Deep Learning Based Plant Disease Detection Using Image Recognition

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Abstract— *Crop diseases in agriculture are among the greatest threats to the food chain around the world both in terms of stability and sustainability. Detection of plant diseases relies heavily on human inspection, with methods that take time, but are not only riddled with inaccuracies but demand a highly specialist approach. To overcome the limitations, This paper presents an ensemble deep learning framework for automatic detection and classification of plant diseases using leaf images. By integrating custom Convolutional Neural Networks (CNN) with pre-trained models such as AlexNet, VGG-19, and ResNet-50, the system achieves improved accuracy, reduced training time, and enhanced adaptability to real-world agricultural environments. The goal is to reduce manual intervention, minimize crop loss, and optimize pesticide use, thereby supporting sustainable and scalable crop disease management.*

Index Terms— **Convolutional Neural Networks (CNN), Transfer Learning, Ensemble Learning, Plant Disease Detection, Deep Learning, Agriculture, Image Recognition**

I. INTRODUCTION

Agricultural productivity is an important component of the world economy; production of food plays a critical role in human welfare and resources. However, the biggest problem that crops face is the disease problem, which not only affects the quality of the yield produced but also has a huge impact in relation to food security on a wide perspective. Contemporary approaches for identifying plant diseases predominantly rely on manual processes, necessitating the involvement of specialists who visually examine plants for indications of illness. Although these techniques are beneficial, they frequently exhibit drawbacks such as slowness, high costs, and susceptibility to human inaccuracies. Furthermore, as agricultural field sizes expand, the challenge of efficiently monitoring crops intensifies. The last couple of years have deeply altered various fields because of the integration of AI and ML into their procedures. Agriculture is not exempted from these disciplines. Deep learning approaches, specifically CNNs, have brought massive effectiveness in image classification and pattern recognition tasks, which, consequently, makes them ideal for being deployed in plant disease identification. The objective is to develop a model that harnesses the functionality of CNNs and transfer learning to identify and classify crop diseases based on the images of leaves. But the primary aim is to create a robust and scalable system, thereby being operational in real-world scenarios, bypassing the stringent limits of the traditional approach. It is mostly aimed at automating the disease detection process so as to increase early diagnoses accuracy, thereby reducing the impact of diseases on crops, improving the quality of yields, and promoting sustainable agricultural methodologies.

II. LITERATURE SURVEY

The use of deep learning in plant disease detection has seen considerable growth, with numerous models designed to improve accuracy and automation in diagnosis. Conventional methods, though valuable, suffer from significant limitations such as reliance on human judgment, time inefficiency, and reduced scalability. In contrast, deep learning models—particularly Convolutional Neural Networks (CNNs)—have demonstrated strong capabilities in image-based classification tasks.Recent studies emphasize the power of transfer learning and ensemble techniques to further enhance model performance.For example, EfficientNetB0 integrated with Explainable AI (XAI) has shown high classification accuracy and interpretability. Ghani et al. utilized continual learning and few-shot learning to address data limitations in wheat disease identification. Islam et al. introduced a lightweight 2D CNN model capable of real-time detection on mobile platforms.Superpixel segmentation methods, as proposed by Khan et al., achieved effective detection in natural environments but require manual optimization. Several researchers, including Mehedi et al. and Ferentinos, have employed pre-trained networks like ResNet, AlexNet, and GoogleNet to classify a wide range of diseases with notable success, although with increased computational cost. UAV-integrated CNN models, such as those by Wu et al., provide scalable field monitoring, albeit with weather and cost constraints.

The literature also highlights the utility of hybrid approaches. Cengil et al. combined AlexNet, ResNet50, and VGG16 with traditional ML classifiers to boost performance. MobileNet and custom deep CNNs offer real-time capability with reduced parameters, suitable for edge devices. Despite these advances, challenges remain in achieving scalability, real-time deployment, and generalization across diverse crops and environmental conditions.This literature forms the foundation for the proposed hybrid model that combines multiple deep learning techniques to enhance robustness, accuracy, and adaptability in real-world agricultural scenarios.

