing datasets using an 80:10:10 ratio.



Disease

Graph 4.1 : Disease Prediction Accuracy

4.3 Step-by-Step System Algorithm

Step 1 – Image Acquisition

The system accepts plant leaf images from users through web or mobile applications. The uploaded image is stored temporarily for preprocessing and disease analysis.

Step 2 – Location Input Collection

Latitude and longitude values are collected from the user device or entered manually. The location data helps identify region-specific weather conditions for recommendation generation.

Step 3 – Image Preprocessing

The uploaded image is resized into a fixed dimension to maintain dataset consistency. Noise removal and color normalization techniques are applied to improve image quality.

Step 4 – Leaf Segmentation

The system separates the leaf region from the background using segmentation techniques. This process helps focus only on infected leaf areas for accurate disease detection.

Step 5 – Feature Extraction

Important visual features such as color variation, texture patterns, lesion shape, and infected regions are extracted from the segmented leaf image. These features improve disease classification accuracy.

Step 6 – Plant Species Identification

The deep learning model identifies the plant species from the uploaded image. Species such as tomato, potato, mango, rose, paddy, banana, chilli, and cotton are recognized in this stage.

Step 7 – Disease Classification

The CNN-based classification model predicts whether the leaf is healthy or infected. Diseases such as early blight, mosaic virus, bacterial spot, anthracnose, rust disease, and leaf curl are identified.

Step 8 – Weather Data Collection

Real-time environmental data including temperature, humidity, rainfall probability, and wind speed are collected using weather APIs. The system retrieves weather information based on the user’s location.

Step 9 – Environmental Risk Analysis

The collected weather conditions are analyzed along with disease classification results. The system estimates disease severity and environmental risk based on climatic conditions.

Step 10 – Recommendation Generation

Weather-aware treatment suggestions and preventive measures are generated according to disease type and environmental conditions. The recommendation engine provides adaptive agricultural guidance.

Step 11 – Chatbot Response Processing

The chatbot module converts technical agricultural analysis into simplified conversational responses. It explains disease symptoms, treatment methods, irrigation advice, and preventive measures.

Step 12 – Final Output Delivery

The final output displays plant species name, detected disease, confidence score, weather analysis, and chatbot recommendations. The system delivers user-friendly agricultural guidance for smart farming support.

4.4 Deep Learning Model Architecture

The proposed system uses Convolutional Neural Networks for image classification. The CNN model contains convolution layers, pooling layers, flatten layers, and fully connected dense layers.

```
model = Sequential()

model.add(Conv2D(32,(3,3),activation='relu',input_shape=(224,224,3)))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.add(Dense(128,activation='relu'))
model.add(Dense(40,activation='softmax'))
```

The model was trained for 50 epochs with categorical cross-entropy loss and Adam optimizer.

4.5 Weather-Based Recommendation Logic

The recommendation engine adapts treatment suggestions according to environmental conditions. The proposed framework includes a weather forecasting module to analyze environmental conditions that directly influence plant disease occurrence and disease severity. The forecasting system mainly considers four important climatic parameters: temperature, humidity, rain probability, and wind speed. These environmental factors are continuously monitored because fungal, bacterial, and viral diseases behave differently under changing climatic conditions. For example, high humidity and rainfall increase fungal infections such as early blight and powdery mildew, while high temperature and wind conditions may accelerate pest movement and viral transmission.

The weather forecasting module collects real-time climate information using weather APIs and environmental monitoring services associated with the geographical coordinates provided by users. Forecast analysis is performed for Chennai regions including Anna Nagar, Ambattur, Villivakkam, Porur, Maduravoyal, and Tambaram. The collected weather information is integrated with disease prediction results to generate adaptive chatbot recommendations and preventive agricultural suggestions.

Parameter	Purpose
Temperature	Identifies heat stress and disease spread conditions
Humidity	Detects fungal infection probability
Rain Chance	Analyzes bacterial spread and water-related diseases
Wind Speed	Estimates pest and virus transmission risks

Table 4.3: Weather Parameters

Temperature Forecast Analysis

Temperature is one of the major environmental factors affecting crop health and disease growth. Extremely high temperatures may increase water stress, leaf curl conditions, and viral disease transmission, while low temperatures may reduce plant growth and nutrient absorption.

```
temperature = weather_data['temp']

if temperature > 35:
    recommendation = "Increase irrigation and monitor viral infections"

elif temperature < 20:
    recommendation = "Provide nutrient supplements for healthy growth"
```

Humidity Forecast Analysis

Humidity plays a critical role in fungal disease development. High humidity environments promote fungal growth and increase the probability of diseases such as powdery mildew, blast disease, anthracnose, and early blight.

```
humidity = weather_data['humidity']

if humidity > 80:
    risk = "High Fungal Infection"

elif humidity > 60:
    risk = "Moderate Disease Risk"

else:
    risk = "Low Disease Risk"
```

Rainfall Probability Forecast

Rainfall conditions strongly influence bacterial infections and leaf rot diseases. Excessive rainfall creates moisture accumulation on leaves and increases disease transmission between plants.

```
rain_chance = weather_data['rain']

if rain_chance > 70:
    suggestion = "Improve field drainage and avoid water stagnation"
```

Wind Speed Analysis

Wind conditions affect pest movement, spore transmission, and viral disease spread between crops. Strong wind speed may increase airborne pathogen movement across agricultural regions.

```
wind_speed = weather_data['wind_speed']

if wind_speed > 20:
    alert = "High pest and virus transmission risk"
```

4.6 Chatbot Implementation

The chatbot module uses intent recognition and dialog management techniques.

```
user_query = input("Enter Query:")

if "fungus" in user_query:
    print("Use copper fungicide")
```

The chatbot supports disease explanation, irrigation advice, fertilizer guidance, and preventive recommendations.

