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Augmented Reality-Powered Plant Disease Detection For Smart Farming

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Abstract: Agriculture is the backbone of food security and economic stability, but crop diseases significantly impact yield and quality. Traditional disease detection methods often require expert intervention, making them time-consuming and inaccessible to many farmers. To address this challenge, this research proposes an Augmented Reality (AR)-Driven Disease Detection System for smarter farming. The system integrates computer vision, deep learning, and AR technology to provide real-time disease identification and treatment recommendations. The proposed framework utilizes image processing and convolutional neural networks (CNNs) to detect plant diseases from images captured by AR-enabled devices such as smartphones. The processed results are overlaid on the plant using AR visualization, allowing farmers to recognize affected areas and access treatment solutions instantly. Additionally, the system provides real-time recommendations, preventive measures, and expert consultation options, ensuring a proactive approach to disease management. By leveraging machine learning, real-time data processing, and AR-based visualization, this solution enhances precision farming, reduces dependency on chemical treatments, and improves crop health monitoring efficiency. Farmers receive immediate, visual feedback on their crops, highlighting potential disease symptoms through AR interfaces. Furthermore, the system facilitates teleconsulting features, enabling farmers to seek expert advice remotely. This approach not only reduces crop losses but also promotes sustainable agricultural practices by minimizing excessive chemical use and optimizing disease management strategies. Implementing this AI-driven smart farming technology aims to empower farmers, enhance decision-making, and contribute to a more efficient and resilient agricultural sector.

Keywords: - Augmented Reality (AR), Disease Detection, Smart Farming, Precision Agriculture, Deep Learning, Computer Vision, Convolutional Neural Networks (CNNs), Real-time Monitoring, Image Processing, Sustainable Agriculture, AI- driven Farming, Smart Crop Management

I. Introduction

Agriculture stands as the backbone of many economies, ensuring food security and livelihoods. However, pests and plant diseases cause up to 40% of global crop losses annually, leading to economic setbacks and threatening farmers' livelihoods. Climate change exacerbates these issues, increasing the urgency for innovative solutions to protect crops and promote sustainable farming. Traditional pest and disease detection methods rely on manual inspections and lab analyses, which are time-consuming, labor-intensive, and often inaccessible to small-scale farmers. While technological advancements have emerged, there remains a gap in providing user-friendly, real-time solutions that cater to diverse agricultural needs. This research introduces an Augmented Reality (AR)-Driven Pest and Disease Detection System, integrating AR, image processing, and deep learning for smarter farming. Using AR-enabled devices, farmers can capture crop images for real-time analysis, detecting pests and diseases while receiving treatment recommendations through an intuitive interface. By providing precise, real-time feedback, the system reduces excessive pesticide use, minimizing environmental impact and costs. The AR interface enhances usability, allowing farmers to visualize affected areas and take swift action. This approach bridges the gap between advanced detection technologies and practical farming needs. The key objectives include developing a highly accurate detection system, offering actionable pest and disease management insights, and demonstrating AR's role in precision agriculture. This research aligns technology with farming needs, contributing to improved yields, reduced losses, and a sustainable future where technology and agriculture work hand in hand.

II. LITERATURE SURVEY

Vijayakumar Ponnusamy, Sowmya Natarajan, et al, [1]proposed an IoT-enabled augmented reality (AR) framework for plant disease detection. Their work integrates AR with cloud-based machine learning, using convolutional neural networks (CNNs) to enhance real-time plant disease identification via a head-mounted display. Advantages of this system include high accuracy (up to 93%), portability, and rapid response times, making it suitable for practical deployment in smart farming. However, limitations include dependency on cloud processing, which may affect latency under poor network conditions, and the current focus on a single type of plant disease, necessitating broader training for diverse applications. This work contributes to precision agriculture by enabling farmers to diagnose plant health on the field with minimal expertise effectively.

