Plant Disease Detection System*

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***Abstract*—Plant diseases significantly affect agricultural productivity and food security worldwide. This study introduces a deep learning-based method for accurate plant disease classification using Convolutional Neural Networks (CNNs). The model was trained on the PlantVillage dataset, which contains 43,456 images spanning 38 distinct classes of healthy and diseased plant leaves. Comprehensive image preprocessing techniques were applied to optimize data quality. The CNN model demonstrated excellent performance, achieving an accuracy of 98.34%. To evaluate the model's effectiveness, a confusion matrix was used, offering insights into precision, recall, and class-wise prediction accuracy. For practical deployment, the trained model was integrated into a Streamlit-based web application, allowing users to upload plant images and receive real-time disease predictions. This interactive platform provides an accessible and efficient tool for farmers and agricultural professionals, facilitating early diagnosis and proactive crop management.**

***Index Terms*—Convolutional Neural Networks (CNN), Plant Disease Classification, Deep Learning, Streamlit**

I. Introduction

Agriculture plays a crucial role in sustaining the economies of many countries, but plant diseases continue to pose a significant challenge to crop yield and global food security. Traditional methods of disease identification often rely on expert knowledge, which is limited, especially in rural regions where access to trained professionals may be scarce. Recent advancements in computer vision and deep learning offer a promising alternative to traditional disease diagnosis methods, enabling rapid and accurate identification of plant diseases.

This research leverages **Convolutional Neural Networks (CNNs)** for image-based plant disease classification, utilizing the well-known **PlantVillage dataset**, which contains over 50,000 labeled images of both healthy and diseased plants. The uniqueness of this study lies in its integration of deep learning techniques with real-time, interactive solutions by deploying the trained model through **Streamlit**, which enables users to upload images of their plants and receive immediate disease classification results.

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The research aims to provide faster, more accurate, and scalable solutions to plant disease detection, contributing to food security and reducing crop losses. By providing a system that empowers users in remote areas to access expert-level diagnostics, this approach offers advantages such as increased accessibility, reduced reliance on human expertise, and the potential to scale the solution to cover various plant species and diseases.

The implications of this research extend to farmers, agricultural professionals, and enthusiasts by improving crop management, enabling early disease detection, and optimizing yields, thus contributing to more sustainable and productive agricultural practices.

II. Literature Review

A. Recent and Relevant Research

Deep learning has become one of the most effective tools for plant disease detection due to its ability to learn complex patterns from images. Several studies in recent years have shown the success of convolutional neural networks (CNNs) in this area:

In this paper A systematic review of deep learning techniques for plant diseases provide a comprehensive review of various deep learning techniques applied to plant disease detection and classification. They analyze multiple CNN architectures, highlighting their strengths and limitations across different datasets and plant types. The review also discusses common challenges such as data imbalance, overfitting, and the need for explainable AI in agriculture. Overall, the paper serves as a valuable resource for understanding the current landscape and future directions of deep learning in plant pathology [1].

In this paper Explainable vision transformer enabled convolutional neural network for plant disease identification:

PlantXViT, which integrates Convolutional Neural Networks (CNNs) with Vision Transformers (ViTs) for accurate plant disease identification. The CNN component captures local spatial features, while the Vision Transformer captures global relationships within the image. To enhance transparency, the model incorporates explainability techniques that visualize attention maps, helping users understand which image regions influenced the prediction. This hybrid architecture not only improves classification performance but also ensures interpretability, making it suitable for real-world agricultural applications [2].

In this paper Deep learning-based leaf disease detection in crops using images for agricultural applications, focusing on convolutional neural networks (CNNs) to classify plant leaf images. They highlight the effectiveness of CNNs in automatically extracting important features, reducing the need for manual intervention. The study also discusses the importance of large and diverse datasets in improving model accuracy and generalization. Their work demonstrates how deep learning can offer a robust and efficient solution for early disease detection in agricultural practices [3].

In this paper Explainability of deep learning-based plant disease classifiers through automated concept identification method to enhance the interpretability of deep learning models used for plant disease classification. Utilizing the InceptionV3 architecture trained on the PlantVillage dataset, ACE automatically identifies human-understandable visual concepts that influence model predictions. This approach uncovers both relevant disease-related features and unintended biases, such as background elements or lighting conditions, that may affect the model's decisions. By providing insights into the specific concepts driving classification outcomes, the study contributes to the development of more transparent and trustworthy AI tools for agricultural disease management [4].

Other researchers have also explored data augmentation and GANs (Generative Adversarial Networks) to create synthetic plant images when datasets are small. However, some of these generated images may not be realistic enough for accurate model training.

