**AI-Based Crop Disease Detecion System**

## **A PROJECT REPORT**

***Submitted by,***

**Mr. Talla Sunil Kumar - 20211CAI0198**

**Mr. Challa Yogesh - 20211CAI0162**

**Mr. Salapakshi Sagar – 20211CAI0094**

**Ms. Gade Prathyusha – 20211CAI0200**

**Mr. Jampana Venkata Arjun Varma -20211CAI0060**

### *Under the guidance of,*

**Dr. Afroz Pasha**

***in partial fulfillment for the award of the degree of***

**BACHELOR OF TECHNOLOGY**

**IN**

**COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence & Machine Learning).**

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**PRESIDENCY UNIVERSITY**

**SCHOOL OF COMPUTER SCIENCE ENGINEERING**

**CERTIFICATE**

This is to certify that the Project report **“AI-BASED CROP DISEASE DETECTION SYSTEM”** being submitted by “**TALLA SUNIL KUMAR, CHALLA YOGESH, SALAPAKSHI SAGAR, GADE PRATHYUSHA, JAMPANA VENKATA ARJUN VARMA**” bearing roll number(s) “**20211CAI0001, 20211CAI0024, 20211CAI0060**” in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence & Machine Learning) is a Bonafide work carried out under my supervision.

|  |  |
| --- | --- |
| **Dr. Afroz Pasha**  Assistant professor Senior Scale  School of CSE  Presidency University | **Dr. ZAFAR ALI KHAN**  Associate Professor & HOD  School of CSE&IS  Presidency University |

|  |  |  |
| --- | --- | --- |
| **Dr. L. SHAKKEERA**  Associate Dean  School of CSE  Presidency University | **Dr. MYDHILI NAIR**  Associate Dean  School of CSE  Presidency University | **Dr. SAMEERUDDIN KHAN**  PRO-VC School of Engineering  Dean -School of CSE&IS  Presidency University |

**PRESIDENCY UNIVERSITY**

**SCHOOL OF COMPUTER SCIENCE ENGINEERING**

**DECLARATION**

We hereby declare that the work, which is being presented in the project report entitled **AI-BASED CROP DISEASE DETECTION SYSTEM** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence & Machine Learning)**, is a record of our own investigations carried under the guidance of **Dr. Afroz Pasha, Assistant professor Senior Scale,** **School of Computer Science Engineering, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

|  |  |  |
| --- | --- | --- |
| **Name of Student** | **Roll Number** | **Signature** |
| Talla Sunil Kumar | 20211CAI0198 |  |
| Challa Yogesh | 20211CAI0162 |  |
| Salapakshi Sagar | 20211CAI0094 |  |
| Gade Prathyusha | 20211CAI0200 |  |
| Jampana Venkata Arjun Varma | 20211CAI0060 |  |

**ABSTRACT**

Agriculture plays a pivotal role in sustaining economies worldwide, providing food, employment, and raw materials for various industries. However, one of the most persistent challenges in the agricultural sector is crop diseases, which can lead to devastating yield losses and severely impact food security. Traditional methods of disease detection rely heavily on manual inspection and expert analysis, which are often time-consuming, expensive, and prone to human error. The inability to detect and diagnose plant diseases at an early stage can result in uncontrolled outbreaks, leading to significant economic losses for farmers and reduced crop productivity.

To address these challenges, this project introduces an AI-powered crop disease detection and diagnosis system, integrating state-of-the-art deep learning, natural language processing (NLP), and geospatial mapping technologies. The system utilizes YOLOv8 (You Only Look Once, version 8), a highly efficient Convolutional Neural Network (CNN) model, to perform real-time image-based detection of plant diseases. The model is trained on an extensive, well-annotated dataset from Roboflow, enabling it to classify and identify various diseases affecting rice, wheat, and maize crops with high accuracy.

In addition to automated disease detection, the system features an AI-driven chatbot based on Large Language Models (LLMs) to provide interactive diagnosis, treatment recommendations, and preventive measures. This chatbot acts as a virtual agricultural expert, offering farmers instant, context-aware advice on how to manage detected diseases, what pesticides or organic treatments to use, and how to prevent future outbreaks. The integration of NLP in the chatbot ensures that farmers can communicate in natural language, making the system accessible and easy to use even for individuals with limited technical expertise.

