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Plant Disease Detection Using Deep Learning

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ABSTRACT
This paper presents an explainable deep learning-based system for plant leaf disease detection using EfficientNetB0. The proposed approach leverages transfer learning to accurately classify plant diseases from leaf images. To enhance transparency and interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is integrated to visualize the regions influencing the model's predictions. The model is trained on a balanced subset of the PlantVillage dataset consisting of 19 classes. Experimental results demonstrate high classification accuracy, indicating the effectiveness of the proposed approach. In addition, the system provides disease-specific precautions and treatment recommendations, making it a practical solution for real-world agricultural applications.

Keywords: *Plant Disease Detection, EfficientNetB0, Deep Learning, Grad-CAM, Explainable AI Image Classification.*

INTRODUCTION

Agriculture is the backbone of many economies around the world, especially in developing countries, where a significant portion of the population depends on it for livelihood. One of the persistent challenges in agriculture is the spread of plant diseases, which can severely affect crop quality and yield. Leaf diseases, in particular, are often the earliest indicators of a plant's deteriorating health and can quickly spread if not diagnosed and treated promptly. Traditionally, the detection and diagnosis of these diseases rely heavily on human expertise, which may not always be readily available in remote or under-resourced areas. Moreover, manual inspection is timeconsuming, prone to human error, and often inconsistent due to varying levels of expertise.In recent years, the emergence of deep learning and computer vision has opened new possibilities for automating plant disease detection with high accuracy. Models such as Convolutional Neural Networks(CNNs) have demonstrated excellent performance in image classification tasks, making them suitable for identifying patterns and features in diseased leaves. However, a common limitation of most AI-based disease detection systems is their lack of transparency. These systems often operate as "black boxes"—making predictions without explaining the rationale behind them. This lack of interpretability can lead to mistrust among end-users, particularly in critical domains like agriculture where decisions have real-world consequencesTo address these challenges, this project introduces an intelligent, end-to-end system for plant leaf disease detection using ensemble learning and explainable AI. The system combines the strengths of two powerful CNN architectures—EfficientNetB0 and ResNet50—to enhance prediction reliability through model ensembling. In parallel, it integrates GradCAM (Gradient-weighted Class Activation Mapping) to generate visual explanations by highlighting the specific regions in the leaf image that influenced the model's decision. This approach enhances user confidence and enables domain experts to validate the AI's reasoning.decision.Beyond detection, the system goes a step further by providing recommended precautions and possible cure for the detected diseases. These suggestions are tailored to the specific disease identified and aim to assist farmers in taking timely and effective action. The combination of high-performance deep learning models, visual explainability, and actionable guidance makes the system practical, trustworthy, and ready for deployment in real agricultural scenarios. In summary, the proposed solution is designed not only to automate the diagnosis of plant leaf diseases but also to bridge the gap between AI predictions and real-world decision-making in agriculture. It empowers users—especially farmers and agricultural workers—with the tools to detect diseases early, understand the cause, and take corrective measures, thereby contributing to more sustainable and productive farming practices.

OBJECTIVE

The primary objective of this project is to develop an efficient and accurate deep learning-based system for automated plant leaf disease detection using EfficientNetB0. The system aims to classify plant diseases from leaf images with high precision by leveraging transfer learning techniques. Another key objective is to enhance the interpretability of the model by integrating Grad-CAM, which provides visual explanations by highlighting the regions of the leaf image that influence the model's predictions. This helps in building user trust and understanding of the model's decision-making process. Additionally, the project aims to provid practical support to farmers and agricultural experts by suggesting disease-specific precautions and treatment measures. The overall goal is to create a reliable, user-friendly, and scalable solution for early detection and management of plant diseases in real-world agricultural environments.

1. To develop an accurate plant disease detection system using EfficientNetB0 and transfer learning.
2. To classify plant leaf images into multiple disease categories with high precision.
3. To integrate Grad-CAM for visual explanation of model predictions and improved interpretability.
4. To evaluate model performance using metrics such as accuracy and confusion matrix.
5. To provide disease-specific precautions and treatment suggestions for practical agricultural use.