B. B. Critical Analysis and Discussion

While deep learning methods have shown excellent performance in plant disease classification, several challenges still exist:

- **Limited Real-World Data:** Many models are trained on datasets like PlantVillage, which contain clean, lab-quality images. These models may not work as well on noisy images taken in the field with different lighting or backgrounds.
- **Generalization Problem:** A model trained on one type of plant may not work properly on another type. There is a need for more diverse datasets and adaptable models.
- **Black Box Models:** Deep learning models often act like a "black box," making decisions that users can't understand. Explainability tools like ACE are helping solve this issue, but more work is needed.
- **Deployment Issues:** High-performance models often require a lot of memory and processing power. Lightweight models like PlantXViT are a step in the right direction, especially for mobile or IoT deployment.

In summary, while CNNs and other deep learning techniques have proven effective for plant disease detection, there's a need to improve real-world performance, model interpretability, and deployment efficiency.

III. Methodology

The methodology adopted in this project comprises several key phases: data collection, data preprocessing, model design, training, evaluation, and deployment.

A. Data Collection:

The dataset used in this study is the PlantVillage dataset, sourced from Kaggle. It contains over 50,000 labeled images across 38 different classes, including healthy and diseased plant leaves. Only the colored image subset was used to preserve rich feature information.

B. Data Preprocessing:

To prepare the data for training, the following preprocessing steps were applied:

- All images were resized to a fixed dimension of 128×128 pixels.
- Pixel values were normalized to the range [0, 1].
- The dataset was split into 80% for training and 20% for validation using Keras' `ImageDataGenerator`.

C. CNN Architecture

The proposed Convolutional Neural Network (CNN) is designed to extract hierarchical image features through a multi-stage architecture that improves learning capacity and generalization. The architecture consists of five convolutional blocks followed by a global average pooling layer and two fully connected (dense) layers. Each convolutional block comprises a convolutional layer using a 3×3 kernel with He-normal initialization and L2 regularization to mitigate overfitting. The convolution operation is followed by batch normalization, which accelerates training by reducing internal covariate shift. The Exponential Linear Unit (ELU) activation function is used after normalization for better convergence over ReLU, especially in deep networks. To enhance generalization, SpatialDropout2D is applied after activation, randomly dropping entire feature maps during training. MaxPooling2D with a pool size of 2×2 is used to reduce spatial dimensions and extract dominant features.

The convolutional blocks use increasing filter depths of 32, 64, 128, 256, and 512 respectively to progressively capture more abstract representations. After the final convolutional block, a GlobalAveragePooling2D layer is used instead of a flatten operation to minimize overfitting and reduce the number of trainable parameters.

The extracted features are then passed through two dense layers with 512 and 256 neurons, respectively. Each dense

TABLE I
CNN ARCHITECTURE FOR PLANT DISEASE CLASSIFICATION

Stage	Layer Type	Units / Filters	Activation	Details
1	Conv2D	32	-	3×3, He-normal, L2(0.0005)
	BatchNormalization	-	-	Normalize activations
	ELU	-	ELU	Faster convergence
	SpatialDropout2D	-	-	Dropout rate = 0.2
	MaxPooling2D	-	-	Pool size = 2×2
2	Conv2D	64	-	Same as Stage 1
	BatchNormalization	-	-	
	ELU	-	ELU	
	SpatialDropout2D	-	-	
	MaxPooling2D	-	-	
3	Conv2D	128	-	Same as above
	BatchNormalization	-	-	
	ELU	-	ELU	
	SpatialDropout2D	-	-	
	MaxPooling2D	-	-	
4	Conv2D	256	-	Same as above
	BatchNormalization	-	-	
	ELU	-	ELU	
	SpatialDropout2D	-	-	
	MaxPooling2D	-	-	
5 Final deep features	Conv2D	512	-	No Dropout
	BatchNormalization	-	-	
	ELU	-	ELU	
	MaxPooling2D	-	-	
6	GlobalAveragePooling2D	-	-	Replaces flattening
7	Dense	512	-	L2(0.0005), Dropout = 0.4
	BatchNormalization	-	-	
	ELU	-	ELU	
8	Dense	256	-	L2(0.0005), Dropout = 0.4
	BatchNormalization	-	-	
	ELU	-	ELU	
9	Output Dense	38	Softmax	Final classification layer

layer is followed by batch normalization, ELU activation, and dropout (0.4) for regularization. The final classification is performed using a Dense layer with a softmax activation function and 38 output units corresponding to the number of classes in the PlantVillage dataset. Label smoothing is applied during training to improve model confidence calibration. The model is compiled using the Adam optimizer with an exponentially decaying learning rate schedule and trained using categorical cross-entropy as the loss function. article amsmath amsfonts graphicx authblk

D. Training and Evaluation

The model was compiled using the Adam optimizer with a learning rate scheduler and trained using categorical cross-entropy as the loss function. Training was conducted over 40 epochs with early stopping and learning rate reduction callbacks. Evaluation was carried out using accuracy, confusion matrix, and classification report metrics to analyze model performance on unseen validation data.