A key innovation in this project is the mapping feature, which leverages OpenStreetMap’s Overpass API to identify nearby plant and pesticide shops based on the farmer’s location. Once a disease is detected, farmers can instantly locate the nearest agricultural supply stores to purchase the required pesticides, fertilizers, or organic treatments. This geospatial integration bridges the gap between disease detection and resource accessibility, making it easier for farmers to take immediate corrective action.

The proposed system offers a holistic, AI-driven solution for crop disease management by combining image-based deep learning detection, chatbot-assisted diagnosis, and geolocation-based resource mapping. By reducing reliance on manual disease identification, improving treatment decision-making, and enhancing access to agricultural resources, this project contributes to a more efficient, technology-driven approach to modern farming. The implementation of real-time, AI-powered disease detection not only enhances agricultural productivity but also helps mitigate economic losses, ensuring a sustainable and resilient food production system.

**Keywords:** Crop Disease Detection, YOLOv8 CNN, Deep Learning in Agriculture, AI Chatbot, Large Language Models (LLMs), Plant Disease Classification, Geospatial Mapping, OpenStreetMap Overpass API, Precision Farming, AI-Powered Smart Agriculture.

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**Talla Sunil Kumar**

**Challa Yogesh**

**Salapakshi Sagar**

**Gade Prathyusha**

**Jampana Venkata Arjun Varma**

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**CHAPTER-1**

**INTRODUCTION**

**1.1 Background**

Agriculture is one of the most vital sectors of the global economy, providing food, employment, and raw materials for various industries. However, the productivity and sustainability of agriculture are constantly threatened by crop diseases, which can cause significant yield losses if not detected and treated in time. Traditional methods of disease detection primarily rely on visual inspection by farmers and agricultural experts. This approach is often subjective, time-consuming, and prone to errors, leading to delayed intervention and potential spread of the disease. In many cases, small-scale farmers, who constitute the majority of agricultural producers worldwide, lack access to expert knowledge, making early and accurate disease identification even more challenging.

With the advancement of artificial intelligence and machine learning, deep learning models have emerged as powerful tools for automating the detection and classification of plant diseases. Convolutional Neural Networks (CNNs) have demonstrated remarkable accuracy in image-based classification tasks, making them highly suitable for disease detection in crops. The YOLO (You Only Look Once) object detection framework, in particular, has gained popularity due to its real-time processing capabilities and high accuracy. Recent advancements in deep learning, particularly with models like YOLOv8, have further improved the speed and precision of disease identification, enabling real-time field applications.

In addition to disease detection, timely diagnosis and treatment recommendations are crucial for effective crop disease management. Large Language Models (LLMs) have revolutionized conversational AI, making it possible to provide intelligent chatbot-based agricultural advisory services. AI-powered chatbots can analyze disease symptoms, provide treatment suggestions, and offer preventive measures, thus serving as virtual agricultural assistants. These chatbots help bridge the knowledge gap for farmers who may not have direct access to agronomists or plant pathologists.

Another critical challenge in agricultural disease management is the accessibility of necessary resources such as pesticides, fertilizers, and disease-resistant plant varieties. Farmers often struggle to locate nearby agricultural supply stores, delaying the procurement of essential disease control measures. To address this issue, geospatial technologies like OpenStreetMap’s Overpass API can be leveraged to provide real-time mapping of plant and pesticide shops. By integrating disease detection, AI-driven diagnosis, and geolocation services, farmers can access a comprehensive support system that assists them in identifying diseases, obtaining expert advice, and finding nearby treatment resources.

**1.2 Problem Statement**

Crop diseases pose a major challenge to agricultural productivity, leading to significant economic losses and food shortages. Farmers often rely on traditional methods of visual inspection for disease detection, which are slow, inaccurate, and dependent on expert knowledge. Delayed detection can result in widespread outbreaks, making control and treatment more difficult. Existing solutions lack an integrated approach that combines real-time detection, expert diagnosis, and resource accessibility. There is a need for an AI-powered system that can automate disease detection, provide intelligent treatment recommendations, and help farmers locate nearby agricultural resources for immediate action.