LITERATURE SURVEY

Upadhyay et al. (2025) explored the application of deep learning and computer vision techniques for plant disease detection, highlighting modern AI-based approaches and their effectiveness in automated crop monitoring using various agricultural image datasets.

Pacal et al. (2024) conducted a systematic review of deep learning techniques for plant disease detection using multiple public datasets. Their study analyzed numerous research works and emphasized the advantages of deep learning models in achieving early and accurate disease identification.

Ahmad et al. (2023) presented a comprehensive survey on deep learning applications in plant disease detection. Their work focused on transfer learning techniques and summarized key research trends, datasets, and challenges faced in implementing AI-based agricultural solutions.

Jackulin et al. (2022) reviewed artificial intelligence-based plant disease detection methods using both machine learning and deep learning approaches. Their study highlighted the growing importance of deep learning models in improving detection accuracy and automation in agriculture.

Lu et al. (2021) focused on convolutional neural networks (CNNs) for plant leaf disease classification. Their research explained how CNN architectures enhance feature extraction and classification performance, making them highly suitable for image-based disease recognition tasks.

METHODOLOGY

The methodology of the proposed system follows this way:

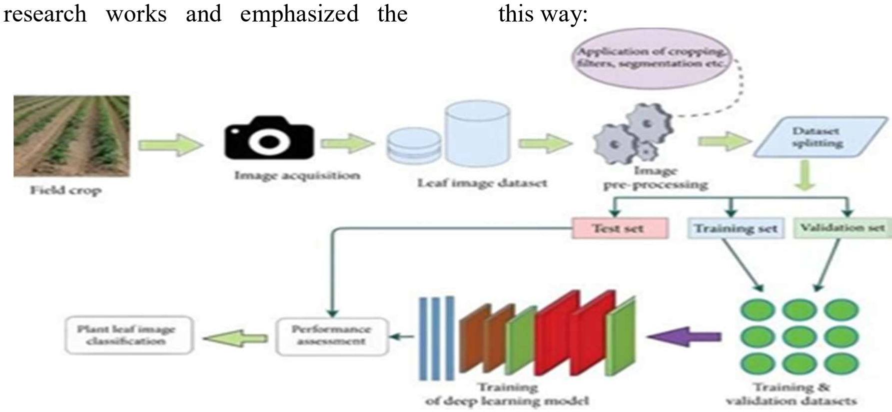

Fig No:1 System Architecture

The methodology is structured into the following key components:

1. **Data collection and preprocessing**

The dataset utilized in this study is sourced from the publicly available **PlantVillage** dataset, which comprises images of plant leaves affected by various diseases, as well as healthy specimens. To ensure consistency and fairness across classes, a total of 19 specific categories were selected, representing a balanced mix of diseases and healthy conditions across different plant types.The chosen classes include: Tomato: Late blight (1527 images), Early blight (800), Healthy (1273)
Grape: Black rot (944), Leaf blight (861), Healthy (339) Potato: Early blight (800), Late blight (800), Healthy (121) Corn (Maize): Northern Leaf Blight (788), Common Rust (953), Healthy (929)
Peach: Bacterial spot (1838), Healthy (288) Apple: Apple scab (504), Black rot (496), Healthy (1316)
Pepper (Bell): Bacterialspot (797), Healthy (1183)
Since the original dataset is imbalanced, each class was carefully adjusted to contain exactly 1,000 images. This balancing was achieved in two ways:

- Undersampling for classes with more than 1,000 images.
- Synthetic data generation for classes with fewer than 1,000 images. To generate additional images for underrepresented classes, data augmentation techniques were employed using the ImageDataGenerator utility in Keras.
- The following parameters were applied:
- rotation_range = 15: Random rotation of images up to 15 degrees.
- zoom_range = 0.1: Random zoom within 10% of the image.
- horizontal_flip = True: Random horizontal flipping.