Janna Huuskonen and Timo Oksanen,[2] proposed an augmented reality (AR) system for supervising autonomous agricultural vehicles to enhance situational awareness for farmers managing multiple robots. The system integrates AR wearable headsets with a mission planner to provide real-time operational data on autonomous tractors. The advantages include improved fleet supervision, enhanced safety, and better real-time decision-making for the operator. However, limitations include hardware constraints in outdoor environments, potential misalignment of virtual objects, and user discomfort due to the AR headset's ergonomics. The study demonstrated that AR can effectively aid in agricultural automation but requires advancements in AR technology for broader practical application.

William Hurst, and Frida Ruiz Mendoza,[3] explored the applications of augmented reality (AR) in precision farming, focusing on how AR integrates with technologies like IoT, GPS, sensors, and machine learning to enhance crop and livestock management. Their work highlights AR's potential in real-time data visualization, aiding tasks like crop disease identification, livestock monitoring, and autonomous machinery supervision. Advantages include improved operational efficiency, reduced resource use, and enhanced decision-making capabilities. However, challenges such as hardware limitations, high development costs, and dependency on accurate location tracking and connectivity remain. The study underscores AR's transformative role in sustainable agriculture and its need for further technological integration.

The authors Mingze Xi, Matt Adcock et al.,[4] the application of augmented reality (AR) for optimizing farm management, specifically in aquaculture, addressing challenges like water quality monitoring, remote collaboration, and efficient training. They highlight advantages such as real-time data visualization, enhanced decision-making, and remote expert guidance, which improve productivity and reduce resource waste. However, the disadvantages include limited AR adoption in agriculture, potential user cognitive load, and dependency on advanced hardware. Their work emphasizes AR's potential to transform farm management through innovative tools, though broader implementation and user adaptation remain critical hurdles.

Sumalatha Aradhya and Navya V [5] propose a Virtual Reality (VR) platform tailored to enhance the Indian agricultural sector. The system integrates modern VR technologies with crop prediction, real-time market visualization, and interactive simulations to aid farmers in managing crops and accessing market trends. Advantages of the work include improved decision-making for farmers, direct farmer-to-consumer interaction, and a significant 98.8% accuracy in crop prediction using Random Forest algorithms. However, challenges such as reliance on advanced hardware, high initial implementation costs, and the steep learning curve for rural farmers limit widespread adoption. The solution presents a transformative approach to bridging technological gaps in agriculture.

Shrikant Salve[6] proposed an augmented reality (AR)--based mobile application for detecting crop diseases among Indian farmers. The methodology involved using a smartphone camera to capture images of infected crop leaves, which were then matched with an online database to identify diseases and suggest preventive measures. The research included field visits to villages near Pune, where farmers' challenges were studied. The advantages of the proposed system include real-time disease identification, ease of use through smartphones, and accessibility for farmers. However, the disadvantages include the need for rigorous testing with actual farmers and the lack of a user interface in local languages.

Nikhil Patil, Bhushan Khope, Kshitij Patil[7] an AI and augmented reality-based crop disease detection application to assist farmers in identifying plant diseases and pests. The methodology involves using AI to compare plant conditions with ideal states and providing treatment suggestions through an AR-enhanced mobile application. The system leverages Google Cloud for data processing, TensorFlow for image classification, and Android for user interface development. Advantages include real-time disease detection, improved pest management, and enhanced decision-making for farmers. However, limitations include dependency on internet connectivity, the need for extensive image datasets for accurate predictions, and challenges in farmer adoption due to technological barriers.

Mudassir Iftikhar et al., [8]proposed a fine-tuned Enhanced Convolutional Neural Network (E-CNN) integrated with a mobile application for early detection and classification of plant diseases in Apple, Corn, and Potato crops. The methodology involved optimizing CNN hyperparameters, applying data augmentation, and integrating the model into a mobile application for real-time disease detection. The study evaluated various deep learning models, fine-tuned them, and compared their accuracy, achieving 98.17% accuracy in fungal disease detection. Advantages of this approach include improved accuracy, accessibility through a mobile app, and real-time disease classification with treatment suggestions. However, limitations include the need for high computational resources, environmental variability affecting disease appearance, and the challenge of generalizing across diverse plant conditions.