**1.3 Objectives**

The primary objective of this project is to develop an AI-driven crop disease detection and diagnosis system that integrates deep learning-based image analysis, chatbot-driven advisory services, and geospatial mapping for agricultural resource accessibility. The system will employ a YOLOv8 CNN model trained on an annotated dataset from Roboflow to accurately detect diseases in rice, wheat, and maize crops. An AI-powered chatbot based on large language models will provide farmers with interactive diagnosis and treatment recommendations. Furthermore, a mapping feature using OpenStreetMap’s Overpass API will help users locate nearby plant and pesticide shops. This integrated approach will enable farmers to take timely and informed actions, reducing crop losses and improving overall agricultural efficiency.

**CHAPTER-2**

**LITERATURE SURVEY**

**2.1 Introduction**

Crop diseases significantly impact agricultural productivity, food security, and economic stability. Early and accurate detection of plant diseases is crucial to preventing large-scale crop losses. Traditional disease detection methods rely on manual visual inspection, which is often inaccurate, slow, and dependent on expert knowledge. With the rise of artificial intelligence (AI), machine learning (ML), and deep learning (DL), automated crop disease detection systems have gained significant attention.

Recent studies have explored the use of Convolutional Neural Networks (CNNs), deep learning models, and transfer learning techniques for real-time crop disease classification. The integration of UAV-based image processing, AI-driven chatbots, and geospatial mapping services has further enhanced the capabilities of smart agricultural systems [1][2]. This chapter reviews recent advancements in AI-powered crop disease detection, chatbot-based diagnosis, and GIS-based agricultural resource mapping.

**2.2 AI-Based Image Processing for Crop Disease Detection**

Deep learning has revolutionized image-based plant disease detection, significantly improving classification accuracy and response time. Several studies have highlighted the effectiveness of CNNs, YOLO-based models, and Transfer Learning techniques in disease identification.

* Shahi et al. (2023) explored the application of UAV-based crop disease detection, integrating deep learning models to classify plant diseases. Their findings demonstrated how high-resolution aerial images could be efficiently processed using CNN architectures to detect infections in wheat and maize crops [1].
* Ale et al. (2019) analyzed the performance of ResNet, VGG16, and MobileNet for plant disease classification, concluding that ResNet-50 achieved the highest accuracy of 94.2%, while MobileNetV2 provided the fastest inference speed [2].
* Singla et al. (2024) investigated the use of machine learning approaches such as Support Vector Machines (SVMs), Decision Trees, and CNNs for automated crop disease detection. Their study found that deep learning outperformed traditional ML algorithms, making it the preferred choice for real-time disease monitoring [3].
* Roy & Bhaduri (2021) introduced a YOLO-based object detection model for real-time crop disease detection, reporting an accuracy improvement of 10% over conventional CNN models [4].

A comparison of deep learning models for crop disease detection is presented below:

| Model | Accuracy (%) | Inference Speed (ms) | Reference |
| --- | --- | --- | --- |
| ResNet-50 | 94.2 | 56.7 | [2] |
| VGG-16 | 92.5 | 74.3 | [2] |
| MobileNetV2 | 91.8 | 32.4 | [2] |
| YOLOv8 | 96.3 | 22.1 | [4] |

Table 1: Comparison of Deep Learning Models for Crop Disease Detection

**2.3 Chatbot-Driven Diagnosis and Treatment Recommendations**

AI-powered chatbots have revolutionized agricultural advisory services, allowing farmers to receive real-time disease diagnosis and treatment recommendations. NLP-based conversational AI models provide expert-level agricultural knowledge in an accessible format.

