AI Meets Nature: Crop Disease Detection with Organic Remedy Recommendations

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Abstract- *Food security and sustainable agriculture are critical global priorities, yet current farming practices heavily reliant on chemical pesticides continue to degrade soil health, reduce biodiversity, and pose risks to human well-being. Most existing AI-based crop disease detection systems focus solely on classification and, when treatment suggestions are provided, they predominantly recommend synthetic chemicals. Such approaches address the symptom but further harm long-term soil fertility and ecosystem balance. This project presents an intelligent, eco-friendly, web-based AI platform that not only detects crop diseases with high accuracy but also recommends sustainable, organic treatments. Advancing beyond conventional Convolutional Neural Network (CNN) models used in prior work, the proposed system leverages Vision Transformers (ViT) for superior global feature extraction, enabling robust detection of subtle disease patterns even under challenging image conditions. To enhance interpretability and facilitate precise localization of infected areas, ViT-based segmentation techniques are integrated, allowing clear visual mapping of diseased regions for better understanding and validation. In addition to detection, the platform incorporates a curated knowledge base of organic and indigenous remedies, rooted in traditional farming wisdom and validated through modern agronomic research. This integration significantly reduces dependence on harmful chemicals, promoting cost-effective, environmentally responsible practices that enhance soil fertility and crop resilience.*

Keywords- Vision Transformer (ViT), Crop Disease Detection, Organic and Indigenous Remedies, Segmentation, Soil Health Restoration.

I. INTRODUCTION

Food security and sustainable agriculture are among the most critical global challenges of the 21st century. With the increasing demand for food, conventional farming practices have become highly dependent on chemical fertilizers and pesticides, which, while effective in the short term, lead to soil degradation, loss of biodiversity, and environmental pollution. Moreover, these chemicals pose significant risks to human and ecological health, emphasizing the urgent need for sustainable and eco-friendly farming alternatives. Traditional crop disease management techniques primarily address visible symptoms without considering long-term ecological impacts.

In recent years, Artificial Intelligence (AI) and computer vision have shown immense potential in automating crop disease detection. However, most existing systems employ Convolutional Neural Networks (CNNs), which, although accurate, struggle to identify subtle disease patterns and frequently suggest chemical treatments that further harm the environment. To overcome these limitations, this project introduces an intelligent, web-based AI platform that integrates disease detection with sustainable treatment recommendations. The system employs Vision Transformers (ViTs), known for their superior feature extraction and global contextual understanding, enabling robust disease identification even under complex image conditions. To ensure interpretability and enhance user trust, segmentation techniques and attention rollout are incorporated to visualize and highlight diseased regions, providing clear insights into the model's predictions. A distinctive component of the platform is its curated knowledge base of organic and indigenous remedies, merging traditional agricultural wisdom with scientifically validated solutions. This integration promotes environmentally responsible, cost-effective, and sustainable farming practices, reducing dependency on synthetic chemicals while improving soil health and crop resilience. Overall, the proposed system represents a step toward AI-driven sustainable agriculture, combining advanced deep learning, explainable visualization, and eco-friendly solutions to empower farmers and promote long-term agricultural sustainability.

This paper presents an AI-based web platform using Vision Transformers (ViTs) and segmentation for accurate crop disease detection and visual interpretation. It recommends organic remedies to reduce chemical use, promoting sustainable and eco-friendly farming practices.

II. RELATED WORK

Recent advancements in artificial intelligence and deep learning have significantly improved plant disease detection and management. Maral et al. developed a CNN-based model for wheat disease detection with 93–96% accuracy, promoting sustainable farming through organic treatments but limited by small datasets [1]. Barman et al. proposed an EfficientNetB0–SVM hybrid model for rice, potato, and corn, achieving 95.29% accuracy though lacking treatment recommendations [2]. Albahli introduced AgriFusionNet, a lightweight EfficientNetV2-B4 model utilizing drone and environmental data, achieving 94.3% accuracy with few misclassifications [3]. Polly and Devi combined YOLOv8, DeepLabV3+, and U-Net for classification and segmentation, reaching 92.89% validation accuracy but depending on chemical treatments [4]. Behera et al. integrated Federated Learning with CNNs for privacy-preserving disease prediction (94% accuracy), though scalability was limited [5]. Drone-based CNN approaches, such as those by Vardhan and Swetha, achieved 92.3% accuracy but required high computation [6]. Islam et al. developed a web-based CNN system (96% accuracy) that included treatment suggestions for limited crops [7], while Niaz et al. designed a smartphone app using SVM, RF, and AdaBoost for wheat detection with 93% accuracy, though dependent on text inputs [8]. Wijekoon et al. used Inception V3 and Mask R-CNN (95–97%) with GIS forecasting but restricted crop range [9], and Yakkala et al. combined CNN and SVM for early detection with 95–97% accuracy, relying on image quality [10].