All images were also resized to a uniform input size suitable for EfficientNet and ResNet models and

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normalized to ensure consistency across the dataset. This preprocessing step helps the models generalize better and improves their learning performance.

2. **Feature Extraction Using Deep Learning:**
The proposed hybrid model integrates EfficientNetB0 and ResNet50 as dual feature extractors to capitalize on the strengths of both architectures.

- **EfficientNetB0**
EfficientNetB0 is a state-of-the-art CNN known for its compound scaling technique, which uniformly scales the network's depth, width, and resolution for optimal performance. It has approximately 5.3 million parameters, making it highly efficient while maintaining high accuracy.It uses a unique compound scaling method that simultaneously scales depth, width, and input resolution, achieving better performance with fewer computations compared to traditional scaling. It is built using Mobile Inverted Bottleneck Convolutions (MBConv) and depthwise separable convolutions, which allow for efficient feature extraction while reducing overfitting and is pretrained on ImageNet hence provides strong generalization for leaf textures and disease patterns when fine-tuned on agricultural datasets.

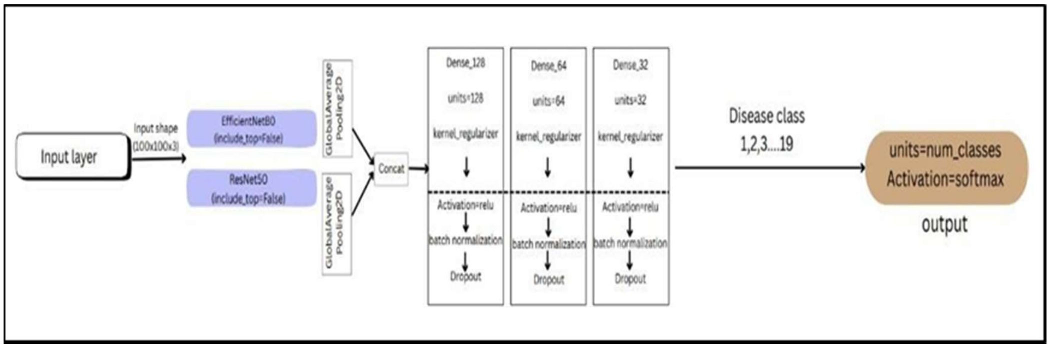

Fig No:2 Model Architecture

3. **Explainable AI (XAI) Integration using Grad-CAM:**
Once a prediction is made, Grad-CAM (Gradient-weighted Class Activation Mapping) is applied to visualize the model's focus area on the input image.This heatmap highlights the diseased region and the leaf border, providing transparency and interpretability for the decision made by the model.

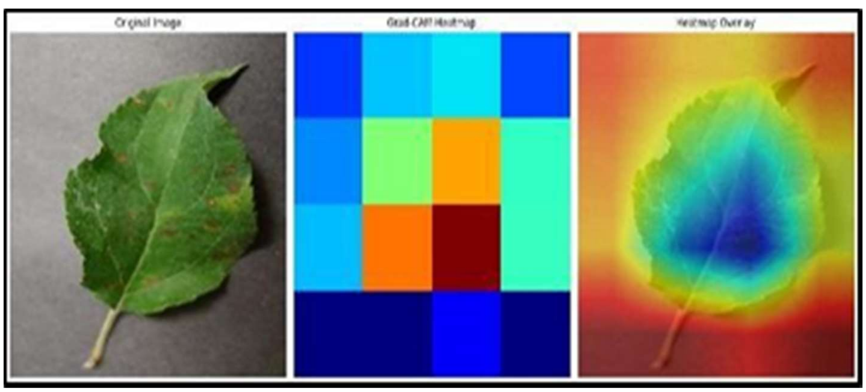

Fig No:3Grad-CAM Result

4. **Precaution and Cure Recommendation:**
Based on the identified disease class, the system retrieves a brief description of the disease, Precautionary measures to prevent its spread, suggested cures or treatments, including organic or chemical options.