Lili Li, Shujuan Zhang, and Bin Wang [9] conducted a comprehensive review on plant disease detection and classification using deep learning. The study focused on the application of deep learning techniques in plant disease recognition, emphasizing their advantages over traditional image processing methods. The methodology involved analyzing various deep learning models, including CNNs, transfer learning, and hyperspectral imaging, while also discussing data augmentation and visualization techniques for improved accuracy. The advantages of deep learning in this domain include automated feature extraction, higher classification accuracy, and faster processing compared to manual or traditional methods. However, the study also highlighted challenges such as the need for large and diverse datasets, difficulties in early disease detection, model robustness issues, and the high computational costs associated with deep learning approaches.

Aminou Halidou et al.,[10] proposed a deep learning-based plant disease diagnosis system using MobileNet-v2 and Inception-v3 architectures for image classification. Their methodology involved training and evaluating these models on a dataset containing over 54,000 leaf images across 38 plant-disease categories, incorporating data augmentation, transfer learning, and optimization techniques such as Adam, RMSprop, RAdam, and Ranger. The study found that Inception-v3 outperformed MobileNet-v2 in terms of precision, making it a more effective tool for plant disease detection. The advantages of the system include high classification accuracy, real-time detection, and smartphone integration for accessibility in agricultural applications. However, limitations include the need for a large dataset to enhance model generalization, challenges with real-world environmental variability affecting accuracy, and high computational resource requirements for model training and optimization.

Plant disease detection plays a crucial role in ensuring food security, reducing the use of harmful chemicals, and improving crop yields through advanced vision-based learning techniques. This study provides a systematic review of various detection methods, focusing on classification techniques, datasets, challenges, and future trends. A rigorous selection process was applied to identify 176 relevant studies from an initial pool of 1,349 research papers, ensuring inclusion based on significance, methodological approach, detection performance, and dataset relevance. The review follows the PRISMA screening process, incorporating abstract and title analysis, duplicate removal, and multiple rounds of relevance assessment. Despite significant advancements, challenges persist, such as detecting plant diseases in natural environments, the absence of standardized performance evaluation metrics, and the limited availability of large, diverse datasets Additionally, the development of lightweight models capable of operating on small devices remains a critical area of research. The integration of drone-based imaging is explored as a promising solution for more effective disease detection compared to conventional digital cameras. This review, conducted by Wasswa Shafik, Ali Tufail, Abdallah Namoun et al.,[11] provides valuable insights intocurrent advancements and future directions in plant disease detection research.

Eman A. Al-Shahari, Ghadah Aldehim et al.,[12] propose an advanced technique for plant disease detection and crop management, termed Automated Plant Disease Detection and Crop Management using a Spotted Hyena Optimizer with Deep Learning (APDDCM-SHODL). This approach integrates a Vector Median Filter (VMF) for preprocessing, the DenseNet201 model for feature extraction, and the Spotted Hyena Optimizer (SHO) for hyperparameter tuning, followed by classification using a Recurrent Spiking Neural Network (RSNN). The proposed system facilitates real-time monitoring of plant health, enabling early disease detection and proactive intervention, which enhances crop yield while minimizing reliance on chemical treatments. Furthermore, this method supports sustainable agriculture by optimizing resource utilization. Future research will focus on improving detection accuracy, incorporating environmental variables, expanding IoT integration to monitor larger agricultural areas, and refining machine learning algorithms to better connect sensor data with environmental factors, further strengthening precision agriculture and sustainable farming practices.