E. Deployment

The final trained model was deployed as a web application using Streamlit. The app allows users to upload a leaf image and receive real-time predictions about the plant disease class along with the model's confidence level.

LOSS FUNCTION

The model is optimized using a combination of **Categorical Cross-Entropy with Label Smoothing** and **L2 Weight Regularization**. The total loss function $\mathcal{L}_{\text{total}}$ minimized during training is defined as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CCE-smoothed}} + \lambda \sum_i \|w_i\|_2^2 \tag{1}$$

where:

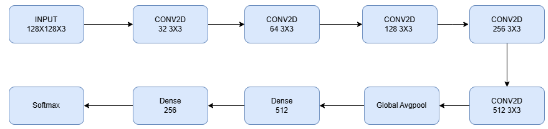


Fig. 1. CNN arcitechture

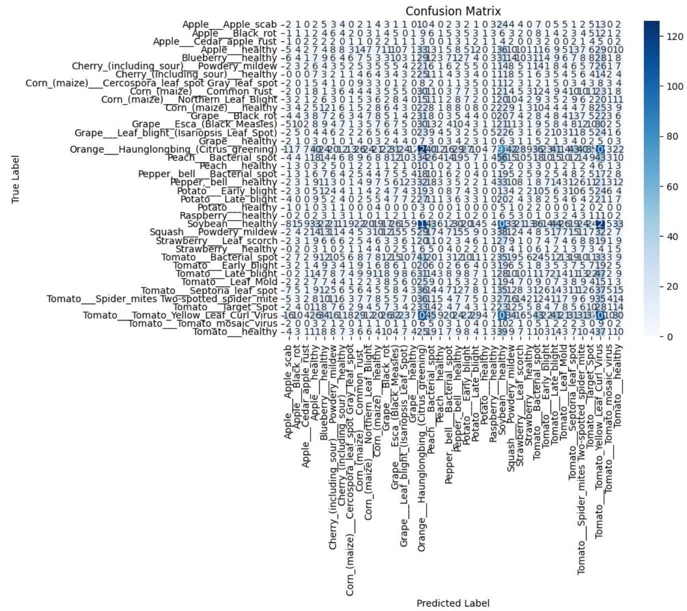


Fig. 2. Confusion matrix representing true vs. predicted classifications for different crop diseases.

- $\mathcal{L}_{\text{CCE-smoothed}}$ is the categorical cross-entropy loss with label smoothing,
- λ is the L2 regularization coefficient (set to 0.0005),
- w_i are the trainable weights in the model (excluding biases).

The smoothed cross-entropy loss is given by:

$$\mathcal{L}_{\text{CCE-smoothed}} = -\sum_{c=1}^{C} \left[(1-\epsilon) \cdot y_c \cdot \log(\hat{y}_c) + \frac{\epsilon}{C} \cdot \log(\hat{y}_c) \right] \tag{2}$$

where:

- C is the number of output classes,
- ϵ is the label smoothing parameter (set to 0.1),
- y_c is the ground-truth label for class c (one-hot encoded),
- $\hat{y}_c$ is the predicted probability for class c.

Label smoothing helps to prevent overfitting and overconfidence by softening the target labels, and L2 regularization discourages large weights, promoting generalization.

RESULTS AND ANALYSIS

Confusion Matrix

Analysis of Class-wise Performance:

The confusion matrix offers insights into model strengths and areas needing improvement.