Tamim et al. presented InsightNet, a MobileNet-based XAI model achieving ~97% accuracy with transparent detection [11]. Pandian et al. developed LeafCheck using ResNet50 (95.3%) for tomato, potato, and bell pepper diseases [12]. Islam et al. introduced PlantCareNet, a mobile AI system (97%) for detection and treatment guidance [13]. Natarajan et al. proposed HerbNet (EfficientNetB0 + CNN + KNN) with 93.95% accuracy emphasizing explainability [14]. Islam et al. later designed a ResNet50-powered web app (95.98%) offering early detection and treatment support [15]. Ramesh and Hebbar achieved 95.01% using EfficientNetV2S for multi-disease detection but noted noise sensitivity [16]. Ibrahim et al. integrated AI and IoT using ResNet50 for real-time monitoring (96.8%), enabling automated farm management [17]. Roumeliotis et al. combined GPT-40 and CNN for multimodal detection (92.12%), enhancing interpretability but requiring high computation [18]. Mohanty et al. conducted a landmark study applying GoogLeNet CNN (95.35%) that pioneered AI-based plant pathology [19].

Additional studies explored optimization and hybrid techniques. Kethineni and Pradeepini applied SVM with Firefly Optimization achieving 91.3% accuracy but faced high computational costs [20]. Mekala et al. proposed a CNN model detecting bacterial spot and blight (96%) with remedy suggestions [21], while Saraswathi et al. developed a CNN-based automatic detection system with 96% accuracy, recommending mobile-friendly deployment [22]. Priya applied Faster R-CNN for cotton disease detection (95.57%) [23]. PrajwalGowda et al. introduced a CNN model for paddy disease detection (93.53%) including remedies [24]. Abinaya and Kavitha Devi proposed a CAE–CNN hybrid (96.73%) incorporating farmer feedback [25]. Rekha et al. built a CNN web platform (94.17%) for tomato diseases suggesting organic remedies [26], and Silviya et al. developed a GUI-based CNN system (94–95%) supporting pesticide reduction [27]. Khandagale et al. introduced FourCropNet (CNN + attention) achieving 99.7% accuracy for four crops [28]. Prakash et al. proposed NLASS (94.54%) using deep learning for leaf disease detection [29], while Jeevitha and Chitra combined CNN and VGG16 with LIME explainability achieving up to 98% accuracy [30].

III. SYSTEM DESIGN

The designed model architecture provides an organized and efficient way for farmers to detect plant diseases accurately and access natural, organic treatment solutions.

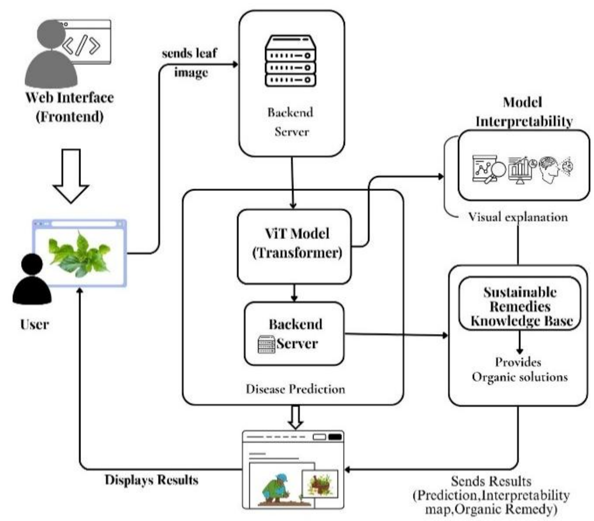

Figure 1: System Architecture

1. Image Upload and Interaction:

At the first stage of the process, users such as farmers or researchers begin by selecting the crop type from a list of Eight available options Apple, Corn, Cotton, Wheat, Paddy, Sugarcane, Chilli or Tomato through a simple and user-friendly web interface. Once the crop type is chosen, users can upload an image of the affected leaf from their device. This interface acts as the entry point to the system, designed with easy navigation and accessibility in mind so that even users with minimal technical knowledge can operate it effortlessly. The system ensures smooth communication with the backend, automatically processing the selected crop and image to initiate the disease detection process. This step enhances the practicality of the system for real-world agricultural use and promotes wider adoption among farmers.