System interface:
The system interface for the proposed hybrid plant disease detection model is designed using HTML, CSS. The model is loaded into flask and passed to system int.When a user uploads a leaf image the system processes the image and displays the predicted disease class along with suggested precautions and potential remedies. The model internally uses Grad-CAM (Gradient-weighted Class Activation Mapping) for explainable AI—highlighting the diseased regions and leaf borders and also displays the heatmap on leaf.The prediction and suggedest cure are presented in a readable format beside the visual output, offering an intuitive and informative experience for agricultural experts, botanists and Farmers.

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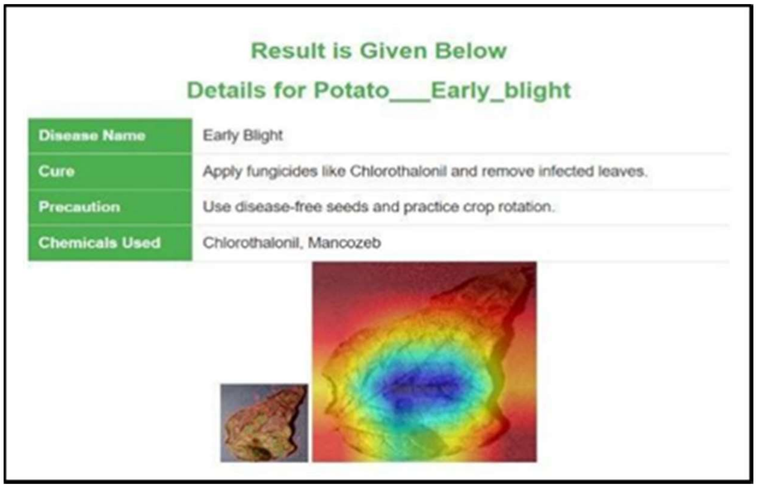


Fig No:4 Result screen

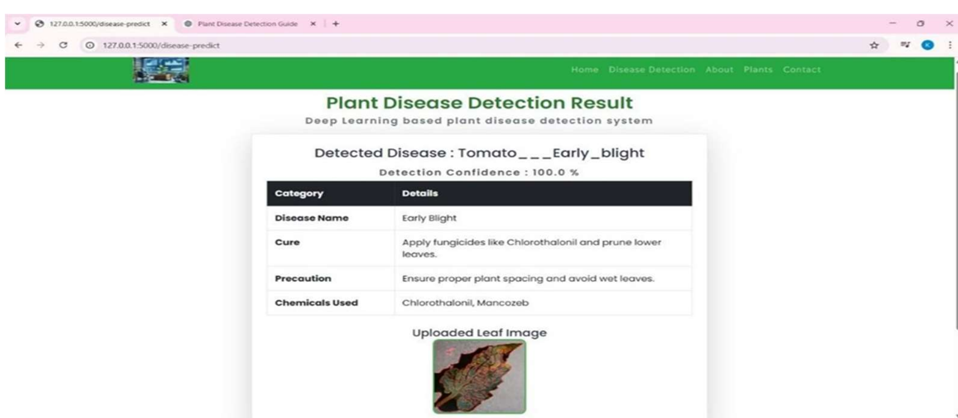
CONCLUSION

The system successfully classifies multiple plant species and disease types with enhanced precision by leveraging the strengths of both architectures—EfficientNetB0's parameter efficiency deep feature extraction capabilities. Furthermore, data imbalance was addressed through image augmentation, and explainable AI using Grad-CAM improved the interpretability of model predictions. The interface presents7 predictions along with disease-specific precautions and treatments, ensuring accessibility and practical utility. To further enhance the scope andimpact of the proposed system, several directions can be pursued in future work:

- Integration with Mobile and IoT Devices: Developing a lightweight, on-device version of the model for smartphones or agricultural drones would allow real-time field diagnosis, especially useful for remote farming regions.
- Multilingual Voice-Based Assistance: Implementing voice feedback in regional languages can make the system more accessible to farmers with limited literacy, enhancing its real-world adoption.