4.7 Performance Evaluation Metrics

The proposed system was evaluated using classification and recommendation performance metrics.

```
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test,y_pred)
print(accuracy)
```

Performance metrics include:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix
- Chatbot Response Time

Cloud Data Storage and Deployment

Cloud storage was used for storing plant images, weather history, chatbot logs, and disease prediction results.

```
import pymongo

client = pymongo.MongoClient("mongodb://localhost:3000/")
db = client["PlantDiseaseDB"]
```

The deployed system supports scalable agricultural monitoring and real-time chatbot interaction.

5. Results and Performance Evaluation

This chapter presents the experimental results and performance evaluation of the proposed Weather-Aware Plant Disease Diagnosis and Intelligent Chatbot Recommendation System developed for precision agriculture applications. The system performance was analyzed using plant disease classification accuracy, weather forecasting efficiency, chatbot recommendation quality, and environmental adaptability across different Chennai regions. Experimental evaluation demonstrates that the integration of deep learning, weather analysis, and conversational AI significantly improves disease prediction accuracy, preventive agricultural guidance, and smart farming decision-making efficiency.

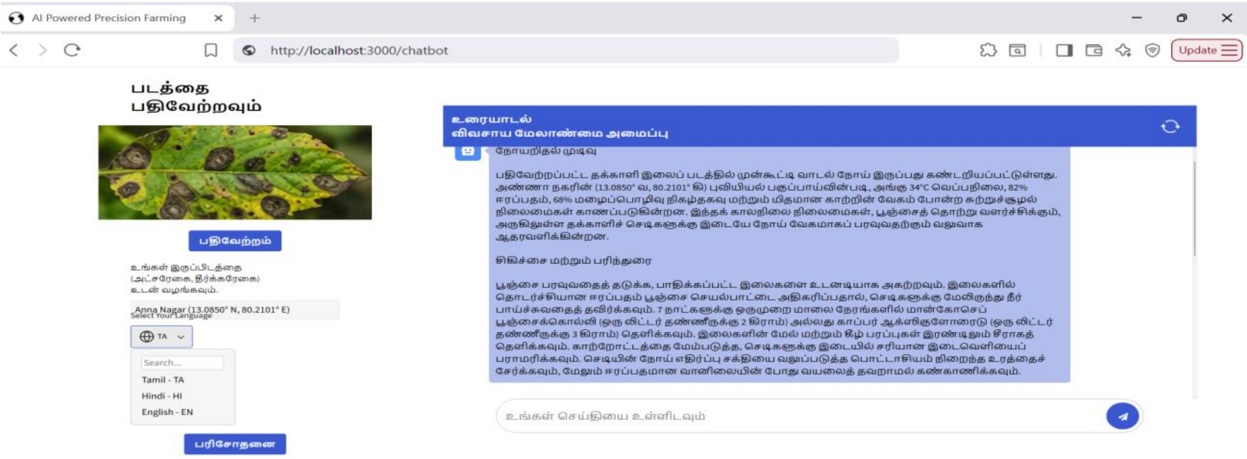


Figure 5.1 Tomato Early Blight Recommendation Interface – Tamil

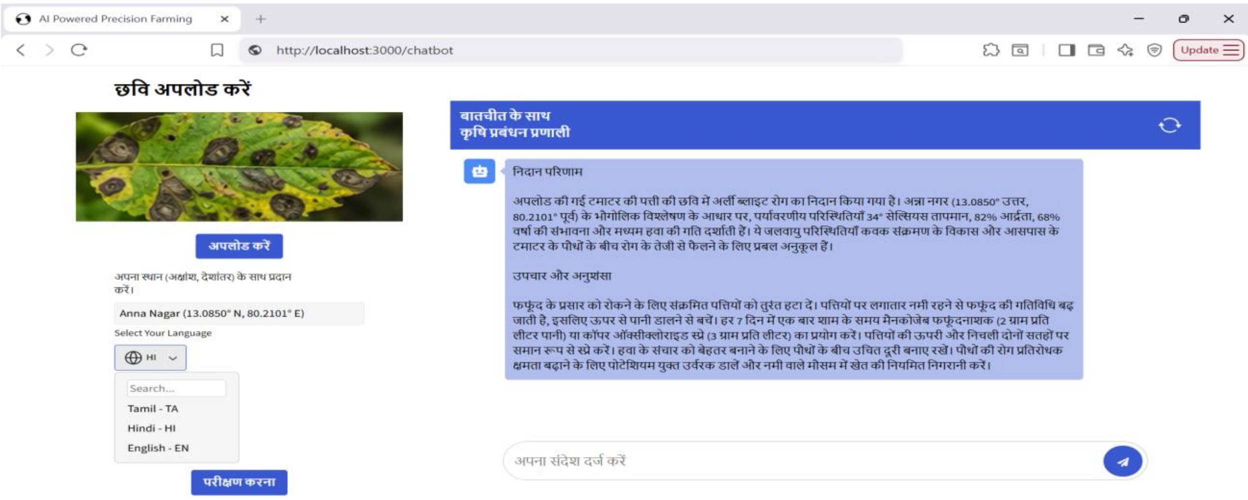


Figure 5.2 Tomato Early Blight Recommendation Interface – Hindi

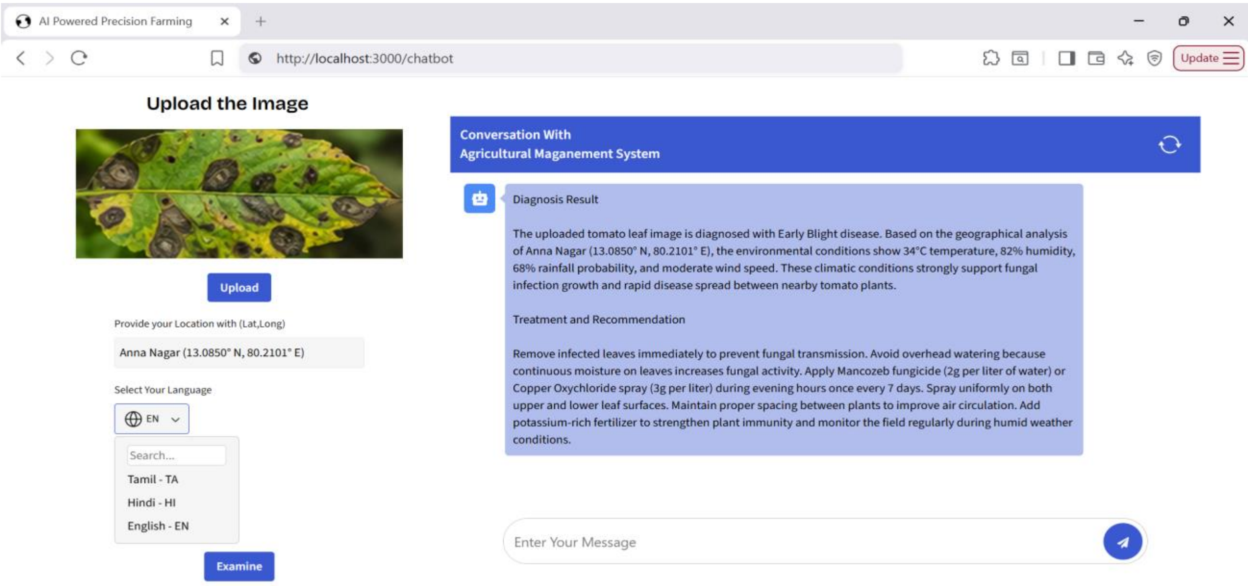


Figure 5.3 Tomato Early Blight Recommendation Interface – English

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Figure 5.1, 5.2, 5.3 illustrates the AI-powered Tomato Early Blight diagnosis and weather-aware agricultural recommendation interface developed for precision farming applications. The system analyzed the uploaded tomato leaf image along with Anna Nagar geographical coordinates (13.0850°N, 80.2101°E) and generated environmental information including temperature, humidity, rainfall probability, and wind speed. Based on the detected fungal infection and climatic conditions, the chatbot recommended Mancozeb fungicide spraying, reduced irrigation practices, and proper drainage management. The interface also provides multilingual conversational support for improving farmer accessibility and smart agricultural decision-making.