2. Data Processing Module:
After the image is uploaded, it is transferred to the backend server for processing. The backend plays a crucial role by managing user requests, handling data flow, and ensuring secure communication between the frontend and the AI model. It performs preprocessing operations such as resizing, normalization, and image enhancement to ensure that the input image meets the model's requirements. This stage also optimizes data for better prediction accuracy and efficiency. Once preprocessing is complete, the backend forwards the refined image to the Vision Transformer (ViT) or Swin Transformer models for analysis. Overall, this layer ensures reliable, fast, and scalable system performance.

3. Vision Transformer (ViT) Model:
The Vision Transformer (ViT) model is a key part of the architecture, using powerful self-attention mechanisms to focus on important image regions for accurate and efficient disease detection. For apple and tomato, ViT captures global visual patterns and fine texture details, while for corn, cotton, paddy, sugarcane, chilli and wheat, the Swin Transformer variant effectively extracts both local and global features through its shifted window approach. Together, these models analyze pre-processed leaf images to classify whether a leaf is healthy or infected and identify the exact disease type, ensuring high accuracy, robustness, and consistency across all crop types.

4. Model Interpretability:
To make the predictions understandable and trustworthy, the system integrates a model interpretability module. This module uses segmentation techniques to visually highlight the diseased portions of the leaf that the ViT model identified during prediction. The segmentation maps clearly outline infected regions, helping users see exactly where the disease occurs. These interpretability features make the model's decisions more transparent and assist researchers and farmers in understanding the reasoning behind each diagnosis. This builds user confidence in the AI system and enhances its usefulness in agricultural education and research.

5. Sustainable Remedies Knowledge Base:
Once the disease is accurately detected, the system interacts with the Sustainable Remedies Knowledge Base. This database contains a collection of organic, eco-friendly, and sustainable treatment methods for various crop diseases. It provides recommendations such as natural fertilizers, biological control methods, or organic pesticide alternatives. By relying on green and chemical-free solutions, this component promotes sustainable agriculture, minimizes environmental harm, and supports long-term soil health. It bridges the gap between technology and sustainability, offering practical guidance for healthy crop production.

6. Results Delivery:
In the final stage, the backend server compiles all the generated outputs disease classification results, segmentation visuals, and suggested organic remedies and sends them back to the frontend. The web interface then displays the results in an organized and easy-to-understand format. Farmers can view the predicted disease, segmented disease areas, and recommended organic treatments all in one place. This integrated output allows users to take quick and informed action, improving crop management efficiency and supporting environmentally responsible farming practices.

IV. METHODOLOGY

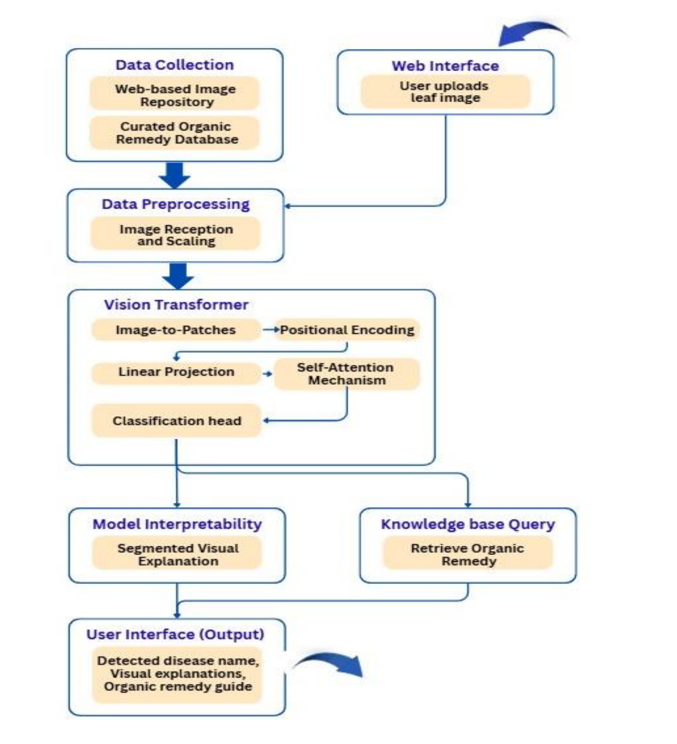

Figure 2: Workflow

Data Collection:
The system starts by collecting leaf images of both healthy and diseased plants from different online sources or field data. It also has an Organic Remedy Database that stores natural and chemical-free treatments for different plant diseases. These two sources help in training the AI model and providing useful remedies after disease detection. The data collected ensures a

wide variety of disease samples, improving the system's ability to recognize multiple crop conditions accurately. It acts as the foundation for creating a reliable and efficient detection model.