RESULT

The proposed hybrid deep learning model combining EfficientNetB0 and sResNet50 was evaluated on a balanced subset of the PlantVillage dataset consisting of 19 classes, with all images resized to (100, 100, 3). The model achieved strong classification accuracy, leveraging EfficientNetB0's parameter efficiency and ResNet50's deep residual learning to capture detailed and abstract features effectively. The final system was deployed using HTML, CSS, Flask allowing users to upload plant leaf images and receive the image of the heatmap over the leaf and disease predictionsalongwith recommended precautions and treatments.



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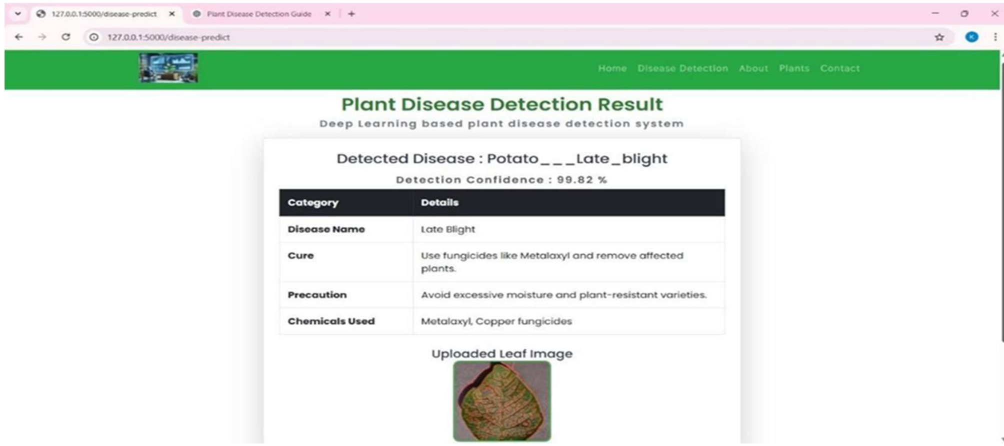

REFERENCES

1. **Shafay, M., et al., 2025.** Recent Advances in Plant Disease Detection: Challenges and Opportunities. Plant Methods.
2. **George, R., et al., 2025.** Past, Present and Future of Deep Plant Leaf Disease Recognition. Computers and Electronics in Agriculture.
3. **Upadhyay, A., et al., 2025.** Deep Learning and Computer Vision in Plant Disease Detection: A Survey. Artificial Intelligence Review.
4. **Pacal, I., et al., 2024.** A Systematic Review of Deep Learning Techniques for Plant Disease Detection. Artificial Intelligence Review.
5. **Abouelmagd, M., et al., 2024.** Capsule Network-Based Tomato Disease Detection. Journal of King Saud University – Computer and Information Sciences.
6. **Anim-Ayeko, P., et al., 2023.** CNN-Based Detection for Potato and Tomato Leaf Diseases. Computers and Electronics in Agriculture.
7. **Kulkarni, A., et al., 2023**. EfficientNetV2 Model for Coffee Leaf Disease Detection. Agricultural Informatics Journal.
8. **Barman, U., & Choudhury, R., 2022**. Citrus Disease Detection Using Hybrid Machine Learning Models. Multimedia Tools and Applications.
9. **Jackulin, C., et al., 2022.** Artificial Intelligence-Based Plant Disease Detection: A Review. Smart Agricultural Technology.
10. **Lu, Y., et al., 2021.** Identification of Plant Leaf Diseases Using Deep Learning: A Review. Agriculture (MDPI).
11. **Abade, A. S., Ferreira, P. A., & Vidal, F. B., 2020.** Plant Disease Recognition on Images Using Convolutional Neural Networks: A Systematic Review. arrive.