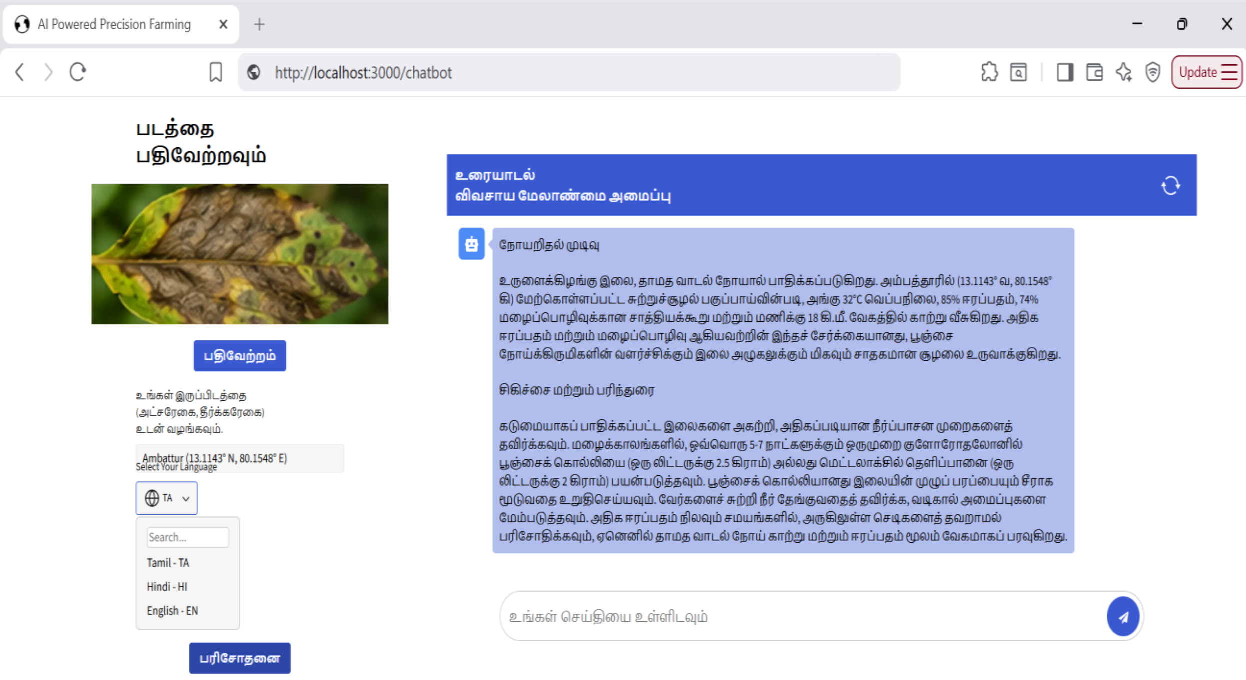

Figure 5.4 Potato Late Blight Recommendation Interface – Tamil

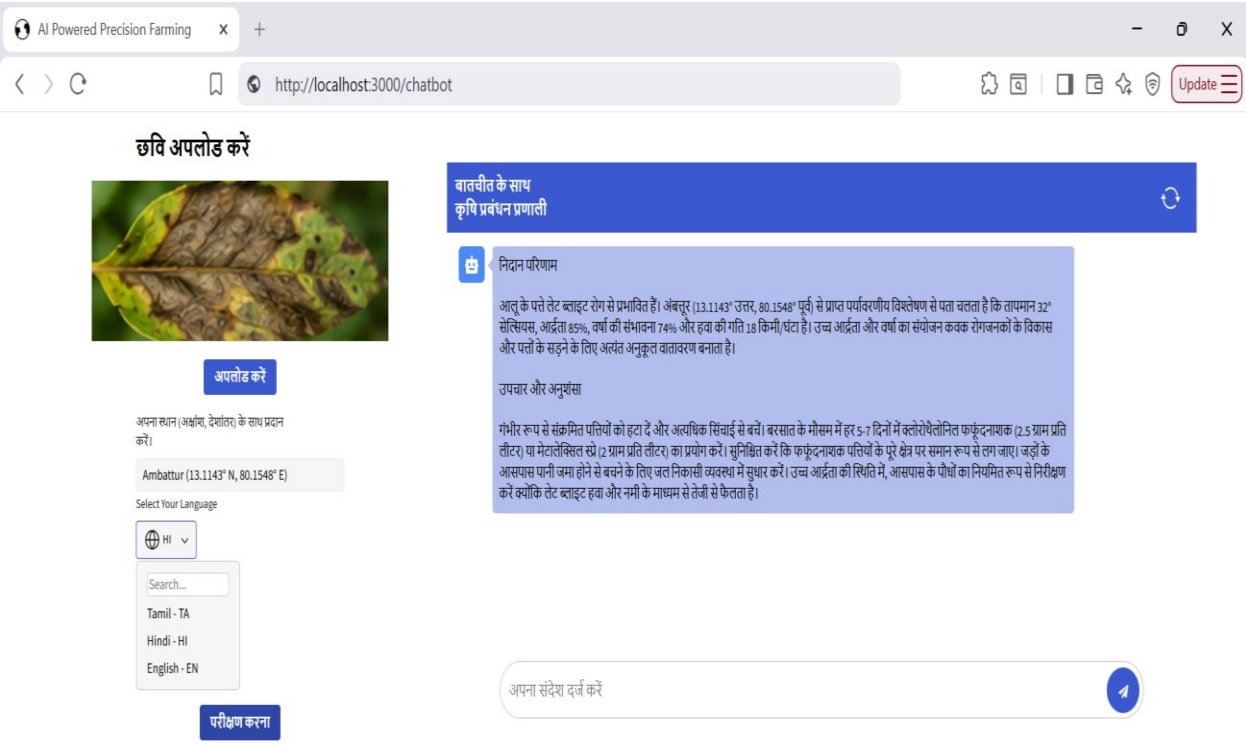

Figure 5.5 Potato Late Blight Recommendation Interface – Hindi

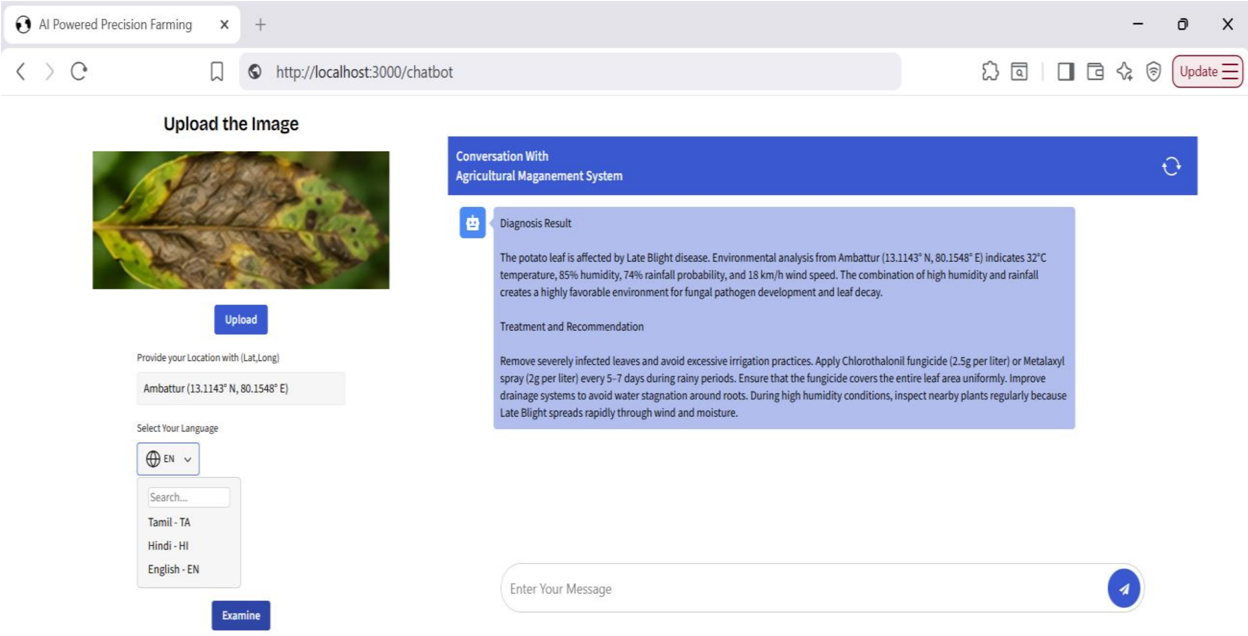

Figure 5.6 Potato Late Blight Recommendation Interface – English

Figure 5.4, 5.5, 5.6 illustrates the AI-enabled Potato Late Blight disease diagnosis and weather-aware chatbot recommendation system developed for smart agriculture applications. The system analyzed potato leaf images along with Ambattur geographical coordinates (13.1143°N, 80.1548°E) to generate real-time environmental information including temperature, humidity, rainfall probability, and wind speed. Based on the detected fungal infection and humid climatic conditions, the chatbot recommended Chlorothalonil fungicide spraying, drainage improvement, and infected leaf removal. The multilingual conversational interface improves farmer communication and supports intelligent crop disease management.