* Chowdhury et al. (2021) developed an AI chatbot trained on plant disease datasets, providing real-time diagnosis and treatment advice through text-based and voice interactions [5].
* J. et al. (2022) integrated deep learning models with chatbot systems, enabling automated identification of crop diseases based on symptom descriptions provided by farmers [6].
* Shoaib et al. (2023) reviewed various AI chatbot architectures and found that Transformer-based models, such as Google's Generative AI, significantly improved the accuracy of chatbot-generated agricultural advice [7].
* Too et al. (2019) introduced a multilingual AI chatbot for plant disease identification, improving accessibility for farmers in non-English-speaking regions [8].

**2.4 Geospatial Mapping for Agricultural Resources**

Farmers often face challenges in locating pesticide suppliers, plant nurseries, and disease treatment centers. GIS-based mapping services have simplified agricultural resource management by providing real-time location tracking.

* Ouhami et al. (2021) investigated the role of OpenStreetMap’s Overpass API in mapping agricultural resources. Their study concluded that open-source GIS platforms provided reliable location data at no cost, making them ideal for farmers [9].
* Waldamichael et al. (2022) designed a real-time pesticide shop locator using machine learning and GPS-based mapping, allowing farmers to find nearby agricultural supply stores instantly [10].
* Saleem et al. (2019) demonstrated how cloud-based AI solutions enhanced GIS-based agricultural resource tracking by integrating real-time IoT sensor data with location mapping services [11].

A comparison of different GIS-based agricultural mapping technologies is shown below:

| Mapping Technology | Accessibility | Accuracy | Integration with AI | Reference |
| --- | --- | --- | --- | --- |
| OpenStreetMap API | Free/Open-Source | High | Yes | [9] |
| Google Maps API | Paid | High | Yes | [9] |
| Esri ArcGIS | Paid | Very High | Limited | [10] |

Table 2: Comparison of Mapping Technologies for Agricultural Resource Locators

**2.5 Integrated AI Systems for Smart Agriculture**

The future of AI-driven agriculture lies in integrated solutions that combine image-based disease detection, chatbot-assisted diagnosis, and geospatial mapping. Some key contributions in this area include:

* Mohanty et al. (2016) developed an end-to-end AI system for plant disease detection, integrating CNN-based classification, chatbot-driven diagnosis, and GIS-based resource mapping [12].
* Li et al. (2021) proposed a cloud-based precision farming system, combining real-time drone imaging, AI-powered chatbots, and geospatial mapping for automated farm management [13].
* Panchal et al. (2021) introduced an IoT-enabled agricultural monitoring system, using AI sensors to detect plant stress levels and suggest appropriate treatments via a chatbot [14].

These studies highlight the growing trend of AI integration in smart agriculture, paving the way for autonomous farm management systems.

**2.6 Conclusion**

The literature review indicates significant advancements in AI-powered crop disease detection, chatbot-driven advisory services, and GIS-based agricultural mapping. Deep learning models like YOLOv8 have improved disease classification accuracy, while AI chatbots provide instant recommendations to farmers. Geospatial mapping services have made agricultural resources more accessible, ensuring timely intervention and treatment.

However, challenges remain in scalability, affordability, and adaptability of AI-based solutions for small-scale farmers. Future research should focus on expanding the dataset for training models, enhancing chatbot NLP capabilities, and optimizing geospatial mapping accuracy. By addressing these gaps, AI-driven solutions can revolutionize modern agriculture, ensuring higher productivity and sustainable farming practices.

**CHAPTER-3**

**RESEARCH GAPS OF EXISTING METHODS**

**3.1 Challenges in Crop Disease Detection**

Despite the advancements in AI-driven plant disease detection, several challenges persist that hinder real-time, scalable, and accessible disease detection for farmers. Many existing models rely on various CNN architectures and older YOLO versions, which, while effective, lack the efficiency and speed offered by YOLOv8. YOLOv8 has outperformed its predecessors (YOLOv3, YOLOv4, YOLOv5, and YOLOv6) in terms of accuracy, inference speed, and model optimization, making it the best choice for real-time plant disease detection.

Most studies have focused on CNN-based or UAV (Unmanned Aerial Vehicle)-assisted disease detection, but UAV models face practical challenges in agricultural environments. UAV-based detection is often affected by weather conditions (wind, rain, fog) and geographical variations (hilly terrain, dense vegetation), making deployment in real-world farming scenarios difficult [1]. In contrast, CNN-based models like YOLOv8 allow for easier on-the-ground implementation, requiring only a mobile device or a simple camera setup, making them more accessible to farmers in rural areas [2].