Web Interface:

A user-friendly web page is designed where farmers or users can first select the crop type such as apple, corn, cotton, paddy, sugarcane, chilli, wheat, or tomato and then upload a picture of the leaf. This makes the system easy to use for everyone, even those without technical knowledge. The web interface acts as the starting point for the entire process, providing clear instructions and feedback during image upload. It ensures smooth communication between the user and the AI system, enabling quick and efficient disease detection.

Data Preprocessing:

After the image is uploaded, it goes through preprocessing steps like resizing and scaling. These steps make sure all images are in the same size and format. This helps the AI model to work better and give more accurate results. Noise reduction and normalization techniques may also be applied to improve image clarity, ensuring that the model receives clean and uniform data for learning.

Vision Transformer Model:

The Vision Transformer (ViT) and Swin Transformer are the main AI models used for leaf image analysis and disease detection. ViT divides the image into patches and uses self-attention to detect key diseased areas, while the Swin Transformer, an advanced variant of ViT, applies shifted windows to efficiently capture both local and global features. Together, they provide faster processing, higher accuracy, and more reliable classification results across different crop types and varying image conditions.

Model Explainability:

To help users understand how the AI made its decision, the system uses image segmentation, which separates and highlights the diseased areas of the leaf from the healthy regions. This provides a clear visual representation of which parts of the leaf are affected, making the results more understandable to users. It also helps developers verify whether the model is accurately detecting the disease-affected regions, thereby improving transparency and reliability in the detection process.

Results Generation and Recommendations:

Once the disease is identified, the system checks the Organic Remedy Database to find the best natural treatment for that disease. The final result shown to the user includes the disease name, a highlighted image showing affected areas, and an organic remedy guide to help the farmer take action easily. This step ensures the solution is not just diagnostic but also prescriptive, supporting sustainable farming by promoting eco-friendly remedies instead of chemical treatments.

V. RESULTS AND DISCUSSIONS

Performance Metrics

The trained crop disease detection models like Apple, Tomato, Wheat, Cotton, Paddy, Sugarcane, Chilli and Corn were evaluated using dedicated test datasets. Each model's performance was analysed using four key evaluation metrics. Accuracy, Precision, Recall, and F1-Score. These metrics collectively measure the models' effectiveness in correctly identifying diseased and healthy leaf samples. The results demonstrate that all models achieved high performance, with accuracies ranging from 97% to 99%, indicating strong reliability and robustness in disease classification across multiple crop types.