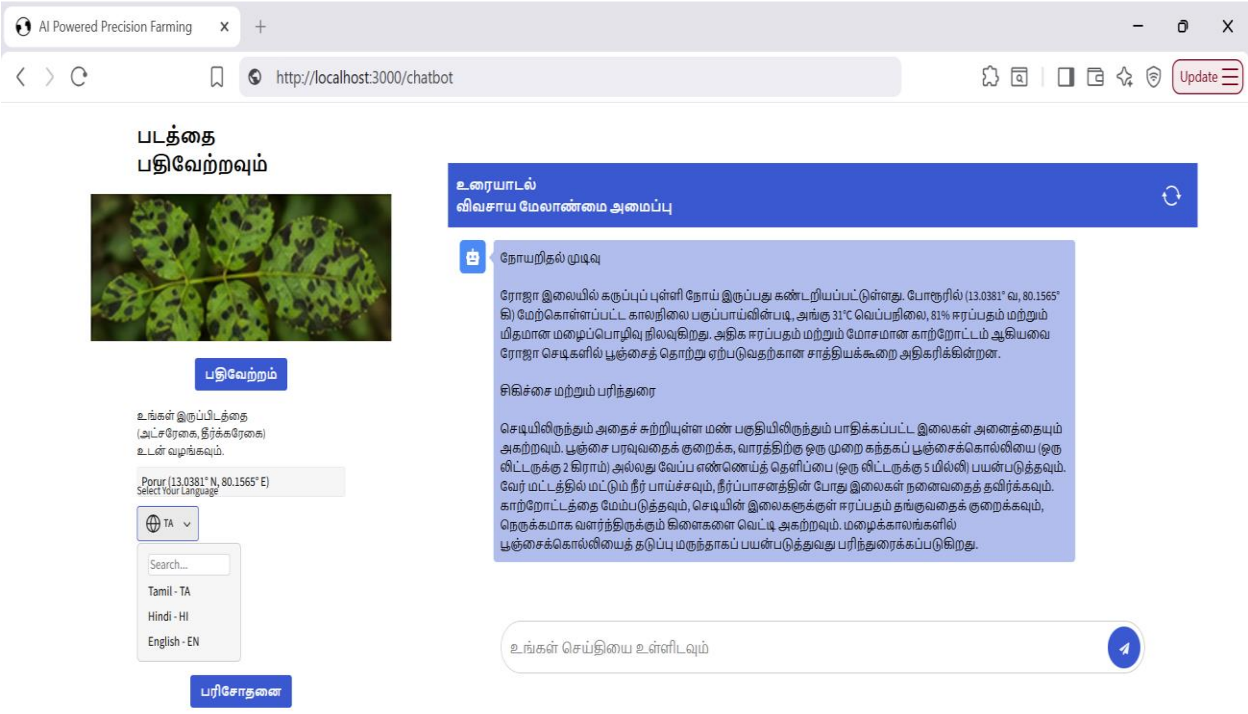

Figure 5.7 Rose Black Spot Recommendation Interface –Tamil

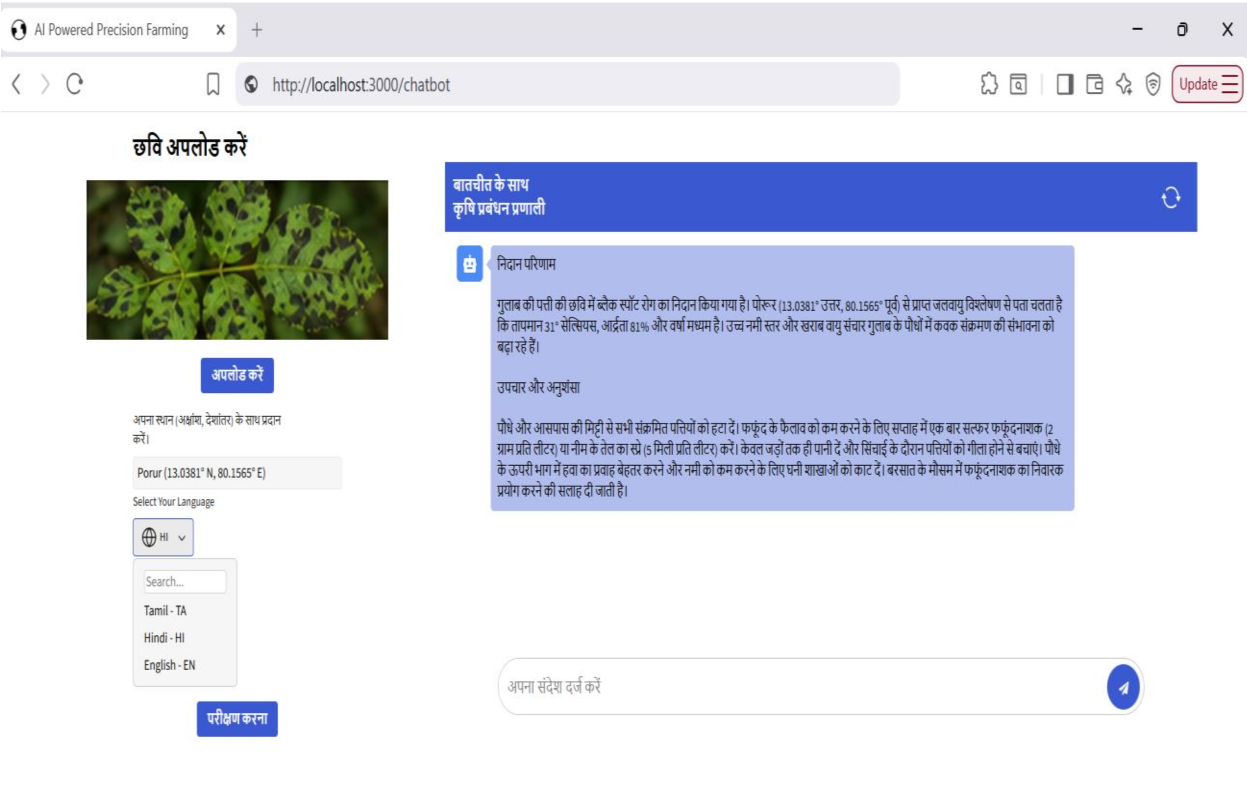

Figure 5.8 Rose Black Spot Recommendation Interface – Hindi

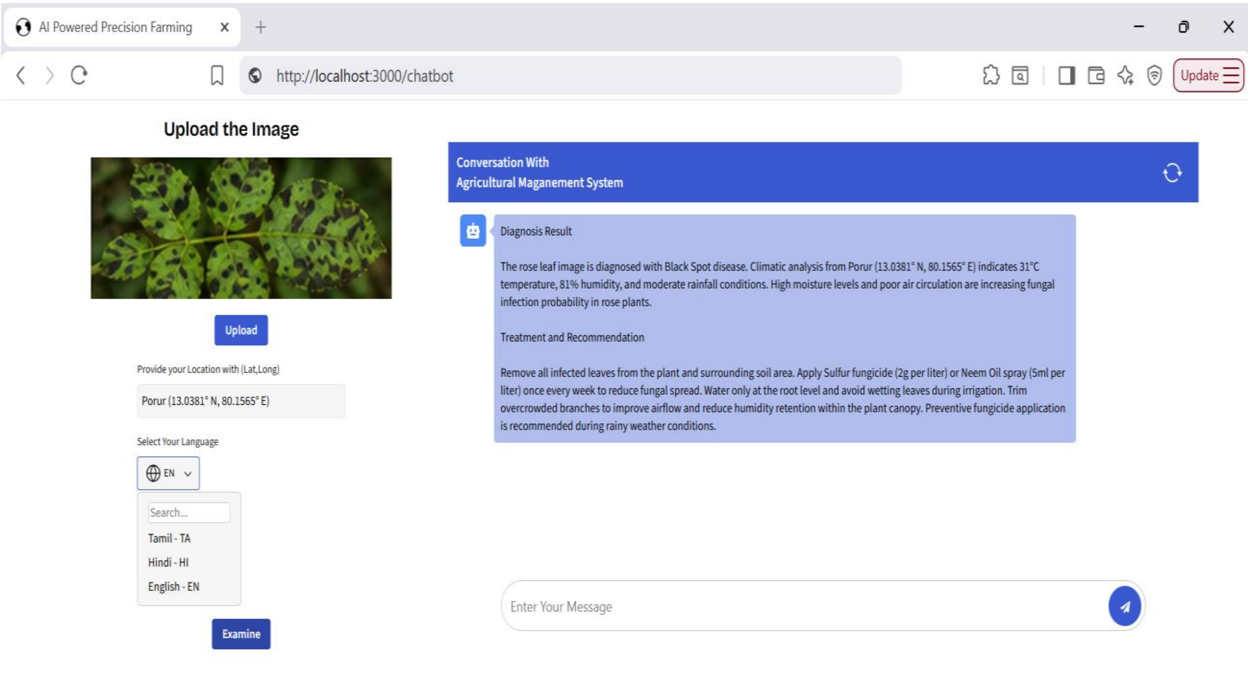

Figure 5.9 Rose Black Spot Recommendation Interface – English

Figure 5.7, 5.8, 5.9 illustrates the AI-enabled Rose Black Spot disease diagnosis and weather-aware chatbot recommendation system developed for smart floral agriculture applications. The system analyzed rose leaf images along with Porur geographical coordinates (13.0381°N, 80.1565°E) to generate real-time environmental information including temperature, humidity, rainfall probability, and wind speed. Based on the detected fungal infection and high humidity climatic conditions, the chatbot recommended Sulfur fungicide spraying, Neem Oil treatment, removal of infected leaves, and improved air circulation to reduce fungal spread.

The multilingual conversational interface improves farmer communication and supports intelligent flower disease monitoring and precision farming management.