Another major limitation is dataset quality and diversity. Most AI models are trained on region-specific datasets, which do not generalize well across different climates, soil types, and crop varieties. Shahi et al. (2023) noted that UAV-based disease detection models struggled with inconsistent lighting conditions, humidity variations, and plant growth stages, affecting their overall performance [1]. Chowdhury et al. (2021) emphasized that many datasets suffer from class imbalances, where certain plant diseases are underrepresented, leading to biased predictions and increased misclassification rates [5].

To overcome these challenges, our project leverages YOLOv8, which has higher accuracy, better real-time performance, and lower computational overhead than other CNN and YOLO models. Additionally, by focusing on ground-based image detection instead of UAV-assisted approaches, we eliminate the hardware constraints of drone-based methods, making our system more practical and accessible for small-scale farmers [6].

**3.2 Real-Time Constraints and Computational Limitations**

For AI-based crop disease detection to be practical for farmers, it must work in real-time with minimal computational overhead. Many deep learning models, particularly older YOLO versions and high-complexity CNN architectures, require significant computational resources, making them difficult to deploy on low-power devices such as smartphones and edge computing devices.

Real-time constraints arise due to several factors:

* High computational power requirements: Singla et al. (2024) noted that deep learning models often require powerful GPUs or cloud-based servers, which limits their usability for farmers who lack access to such infrastructure [3].
* Network latency: Mohanty et al. (2016) highlighted that many AI-based agricultural applications rely on cloud computing, which introduces delays in processing and decision-making, particularly in rural areas with poor internet connectivity [12].
* Energy efficiency concerns: Panchal et al. (2021) found that mobile and drone-based disease detection systems consume excessive power, reducing their practicality for long-term field use [14].

To address these real-time constraints, our project:

1. Uses YOLOv8, which is faster and more efficient than older YOLO models and traditional CNN architectures, making it ideal for mobile and edge computing deployment.
2. Optimizes models for on-device inference, allowing farmers to use the system without internet dependency.
3. Removes reliance on UAV-based methods, which are often slower and less practical due to weather constraints.

By leveraging YOLOv8’s efficiency and minimizing hardware and computational dependencies, our project ensures real-time, field-ready disease detection without the need for cloud-based AI inference.

**3.3 Lack of Chatbot and Mapping Features in Existing Systems**

One of the major gaps in existing plant disease detection solutions is the absence of integrated advisory and resource-locating systems. Most AI-powered crop disease detection systems only identify plant diseases but do not provide:

1. An interactive chatbot for guiding farmers on disease treatment, pesticide use, and preventive measures.
2. A mapping feature that helps farmers locate nearby pesticide and plant shops for immediate action.

Many studies focus only on detection and classification. J. et al. (2022) pointed out that most AI-based agricultural advisory systems lack real-time disease detection integration, requiring farmers to manually enter symptoms instead of using an automated image-based approach [6]. Shoaib et al. (2023) demonstrated that AI-powered chatbots significantly improved farmer engagement, but existing solutions do not integrate chatbot-based treatment recommendations with real-time detection models [7].

Furthermore, no existing AI-driven plant disease detection model includes a mapping feature for finding nearby plant and pesticide shops. Waldamichael et al. (2022) noted that farmers struggle to find nearby suppliers for pesticides, fertilizers, or disease-resistant seeds, delaying the treatment process and leading to further crop damage [10].

Our project addresses these critical gaps by integrating:

1. An AI-powered chatbot, capable of providing instant disease diagnosis, treatment plans, and prevention strategies, ensuring farmers get immediate guidance after disease detection.
2. A mapping feature using OpenStreetMap’s Overpass API, allowing farmers to locate nearby agricultural supply shops and purchase necessary resources without delay.

This integrated approach ensures faster decision-making, reduces reliance on external experts, and empowers farmers with AI-driven disease management solutions.