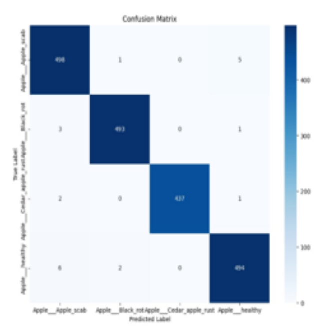

Figure 3: Apple Metrics

Figure 4: Tomato Metrics

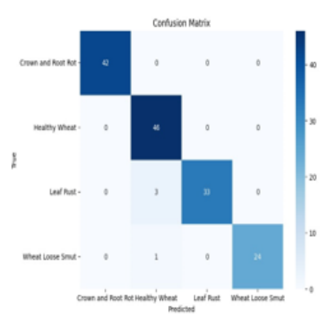

Figure 5: Wheat Metrics

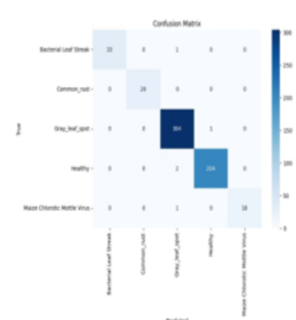

Figure 6: Corn Metrics

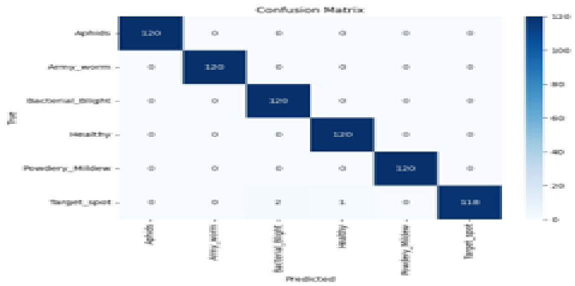

Figure 7: Cotton Metrics

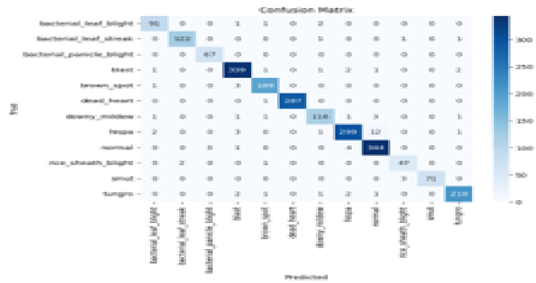

Figure 8: Paddy Metrics

Figure 9: Chilli Metrics

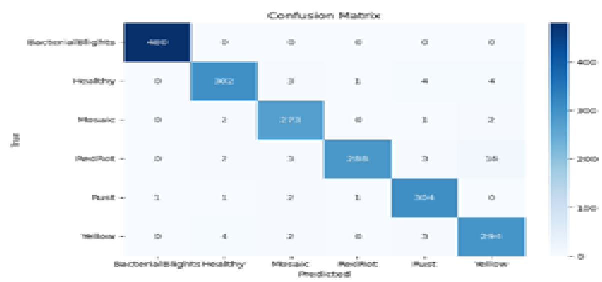

Figure 10: Sugarcane Metrics

Performance	Apple	Tomato	Wheat	Cotton	Corn	Paddy	Sugarcane	Chilli
Accuracy	0.9992	0.9700	0.9732	0.9958	0.9915	0.9698	0.9724	0.9912
Precision	0.9990	0.9800	0.9753	0.9959	0.9916	0.9699	0.9730	0.9920
Recall	0.9990	0.9800	0.9732	0.9958	0.9915	0.9698	0.9724	0.9912
F1 Score	0.9990	0.9800	0.9732	0.9958	0.9915	0.9698	0.9724	0.9911

Fig 11: Performance Metrics Table

The proposed models were successfully integrated with a user-friendly web interface that allows farmers and users to interact with the trained Vision Transformer and Swin Transformer models in real time. Through this interface, users can select a crop type, upload an image of the affected leaf, and instantly receive disease detection results along with visual segmentation of the infected areas. The interface displays the predicted disease name, segmented visualization, and corresponding organic remedy recommendations, making the system both diagnostic and prescriptive. The integration ensures seamless communication between the frontend and backend, enabling fast processing and accurate predictions even on moderate hardware. This real-time implementation demonstrates the practicality of the proposed model in real agricultural scenarios, helping farmers make quick, informed, and eco-friendly decisions for effective crop management.

VI. CONCLUSION AND FUTURE WORK

The AI Crop Disease Detection System represents a remarkable step toward transforming traditional agriculture into a smarter, more sustainable, and technology-driven practice. By integrating artificial intelligence with deep learning and computer vision, the system provides an efficient way for farmers to detect plant diseases accurately from leaf images through an easy-to-use web interface. Once a user uploads an image, the model analyzes it using advanced techniques like segmentation and Vision Transformers (ViT) to identify the disease, display the confidence score, and suggest suitable remedies and preventive measures. Beyond detection, the platform offers a holistic experience with sections like the Disease Finder, which gives detailed information about various plant diseases and treatments, and the Method of Making page, which promotes the preparation of organic fertilizers and natural remedies such as Bijamrut, Jeevamrutham, and Panchagavya encouraging eco-friendly farming. Its modern interface, seamless navigation, and ability to provide instant feedback make it a reliable digital assistant for farmers and agricultural researchers alike.

Looking ahead, the future scope of this project is vast. It can evolve into a comprehensive smart-farming ecosystem by incorporating IoT sensors for real-time crop health monitoring, satellite-based disease prediction, and integration

with weather forecasting systems. A dedicated mobile application can make it more accessible to farmers in remote regions, while multilingual and voice-assistant features can overcome language barriers. Further, expanding the dataset to include more crop varieties and regional diseases will enhance model robustness and accuracy. Overall, this project not only demonstrates how AI can revolutionize agriculture but also lays the foundation for a future where technology and sustainability work hand in hand to ensure healthier crops, reduced losses, and improved livelihoods for farmers worldwide.

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