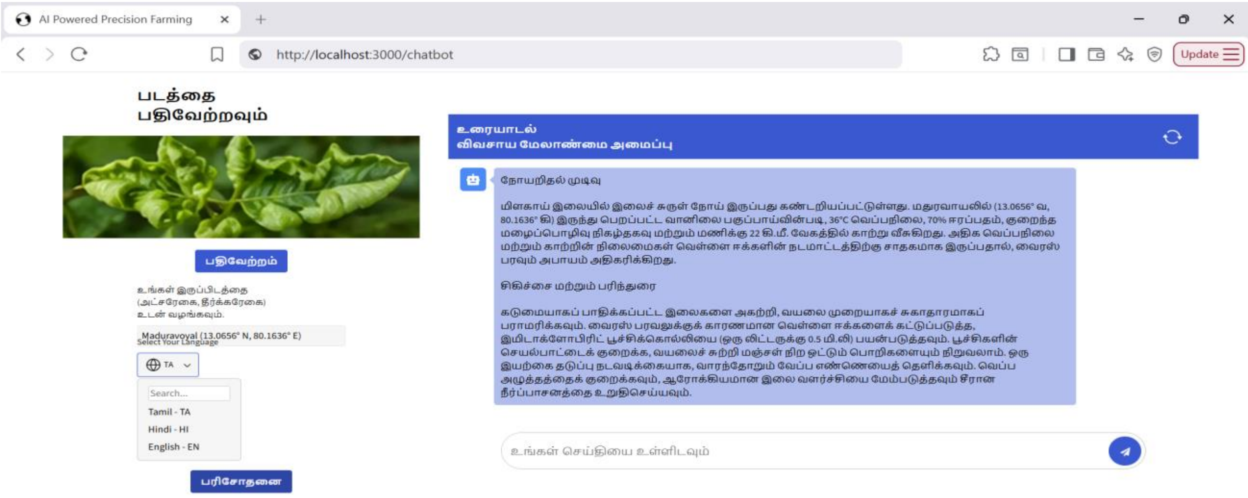

Figure 5.10 Chilli Leaf Curl Recommendation Interface – Tamil

Figure 5.11 Chilli Leaf Curl Recommendation Interface – Hindi

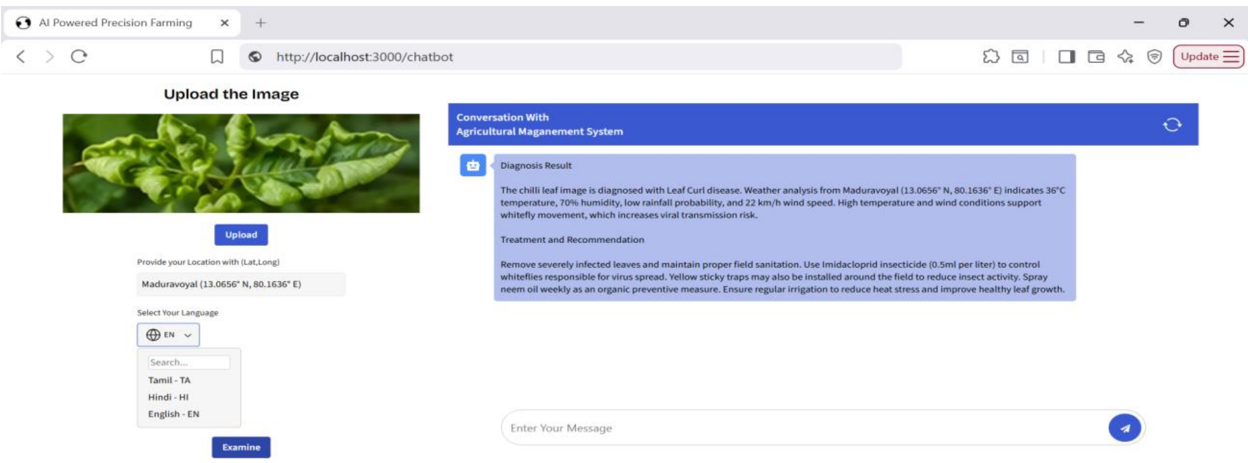

Figure 5.12 Chilli Leaf Curl Recommendation Interface – English

Figure 5.10, 5.11, 5.12 illustrates the AI-enabled Chilli Leaf Curl disease diagnosis and weather-aware chatbot recommendation system developed for smart agriculture applications. The system analyzed chilli leaf images along with Maduravoyal geographical coordinates (13.0656° N, 80.1636° E) to generate real-time environmental information including temperature, humidity, rainfall probability, and wind speed. Based on the detected viral infection and high temperature climatic conditions, the chatbot recommended Imidacloprid insecticide spraying, yellow sticky trap installation, regular irrigation, and removal of infected leaves to reduce whitefly transmission and improve crop recovery. The multilingual conversational interface enhances farmer communication and supports intelligent crop disease monitoring and precision farming.