Vasileios Balafa, Emmanouil Karantoumanis, Malamati Louta, Nikolaos Ploskas et al.[13] present a comprehensive study on machine learning (ML) and deep learning (DL) algorithms for plant disease detection and classification. Their work encompasses a detailed review of recent advancements, a novel classification scheme for organizing relevant studies, a summary of existing datasets used in plant disease detection, and an extensive computational analysis comparing state-of-the-art object detection and classification models on a widely used dataset. The study highlights classification and object detection as the two primary methodologies, emphasizing the advantages of object detection in cases where multiple diseases are present or when analyzing large crop areas. By facilitating early disease detection, these techniques play a critical role in increasing crop yields and advancing precision agriculture Future research directions include improving computational efficiency, developing diverse datasets that reflect real-world agricultural conditions, exploring object detection for more precise disease localization, ensuring model consistency across different datasets, and enhancing dataset annotation for early stage and small-leaf disease identification.

Diana Susan Joseph, Pranav M. Pawar, Kaustubh Chakradeo et al [14] present a study focused on developing real- time datasets for three major food grains-rice, wheat, and maize to train and evaluate deep learning models for plant disease detection and classification. The dataset includes images of common diseases at different stages (early, advancing, and severe), which were augmented from 100 to approximately 5,000 per class to enhance model training. The study fine-tuned eight pre-trained deep learning models, including Xception and MobileNet, and introduced a new MRW-CNN model, which achieved high testing accuracy exceeding 95% across all three datasets. The results demonstrate the dataset's effectiveness in enabling high-performance disease detection. Future directions include accounting for climatic variations in disease progression, integrating annotated images into object detection models like Mask R-CNN for severity assessment, and expanding the dataset to include additional food grains and multiple diseases on a single leaf to improve real-world applicability.

Prameeta Pai, Shubhan S. Bhat, et al, [15]propose the development of an autonomous wheeled robot equipped with deep learning and lot for real-time plant disease detection and treatment. The system leverages CNNS, YOLOV8, and ResNet for disease classification, with the YOLOV8 model trained in a Google Colab environment using a free GPU. The hardware setup includes a Raspberry Pi board, an 8-channel relay board, and a medicine dispensing module, enabling automated detection and immediate treatment of diseased plants. This approach ensures accurate and early disease detection through deep learning-based image analysis, real-time data collection via IoT, and proactive treatment, ultimately improving crop resilience and agricultural productivity.

III. METHODOLOGY

The development of the AR-powered plant disease detection system follows a multi-stage pipeline involving data collection, image preprocessing, deep learning model training, augmented reality integration, and real-time deployment. The objective is to create an intuitive, accurate, and interactive tool that aids users—particularly farmers and agricultural professionals—in diagnosing plant diseases effectively using mobile devices. The foundation of the system lies in a robust dataset comprising 61,486 images spanning 39 distinct plant disease classes, sourced from publicly available agricultural databases and curated datasets. To increase the model's ability to generalize across varied environments and lighting conditions, the dataset was augmented using six augmentation techniques, including rotation, flipping, zooming, shifting, brightness adjustment, and noise addition. For disease classification, a Convolutional Neural Network (CNN) was developed and trained using the TensorFlow framework. The model's performance was optimized through hyperparameter tuning, dropout layers to prevent overfitting, and early stopping to halt training at optimal performance. Evaluation metrics such as accuracy, precision, recall, and confusion matrix were used to assess the model, achieving competitive results in distinguishing between healthy and infected plant leaves. To bridge the model's predictions with an interactive experience, an Augmented Reality (AR) application was developed using Unity 2022.3.49f1 integrated with AR Foundation. This mobile application enables users to scan live leaves using their device camera, where the disease prediction is overlaid on the real-world view in real time. To improve visualization, background removal and cutoff shaders were implemented, isolating the plant leaf and enhancing prediction clarity. The real-time inference is facilitated by a Python-based Flask API, which allows smooth communication between the AR front end and the model hosted on the server. The application sends the captured and preprocessed images to the backend, receives predictions, and renders them directly into the AR environment. The entire system is deployed on a cloud-based server to ensure scalability, low-latency response times, and accessibility from various geographical locations. Continuous refinement of the system was guided by feedback from agricultural experts and farmers, ensuring the solution remains practical, user- friendly, and adaptable to real-world field conditions.