III. METHODOLOGY

This proposed ensemble learning or hybrid model combines the strengths of multiple deep learning approaches and compensates for the inherent limitations of individual models. The proposed method integrates transfer learning models such as VGG16, ResNet-50, and a custom CNN to tap into the diverse capabilities of the architectures. While transfer learning models have been pre-trained on massive datasets and are better at general feature extraction, there is a designed CNN tailor-made to capture peculiar domain features regarding plant disease detection. The ensemble learns complementary features from each of the two constituent models, thus alleviating some of the challenges from subtle visual distinctions among diseases to overlapping symptoms as every disease has. Furthermore, the joined technique enhances the model's generalization across various categories of diseases and contexts of the environment to ensure the resilience of the model even in situations characterized by noisy or incomplete information. Overfitting and bias are further reduced using the ensemble technique, and thus the well-rounded model provides uniform and dependable predictions. The synergy of these models not only enhances the accuracy of detections but also promotes early and accurate identification of plant diseases, thus timely interventions and better crop health management.

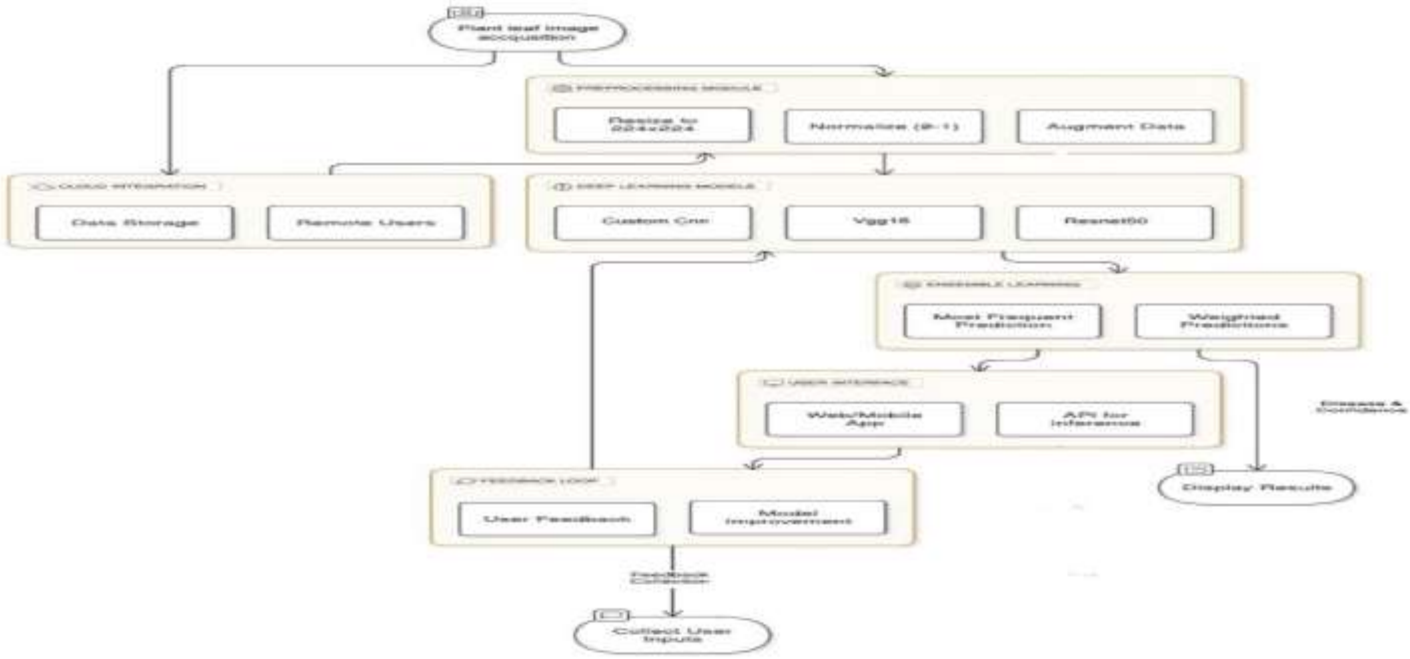


Figure: System Architecture

The architecture of the proposed plant disease detection system can be visualised as follows:

1. Plant Leaf Image Acquisition

- This step involves capturing images of plant leaves, which are the primary input for the system. The images can be acquired through mobile devices, cameras, or specialized imaging hardware.