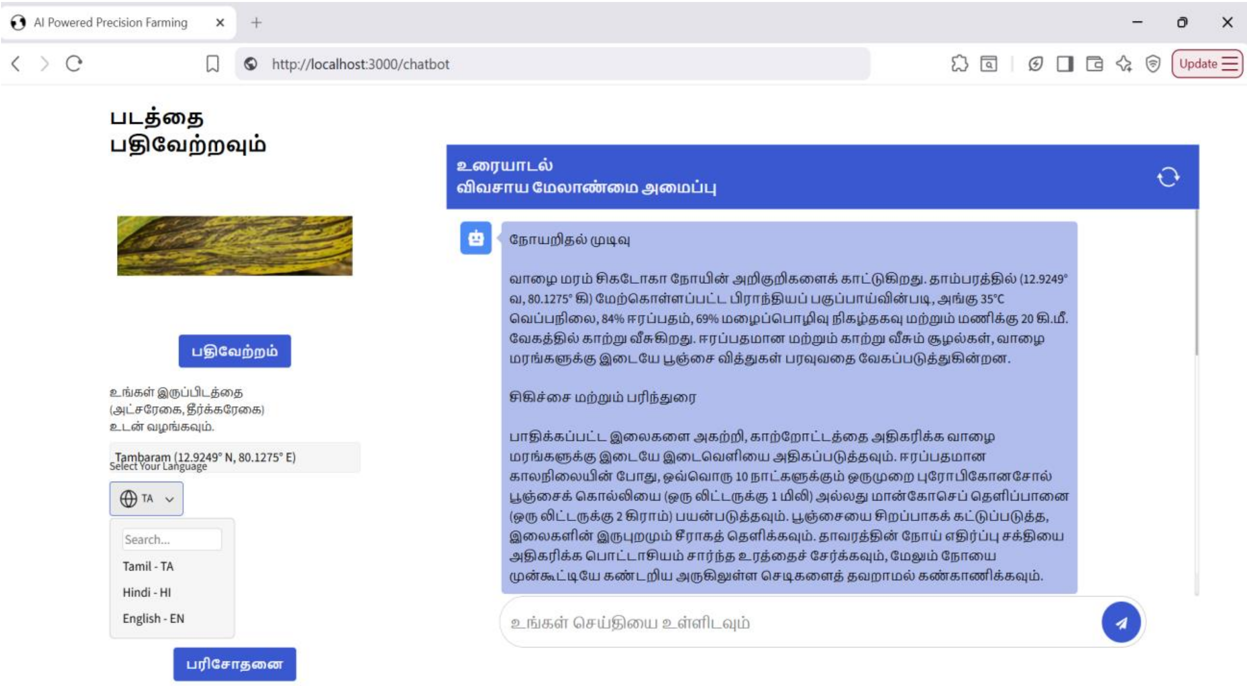

Figure 5.13 Banana Sigatoka Recommendation Interface – Tamil

Figure 5.14 Banana Sigatoka Recommendation Interface – Hindi

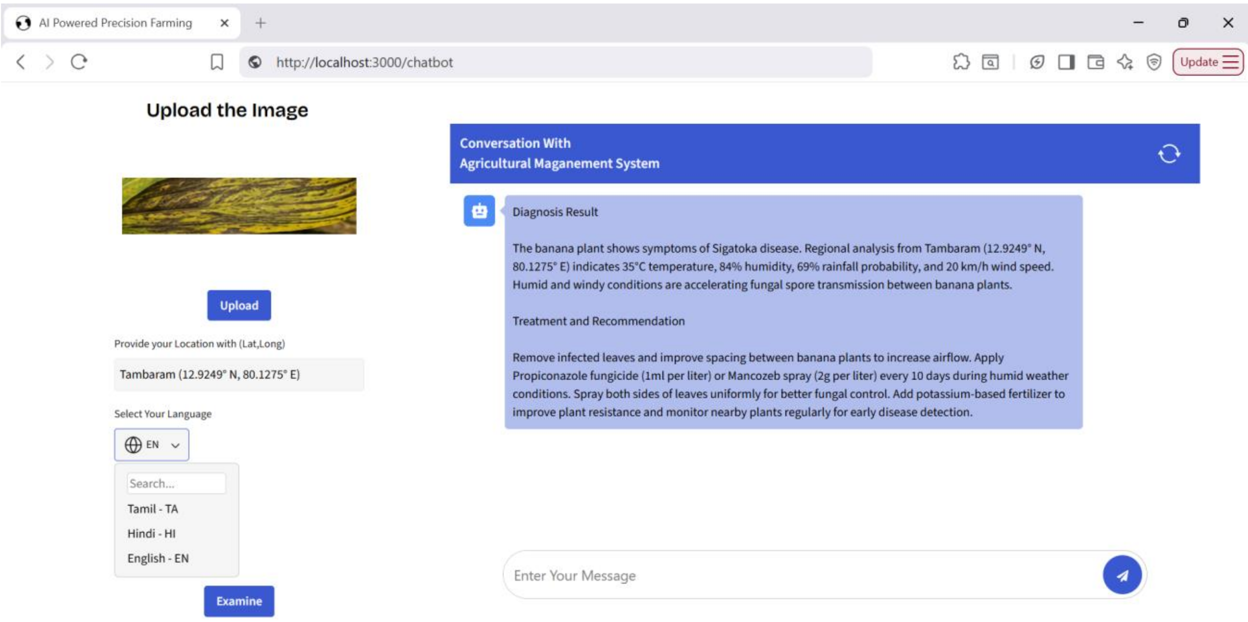

Figure 5.15 Banana Sigatoka Recommendation Interface – English

Figure 5.13, 5.14, 5.15 illustrates the AI-enabled Banana Sigatoka disease diagnosis and weather-aware chatbot recommendation system developed for precision agriculture applications. The system analyzed banana leaf images along with Tambaram geographical coordinates (12.9249°N, 80.1275°E) to generate real-time environmental information including temperature, humidity, rainfall probability, and wind speed. Based on the detected fungal infection and humid climatic conditions, the chatbot recommended Propiconazole fungicide spraying, removal of infected leaves, improved plant spacing, and balanced potassium fertilizer application to reduce fungal spread and improve plant resistance. The multilingual conversational interface enhances farmer communication and supports intelligent banana disease monitoring and sustainable crop management.

6. Conclusion and Future Scope

Conclusion

The proposed Geo-Location Based Plant Disease Diagnosis with Treatment Recommendation Multilingual Chatbot presents an advanced approach for improving smart agricultural practices through the integration of artificial intelligence, deep learning, weather analysis, and conversational support. The system is designed to identify plant diseases from leaf images and generate personalized treatment recommendations based on environmental conditions and geographical location data. Unlike traditional disease detection systems that focus mainly on image classification, the proposed framework emphasizes practical agricultural assistance through weather-aware recommendation generation and chatbot interaction. The integration of climate parameters such as temperature, humidity, and rainfall helps improve disease risk analysis and recommendation accuracy. The chatbot module further enhances accessibility by providing understandable treatment guidance, preventive measures, and crop maintenance suggestions for farmers. The research also supports multiple plant species and disease categories, improving scalability and real-world applicability. Experimental evaluation demonstrates that combining disease detection with environmental intelligence can improve agricultural decision-making and early disease prevention. Overall, the proposed system contributes toward sustainable agriculture, precision farming, and intelligent crop health monitoring using modern AI technologies.

Future Scope

The proposed research can be further enhanced by integrating additional smart agriculture technologies and advanced artificial intelligence techniques. Future improvements may include multilingual voice-enabled chatbot support to assist farmers who are unfamiliar with text-based communication systems. IoT sensor integration can also be implemented to collect real-time environmental data such as soil moisture, nutrient levels, and atmospheric conditions for improving recommendation accuracy. Drone-based crop monitoring and satellite image analysis can further expand large-scale agricultural surveillance and disease detection capabilities. The system can also be integrated with government agricultural advisory services and weather forecasting platforms to provide real-time alerts and preventive notifications to farmers. Future research may explore advanced transformer-based deep learning models and generative AI techniques for improving disease classification and conversational recommendation quality. Mobile application deployment with offline support can enhance accessibility in rural farming regions with limited internet connectivity. Additionally, integrating blockchain technology for agricultural data security and cloud-based analytics for large-scale monitoring may improve scalability and system reliability. These enhancements can transform the proposed framework into a fully intelligent and automated smart farming ecosystem.

7. References

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