IV. DATASET

The dataset consists of 61,486 images belonging to 39 different classes of plant leaves, including both healthy and diseased samples. To enhance model performance and ensure robustness, six data augmentation techniques were applied: flipping, Gamma correction, noise injection, PCA color augmentation, rotation, and scaling. These techniques helped improve generalization by simulating diverse real-world conditions. The dataset was sourced from publicly available repositories and supplemented with custom- collected images for validation. All images were preprocessed by resizing, normalizing, and removing backgrounds to enhance classification accuracy. This dataset serves as the foundation for training the CNN model to distinguish plant diseases effectively.

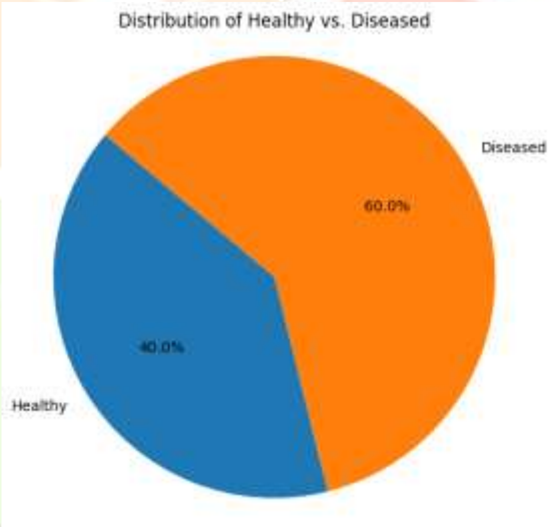

Figure 1: Distribution of Healthy vs. Diseased

IV.1. IMPLEMENTATION

The system implementation involves model training, AR integration, website development, API deployment, cloud hosting, and system evaluation to enable real-time, intelligent plant disease detection across platforms. Four deep learning models—Convolutional Neural Network (CNN), VGG-19, ResNet-50, and Recurrent Neural Network (RNN)—were explored for plant disease classification. The CNN was custom-built with convolutional, pooling, and dense layers to extract essential spatial features efficiently. VGG-19, with its deep 19-layer architecture, improved classification accuracy by capturing hierarchical patterns, while ResNet-50 leveraged residual connections to enable deeper feature extraction without vanishing gradients. RNN, though primarily used for sequential data, was also evaluated to understand its performance in image classification; however, it showed limited effectiveness compared to the other models. All models were trained using TensorFlow and Keras on a dataset comprising 61,486 images across 39 plant disease categories. Images were preprocessed through resizing, background removal (using OpenCV), normalization, and data augmentation with six techniques: flipping, rotation, PCA, gamma correction, noise injection, and zooming. Model performance was optimized using hyperparameter tuning, dropout regularization, and early stopping.

The AR application, developed in Unity 2022.3.49f1 with AR Foundation and ARCore SDK, enables users to scan leaves using a smartphone camera. It overlays real-time disease predictions, including disease name, confidence score, and treatment suggestions, directly on the live camera feed. Background segmentation and custom shaders were implemented to enhance visual clarity and user interaction. A responsive web application, built using HTML, CSS, JavaScript, and Flask, allows users to upload images for diagnosis. Results are displayed with corresponding disease names, descriptions, and treatment recommendations. The web interface includes multilingual support (e.g., English, Tamil, Kannada) to improve usability among diverse users, especially in rural areas. A Flask-based REST API facilitates communication between the frontend (web and mobile) and the backend model. It accepts image inputs, performs necessary preprocessing, and returns predictions in structured JSON format. The API was designed for lightweight operation and optimized for real-time responses even on mobile networks.

To ensure scalability, accessibility, and reliability, the entire backend, including trained models and API services, was deployed on a cloud server (e.g., AWS or Heroku). This allows remote access, fast inference, and secure communication using HTTPS protocols.