**3.4 Conclusion**

While AI-based crop disease detection models have significantly evolved, existing solutions lack real-time efficiency, practical field deployment, and advisory system integration.

Key research gaps in previous systems include:

* Reliance on older CNN and YOLO models: Many studies use YOLOv3, YOLOv4, or standard CNN architectures, which are less efficient than YOLOv8. Our project chooses YOLOv8 for its superior speed, accuracy, and lightweight deployment.
* Dependence on UAV-based detection: While drone-based detection is promising, it faces significant challenges in real-world farming conditions, including weather constraints, limited battery life, and high operational costs. Our project prioritizes on-ground image-based detection using smartphones or cameras.
* Absence of AI-powered chatbot support: Most existing projects only detect diseases but fail to provide immediate treatment recommendations. Our project integrates a chatbot for disease diagnosis, treatment plans, and preventive measures.
* Lack of resource-mapping functionality: Farmers currently lack a way to find nearby agricultural supply stores after a disease is detected. Our project introduces a mapping feature to help users locate pesticide and plant shops in real time.

By addressing these gaps, our project delivers a first-of-its-kind AI-powered crop disease detection system that integrates real-time detection, chatbot-based disease management, and geospatial mapping to provide a complete agricultural assistance solution. Future work should focus on expanding the model to support more crop varieties, enhancing chatbot capabilities with regional agricultural knowledge, and improving geospatial mapping accuracy.

**CHAPTER-4**

**PROPOSED METHODOLOGY**

**4.1 Overview**

The proposed methodology presents a real-time AI-powered crop disease detection and diagnosis system that integrates deep learning, natural language processing (NLP), and geospatial mapping to provide farmers with a comprehensive and interactive disease management tool. Unlike traditional plant disease detection systems that rely solely on visual inspection or limited AI-based classification, our project integrates three essential components:

1. Real-time crop disease detection using YOLOv8 CNN models, trained on high-quality annotated datasets from Roboflow, providing fast and accurate identification of diseases in rice, wheat, and maize crops.
2. An interactive AI-powered chatbot using Google Gemini Flash, which provides detailed diagnosis, causes, treatment recommendations, and preventive measures based on detected diseases.
3. A mapping feature leveraging OpenStreetMap’s Overpass API to help farmers locate nearby plant and pesticide shops, enabling immediate action after disease detection.

By combining computer vision, NLP, and geospatial analytics, this system provides an intelligent, real-time solution that is accessible to farmers through a user-friendly web-based interface built using Streamlit.

**4.2 Detailed Workflow**

* Step 1: Image Capture and Upload
  + The user captures an image of a diseased plant leaf using a smartphone, tablet, or camera.
  + The image is uploaded to the web application via the Streamlit-based interface.
* Step 2: Real-time Disease Detection Using YOLOv8
  + Once the image is uploaded, it is processed using a YOLOv8 CNN model trained on an annotated dataset.
  + YOLOv8 is chosen over older YOLO versions (YOLOv3, YOLOv4, YOLOv5) due to its superior speed, accuracy, and optimized performance.
  + The model detects plant diseases in rice, wheat, and maize crops, identifying specific conditions like leaf blight, rust, powdery mildew, and bacterial streaks.
  + The detected disease label is stored in Streamlit session state for further diagnosis.
* Step 3: AI-powered Chatbot for Diagnosis and Treatment Using Google Gemini Flash
  + After detection, the user can interact with a Google Gemini Flash-powered chatbot for a detailed diagnosis, causes, treatment recommendations, and preventive measures.
  + The chatbot processes a structured query such as:
    - "Provide details about wheat rust disease, including symptoms, causes, treatments, and preventive measures."
  + The chatbot responds with an in-depth diagnosis, including:
    - Detected Disease: Name of the disease affecting the plant.
    - Causes: Possible environmental, fungal, bacterial, or viral factors.
    - Treatment Options: Organic and chemical-based treatment strategies.
    - Preventive Measures: Best agricultural practices to prevent future outbreaks.
  + Google Gemini Flash was selected over OpenAI’s models due to its faster response time, lightweight architecture, and cost efficiency, making it ideal for real-time chatbot interactions in resource-limited settings.
* Step 4: Mapping Feature to Locate Nearby Plant & Pesticide Shops
  + The user is prompted to enter their location (e.g., "Yelahanka, Bangalore").
  + The entered location is geocoded using OpenStreetMap’s Nominatim API to obtain latitude and longitude coordinates.
  + The system queries OpenStreetMap’s Overpass API to find:
    - Nearby plant nurseries and garden centers.
    - Pesticide and agricultural supply shops.
  + The identified shops are marked on an interactive map using Folium and displayed in the web application.
  + A list of shop names, addresses, and coordinates is also provided below the map for easy reference.
* Step 5: User Interaction and Decision-Making
  + The user reviews the disease detection results, chatbot-generated diagnosis, and nearby shop locations.
  + Additional options are available for further exploration:
    - List of recommended pesticides (based on disease conditions).
    - Detailed long-term impact analysis of the disease on crop yield and soil health.
    - Preventive strategies tailored to regional agricultural practices.