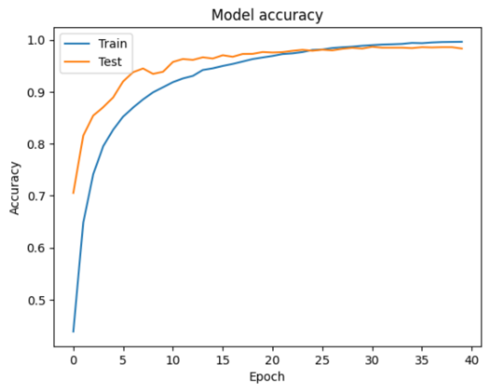


Fig. 3. Model accuracy

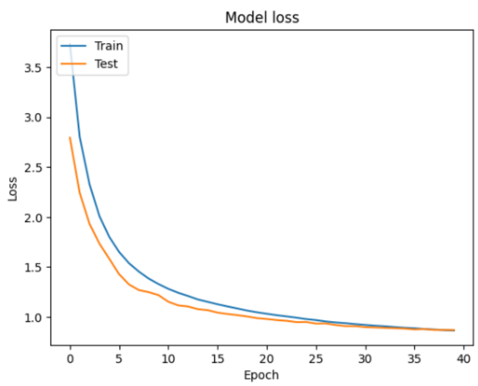


Fig. 4. Model loss

Well-Predicted Classes: leftmargin=1.5em

- **Apple – Apple scab**, **Tomato – Healthy**, and **Potato – Late blight** show strong diagonal dominance, indicating high prediction accuracy.
- **Grape – Black rot** and **Blueberry – Healthy** also perform well, possibly due to distinctive visual features.

Confused or Weakly Predicted Classes: leftmargin=1.5em

- **Tomato diseases** (*Leaf mold*, *Target spot*, etc.) are often confused due to similar leaf appearances.
- **Corn** (*Cercospora leaf spot*, *Common rust*, *Healthy*) also exhibits overlap.
- **Grape – Esca (Black measles)** shows occasional misclassification, likely due to shared symptoms.

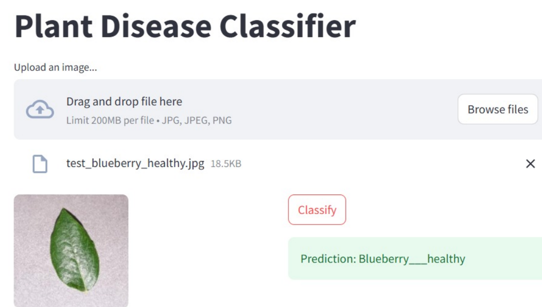
Training and Validation Performance

Analysis of Accuracy and Loss Trends: leftmargin=1.5em

- **Loss Decrease:** Rapid drop in both training and validation loss in early epochs, indicating efficient learning.
- **Accuracy Increase:** Accuracy improves from 50% to above 95% by epoch 30, then stabilizes.
- **Generalization:** Training and test accuracy closely follow each other, suggesting no major overfitting.

Conclusion: The model shows strong learning ability and generalization. A few classes with visual similarity remain challenging. Improvements such as targeted augmentation or class rebalancing can help further boost precision.

UPLOADED IMAGE



PREDICTION RESULT

The uploaded image was processed using the Plant Disease Classifier web interface. The file name was `test_blueberry_healthy.jpg`, and the classifier returned the following result:

Prediction: Blueberry___healthy

ANALYSIS

Based on the visual inspection and classifier output:

- The leaf appears to be a typical blueberry leaf, showing no visible signs of disease such as discoloration, spots, or wilting.
- The classifier has successfully recognized the plant species and confirmed it is healthy.
- This suggests that the classifier is functioning correctly for this category and the input image was suitable for accurate recognition.

IV. CONCLUSION

The advancement of machine learning and computer vision technologies has paved the way for intelligent plant disease diagnosis systems that can support farmers and agricultural experts in early detection and intervention. In this study, we explored the functionality of a Plant Disease Classifier through a practical case involving a blueberry leaf. The classifier successfully identified the leaf as healthy, validating its ability to correctly recognize plant species and assess their condition based on visual data.

This result exemplifies the potential of such systems in real-world agricultural applications, where rapid and reliable assessments are crucial for crop management. The classifier's performance indicates that, with proper training and data quality, AI-driven tools can complement traditional agricultural practices by reducing human error, improving diagnostic speed, and supporting precision agriculture.

Moving forward, the integration of more diverse datasets, real-time mobile interfaces, and continual learning mechanisms could further enhance the robustness and scalability of such classifiers. Ultimately, these tools can contribute significantly to sustainable farming practices, food security, and the global agricultural ecosystem.

References

[1] I. Pacal, I. Kunduracioglu, and M. Alma, "A systematic review of deep learning techniques for plant diseases," *Artificial Intelligence Review*, vol. 57, p. 304, 2024.

[2] P. Thakur, P. Khanna, T. Sheorey, and A. Ojha, "Explainable vision transformer enabled convolutional neural network for plant disease identification: Plantxvit," *arXiv preprint arXiv:2207.07919*, 2022.

[3] R. Singh *et al.*, "Deep learning-based leaf disease detection in crops using images for agricultural applications," *Agronomy*, vol. 12, no. 10, p. 2395, 2022.

[4] J. Amara, B. König-Ries, and S. Samuel, "Explainability of deep learning-based plant disease classifiers through automated concept identification," *arXiv preprint arXiv:2412.07408*, 2024.