IV.2. SYSTEM ARCHITECTURE

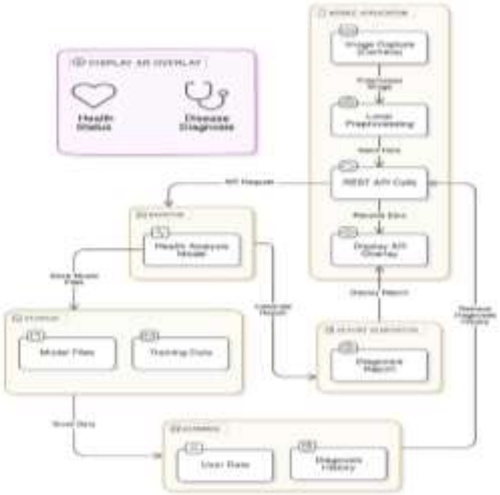

Figure 2: Architecture diagram

The system architecture begins with a mobile application that captures plant images using the device camera. These images are locally pre-processed to enhance quality before being sent via REST API calls to the backend server. The backend houses a Health Analysis Model trained on various plant disease datasets using CNN, VGG-19, ResNet-50, and RNN models. These model files, along with the training data, are stored in the storage module for efficient access and scalability. Once the image is analyzed, a diagnosis report is generated and sent back to the mobile app. The app then overlays the diagnosis results and health status directly onto the live camera feed using Augmented Reality (AR) through Unity and AR Foundation. All diagnosis results and user details are saved in the database, which contains both user data and historical diagnosis records. This allows users to retrieve and review past analyses anytime. The integration of real-time AR, cloud-based AI inference, and user-centric design ensures a seamless and interactive experience for plant health monitoring and disease detection.

V. RESULTS

The performance of various deep learning models for plant disease detection using image classification was investigated. The models evaluated include Convolutional Neural Networks (CNNs), VGG-19, ResNet-50, and Recurrent Neural Networks (RNNs) to determine their effectiveness in classifying plant diseases. Key evaluation metrics such as test accuracy and loss were considered to measure their performance. Accuracy is calculated as:

$$\text{Accuracy}=\frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}*100 \qquad (1)$$

Loss was computed using categorical cross-entropy, defined as:

$$\text{Loss} = -\sum_{i=1}^{C} y_i \,.\log(\widehat{y_i}) \qquad (2)$$

where $y_i$is the true class label, $\widehat{y_i}$ is the predicted probability for class i, and C is the total number of classes. Equations 1 and 2 are used to calculate the accuracy and loss values presented in Table 1.

The results reveal notable differences in model performance. The custom CNN achieved the highest test accuracy of 61.87%, with a training accuracy of 62.94% and a validation accuracy of 57.63%, demonstrating its ability to learn disease-specific patterns from images effectively. ResNet-50 followed with a test accuracy of 36.44%, showing a moderate ability to extract relevant features. RNN performed similarly, with a test accuracy of 36.03%, but struggled with feature extraction due to its sequential nature. VGG-19 exhibited the lowest performance, achieving a test accuracy of 28.79%, indicating challenges in generalizing across the dataset. These findings highlight that CNN-based architectures outperform RNNs and deeper networks like VGG-19 in plant disease detection.

Table 1**:** Results for Our Dataset

Algorithm	Accuracy	Loss
CNN	61.87	-
ResNet-50	36.44	1.7682
VGG-19	28.79	1.9637
RNN	36.03	1.7715

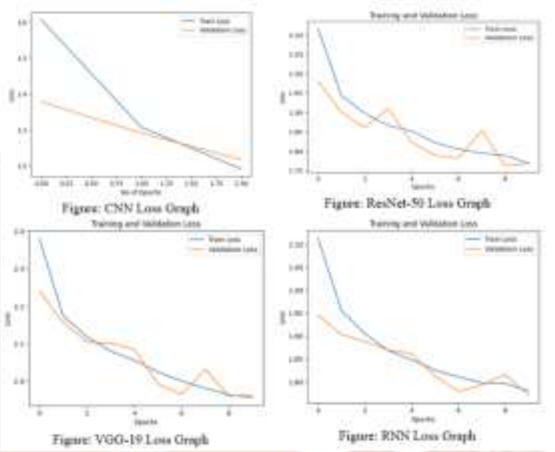

Figure 3: Loss Graph

To enhance the accessibility and usability of the AI-powered disease detection system, a web-based platform was developed, enabling users to identify plant diseases by uploading leaf images. The results are categorized into five key components:

1. **User Interface and Crop Selection**
   The homepage provides an intuitive interface where users can select different crop types. The system is designed for easy navigation, ensuring accessibility for farmers and agricultural professionals.

Figure 4: Home Page

2. **Disease Detection and AI Engine Performance**
   Once a crop is selected, users are directed to the AI engine, where they can upload an image of a plant leaf. The deep learning model analyzes the uploaded image and detects potential diseases with high accuracy.

3. **Disease Diagnosis and Recommendations**

   The system identifies specific plant diseases and provides a brief description, symptoms, and best preventive measures. Additionally, it suggests suitable fungicides and fertilizers for effective disease management.

Figure 5.1: Diagnosis Report

Figure 5.2: Diagnosis Report in Kannada Language

4. **Supplement and Fertilizer Suggestions**

   Based on the detected disease, the system recommends appropriate fertilizers and supplements. This feature integrates product recommendations, helping users take immediate action for disease control**.**

Figure 6: Supplements

5. **Contact and Support System**

   To enhance user experience, the platform includes a dedicated support section where users can seek expert advice or technical assistance.

Figure 8: Contact Page

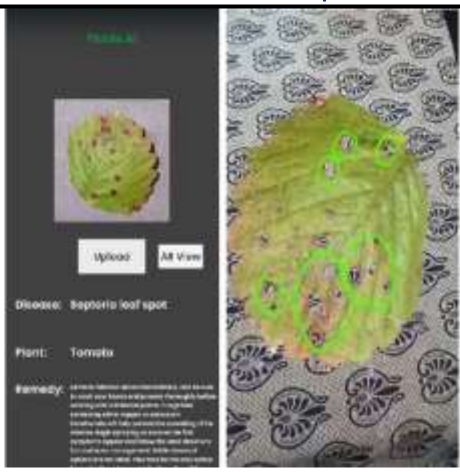

Figure 9: Septoria Leaf Spot

The image on the left shows the web-based interface of the Plant Disease Detection system identifying Septoria Leaf Spot on a tomato leaf. It displays the uploaded image, predicted disease, plant type, and a detailed remedy. The image on the right demonstrates the AR feature of the mobile application, where affected regions on the physical leaf are highlighted in real-time using augmented reality. This visual overlay helps farmers instantly identify diseased areas in the field, improving accuracy and aiding timely intervention.

VI. RESEARCH MOTIVATION AND CONTRIBUTIONS

Augmented Reality-Driven Disease Detection enhances precision agriculture by integrating AR with deep learning for real-time crop disease identification. Traditional manual methods are slow and inaccurate, leading to significant losses. This system uses CNNs trained on extensive datasets to classify diseases and overlay AR visuals, aiding quick decision-making.

By open-sourcing models and datasets, the research promotes sustainable farming, reducing pesticide overuse and improving resource management. Cloud-based storage and predictive analytics track disease trends for proactive interventions. This AI-AR fusion democratizes advanced agricultural technology, empowering farmers and fostering resilient, data-driven farming practices.

VII. CONCLUSION

The system classifies plant diseases from leaf images using deep learning, with a custom CNN achieving the highest accuracy of 61.87%. A web-based interface allows users to upload images, receive diagnoses, and access treatment recommendations. By integrating AI and deep learning, the system enhances early disease detection and treatment strategies. Future improvements include fine-tuning hyperparameters, transfer learning, and dataset expansion. AR-based visualization could further improve diagnosis and user engagement, promoting sustainable and efficient agriculture.

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