2. Preprocessing Module

- Resize to 224x224: Images are resized to a uniform dimension (224x224 pixels) to meet the input requirements of the deep learning models.
- Normalize (0-1): The pixel values of the images are normalized to a range of 0 to 1 to improve model performance.
- Augment Data: Data augmentation techniques (like rotation, flipping, and zooming) are applied to enhance the diversity of the training dataset and prevent overfitting.

3. Cloud Integration

- Data Storage: Acquired and processed images are stored in a cloud-based system for easy access and scalability.
- Remote Users: Enables users to interact with the system from remote locations through cloud services.

4. Deep Learning Models

- The architecture uses multiple deep learning models to analyze the plant leaf images:
    - Custom CNN: A Convolutional Neural Network designed specifically for this task.
    - VGG16: A pre-trained deep learning model known for its strong performance in image classification tasks.
    - ResNet50: Another powerful pre-trained model capable of handling complex image recognition tasks.

5. Ensemble Learning

- Predictions from the individual models are combined using ensemble techniques:
    - Most Frequent Prediction: Determines the final result based on the most common prediction from the models.
    - Weighted Predictions: Combines the predictions by assigning weights to each model based on its reliability or performance.

6. User Interface

- Web/Mobile App: Provides a user-friendly interface for end-users to upload leaf images and view results.
- API for Inference: Offers an API to integrate the detection system with other applications or systems.

7. Display Results

- The system displays the detected plant disease along with the confidence score to the user.

8. Feedback Loop

- User Feedback: Allows users to provide feedback on the system’s predictions, which helps in evaluating the system's accuracy and usability.
- Model Improvement: Incorporates user feedback to improve the model through retraining and fine-tuning.

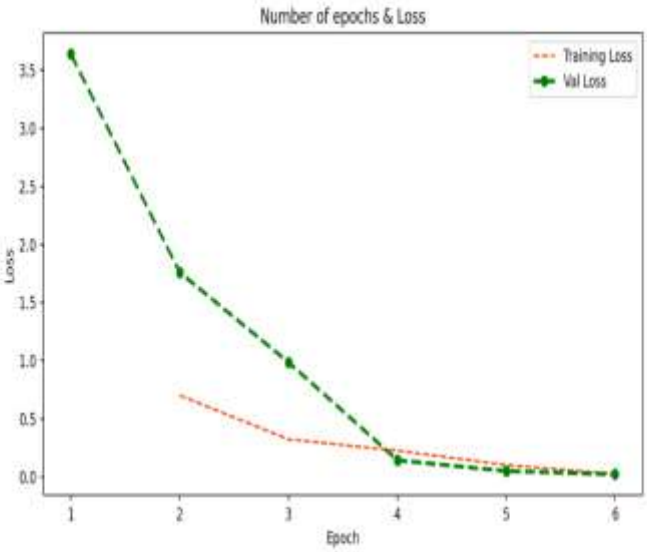
9. Collect User Inputs

- User inputs are collected systematically for further analysis and to refine the system's performance iteratively.