**4.3 Key Implementation Steps**

* A. Dataset Collection and Annotation
  + The dataset used for training consists of high-quality annotated images of plant diseases sourced from publicly available agricultural databases and Roboflow.
  + The dataset includes multiple plant diseases affecting rice, wheat, and maize crops, covering:
    - Fungal diseases (e.g., rust, powdery mildew).
    - Bacterial diseases (e.g., bacterial blight, bacterial streak).
    - Viral infections (e.g., maize streak virus).
  + The images are annotated using Roboflow, ensuring accurate bounding box labeling for effective model training.
* B. Training the YOLOv8 CNN Model
  + The YOLOv8 model is trained on the annotated dataset using PyTorch and the Ultralytics YOLOv8 framework.
  + Training involves:
    - Data augmentation (random rotations, brightness adjustments) to improve robustness.
    - Loss function optimization to minimize classification errors.
    - Model validation using separate test sets to ensure generalization.
  + The final trained model is deployed in the Streamlit web application for real-time inference.
* C. Chatbot Integration with Google Gemini Flash
  + A Google Gemini Flash-powered chatbot is integrated to enhance user interaction and provide detailed disease diagnosis and treatment recommendations.
  + The chatbot interacts dynamically, allowing users to ask follow-up questions related to:
    - Alternative treatments.
    - Organic vs. chemical pesticides.
    - Best farming practices for disease prevention.
* D. Implementing the Mapping Feature for Shop Location
  + The maps feature is implemented using OpenStreetMap’s Overpass API.
  + User Input: The user enters a location (e.g., "Mysuru, Karnataka").
  + Geolocation Retrieval: The location is converted into latitude and longitude coordinates using Nominatim API.
  + Shop Search Query: A query is sent to OpenStreetMap to fetch nearby plant nurseries and pesticide shops.
  + Visualization: The results are displayed on a Folium interactive map.
  + Shop Listing: Below the map, the shop names, addresses, and coordinates are listed for easy access.

**4.4 Advantages of the Proposed System**

* Real-Time Disease Detection: YOLOv8 enables instant identification of plant diseases with high accuracy.
* Accessible and Easy-to-Use: The web application ensures farmers can use the system without technical expertise.
* AI-powered Diagnosis and Treatment Recommendations Using Google Gemini Flash: The chatbot offers detailed insights, reducing reliance on human experts.
* Geospatial Mapping for Quick Resource Access: The maps feature bridges the gap between disease detection and treatment availability.
* Low Hardware Requirements: Unlike UAV-based detection, which depends on expensive drone setups, this system runs on simple mobile or desktop devices.
* Scalable and Customizable: The model can be expanded to include more crops and diseases.

**4.5 Future Enhancements**

* Multi-Crop Support: Extend the model to detect more crop diseases, including vegetables, fruits, and cash crops.
* Mobile App Development: Convert the web application into a mobile-friendly app for offline disease detection.
* Integration with Agricultural Databases: Link chatbot responses with real-time agricultural research updates.
* Advanced Mapping Features: Implement predictive geospatial analytics to recommend best pesticide sources based on availability and pricing trends.

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