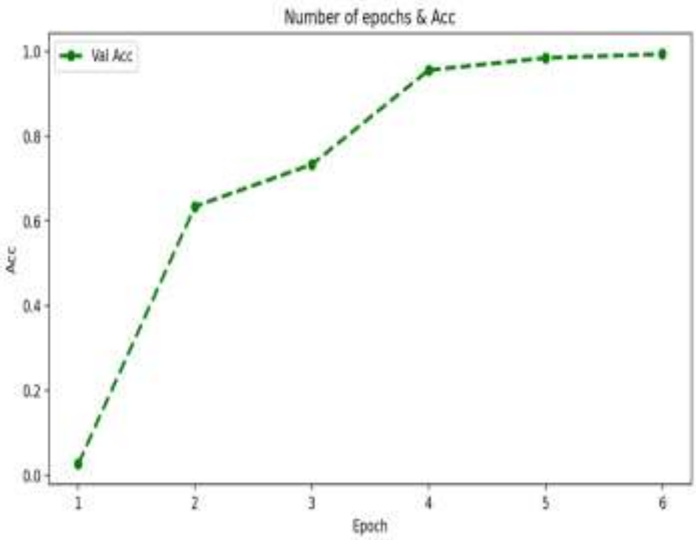
IV. Experiments and Results

. The system integrates a custom Convolutional Neural Network (CNN), VGG16, and ResNet50 models, each trained and fine-tuned for image classification of plant leaf diseases. The custom CNN achieved the highest accuracy of 99.35%, with precision, recall, and F1-score values exceeding 95%, indicating strong generalization and minimal overfitting. In comparison, the VGG16 model, fine-tuned with a custom classifier, achieved 97.36% accuracy, while ResNet50 used as a feature extractor combined with Random Forest and K-Nearest Neighbors classifiers achieved 85.28% and 82.30% accuracy, respectively. These results outperform many existing models that typically range between 85%–92% accuracy on smaller datasets.

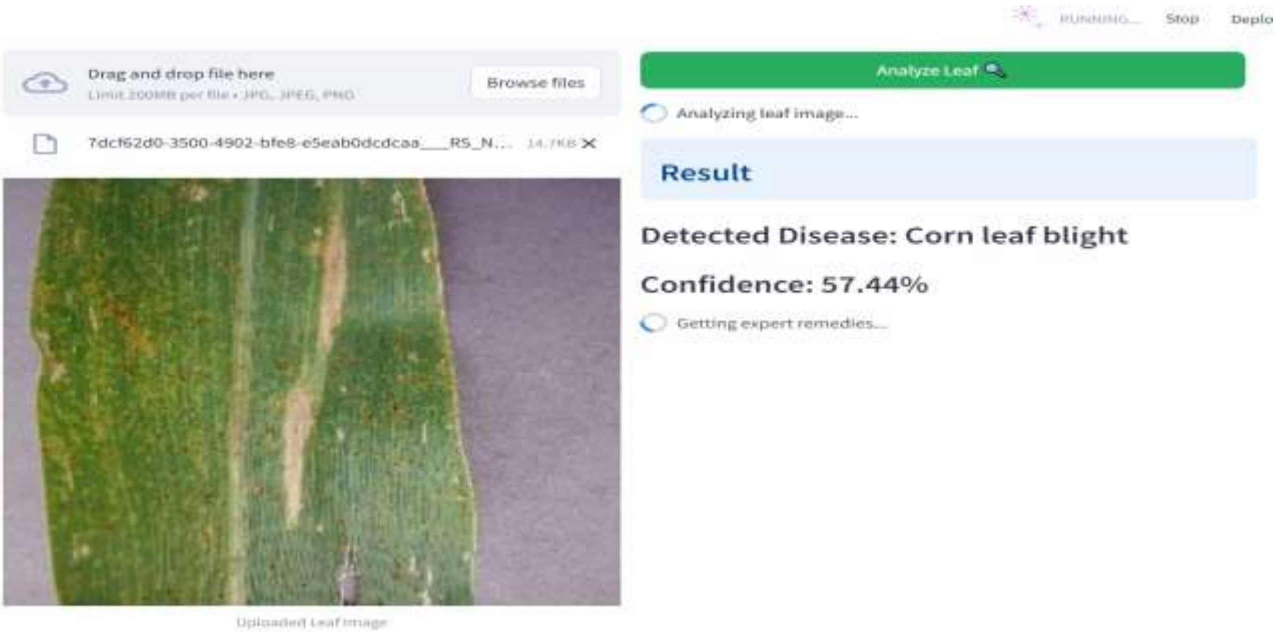
(a)

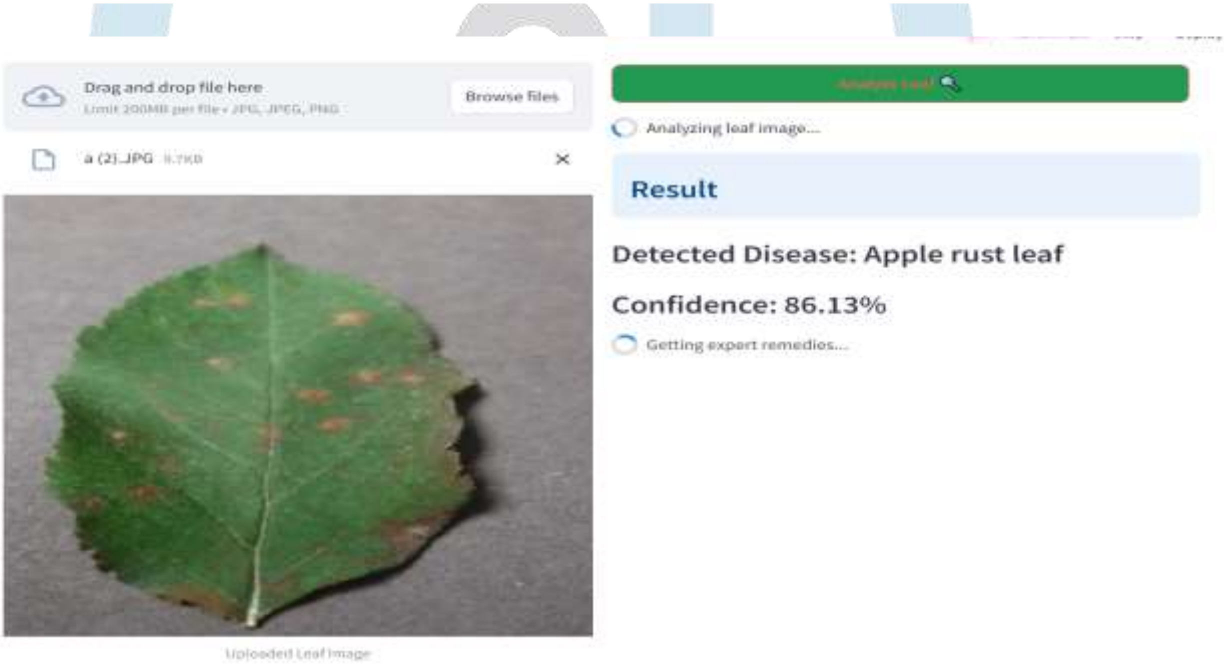


(b)



The two graphs together depict the performance of a model over 6 training epochs in terms of loss and accuracy on the validation dataset. In the first graph, we see both training and validation loss consistently decreasing, with validation loss showing a sharp drop from above 3.5 to nearly 0, suggesting the model is learning effectively and generalizing well without overfitting. The second graph complements this by showing a steep and consistent rise in validation accuracy, climbing from a meager 3% to nearly 100%, indicating the model is becoming highly accurate with each epoch. Together, these trends suggest a well-behaved and efficiently trained model — basically, the AI glow-up arc


Stop
Deplo
Drag and drop file here
Browse files
Analyze Leaf
Analyzing leaf image...
Result
Detected Disease: Corn leaf blight
Confidence: 57.44%
Getting expert remedies...
Uploaded Leaf Image


Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
a (2).JPG
Analyzing leaf image...
Result
Detected Disease: Apple rust leaf
Confidence: 86.13%
Getting expert remedies...
Uploaded Leaf Image


Drag and drop file here
Browse files
Analyzing leaf image...
Result
Detected Disease: Tomato Septoria leaf spot
Confidence: 55.02%
Getting expert remedies...

V. Conclusion

This project successfully developed a Plant Disease Detection system using Custom CNN and Transfer learning model vgg16 and Resnet50 using the ensemble approach for Detecting Plant diseases and providing treatment details. The proposed system promises a reduction in the manual time taken for disease detection, leads to crop management excellence, and results in real-time scalable solutions for the farmers. This paper demonstrates the effectiveness of an ensemble deep learning approach—combining custom CNNs with VGG16 and ResNet-50—for the automatic detection and classification of plant diseases using leaf images. The proposed system achieves high accuracy (up to 99.35%), adaptability across diverse conditions, and real-time readiness, outperforming many existing models. By integrating cloud services, feedback loops, and a user-friendly interface, the framework promotes early diagnosis, reduced crop loss, and scalable, sustainable agricultural practices.

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