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A DEEP LEARNING-BASED WEB APPLICATION FOR PLANT LEAF DISEASE CLASSIFICATION USING MOBILENETV2

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Abstract : Agriculture plays a critical role in the global economy, and early detection of plant diseases is essential for improv- ing crop health and productivity. Traditional disease diagnosis methods often require expert knowledge and are time-consuming, making them less accessible to farmers and small-scale agricultural practitioners. In this paper, a deep learning-based plant disease detection system is proposed using transfer learning with the MobileNetV2 architecture. The model is trained to classify 38 different classes of plant leaf diseases from RGB images. To improve usability and interpretability, the trained model is deployed as a web application using Streamlit, enabling real-time disease prediction through an interactive user interface. In addition, Grad-CAM is integrated to provide visual explanations of model decisions by highlighting the image regions influencing predictions. Experimen- tal results demonstrate that the proposed system achieves high classification performance while remaining computationally efficient, making it suitable for lightweight and real-time agricultural applications. The proposed approach offers an accessible, scalable, and explainable solution for automated plant disease diagnosis.

IndexTerms - Plant Disease Detection, Deep Learning, Transfer Learning, MobileNetV2, Convolutional Neural Network, Grad- CAM, Streamlit, Explainable AI, Image Classification

I. INTRODUCTION

Agriculture is one of the most important sectors contributing to food security and economic development. Plant diseases sig- nificantly affect crop yield and quality, causing major losses to farmers and agricultural industries worldwide. Early and accurate detection of plant diseases is therefore essential for effective crop management and prevention of large-scale damage.

Traditionally, plant disease diagnosis is performed manually by agricultural experts through visual inspection of leaves and stems. However, this process is often slow, subjective, and inaccessible to farmers in remote or under-resourced regions. With the rapid growth of artificial intelligence and computer vision, automated plant disease detection systems have emerged as a promising solution.

Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable performance in image classification tasks. In this work, a lightweight and efficient plant disease detection system is proposed using MobileNetV2, a pretrained CNN architecture optimized for mobile and embedded applications. The model classifies plant leaf images into 38 disease categories, enabling automated diagnosis from visual data.

To make the system practical and user-friendly, the trained model is deployed as a Streamlit-based web application. Additionally, Grad-CAM is integrated to enhance explainability by visualizing the regions of the leaf image that most influenced the model's prediction.

A. Objectives of the proposed work

To build an automated plant disease classification model using deep learning to leverage transfer learning for efficient training and improved performance and classify plant leaf images into 38 disease categories to develop an interactive web application for real-time disease prediction and provide model interpretability using Grad-CAM visualizations.

II. Related Work

Plant disease detection has become an important application of deep learning in smart agriculture. Traditional approaches for disease identification relied on manual inspection by agricultural experts, which is often time-consuming, subjective, and not always accessible in rural areas. To overcome these limitations, researchers have explored machine learning and computer vision-based approaches for automated diagnosis.

Earlier methods used handcrafted image features such as color, texture, and shape, combined with machine learning classifiers like Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN). Although these approaches achieved moderate results, they were limited by feature engineering complexity and poor generalization to diverse datasets.

In recent years, Convolutional Neural Networks (CNNs) have shown significant improvements in image-based plant disease detection. Deep learning architectures such as AlexNet, VGG16, ResNet, InceptionNet, and DenseNet have been applied to classify plant leaf diseases with high accuracy. However, many of these architectures are computationally expensive and less suitable for lightweight deployment.

To address this issue, lightweight transfer learning models such as MobileNet and EfficientNet have gained attention due to their reduced parameter size and faster inference. Among them, MobileNetV2 is especially suitable for practical applications because it provides a strong balance between performance and efficiency.

Another important aspect in modern AI systems is interpretability. Explainable AI methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) allow visualization of the image regions influencing the model's decision. This improves trust, transparency, and usability in real-world agricultural applications.

The present work builds upon these developments by proposing a MobileNetV2-based plant disease detection model integrated with Grad-CAM and deployed through a Streamlit web application.

III. Proposed Methodology

The proposed system is designed to automatically classify plant leaf diseases from uploaded images using a deep learning-based image classification pipeline. The methodology combines transfer learning, image preprocessing, prediction visualization, and web deployment.

A. System Overview

The overall workflow of the proposed system consists of the following steps: 1) User uploads a plant leaf image through the web interface. 2) The image is preprocessed and resized. 3) The preprocessed image is passed to the trained MobileNetV2 model. 4) The model predicts the disease class. 5) Top-3 prediction probabilities are displayed. 6) Grad-CAM heatmap is generated for visual explanation. This pipeline enables real-time and interpretable plant disease detection.

B. Dataset Description

The model is trained on a labeled dataset of plant leaf images containing 38 classes of healthy and diseased leaves. The dataset includes images from different crops such as tomato, potato, pepper, grape, corn, and others. Each image is assigned a class label corresponding to a specific disease or healthy leaf category. The dataset supports supervised learning for multi-class classification. The dataset used in this work is based on the Plant Village dataset, which is widely used as a benchmark dataset for plant disease classification tasks.

C. Image Preprocessing

Before training and inference, the input images are preprocessed to ensure consistency and compatibility with the model. The preprocessing steps include:

- Resizing images to 224×224 pixels.
- Converting images into RGB format.
- Normalizing pixel values.
- Preparing labels for multi-class classification.

These steps improve model performance and reduce input variation during training and prediction.

D. Model Architecture

The proposed classification model is based on MobileNetV2, a lightweight convolutional neural network architecture pretrained on the ImageNet dataset. Transfer learning is used in this work to leverage previously learned image features, allowing the model to converge faster and perform better even with limited computational resources.

The model architecture includes:

- Base Model: MobileNetV2 (pretrained on ImageNet)
- Input Size: $224 \times 224 \times 3$
- Feature Extraction Layers: Depthwise separable convolutions and inverted residual blocks
- Classifier Head: Dense layer(s) followed by softmax activation
- Output Layer: 38 neurons representing 38 disease classes

The final softmax layer produces probability scores for all classes, and the class with the highest probability is selected as the final prediction

```
# model summary
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
flatten (Flatten)	(None, 186624)	0
dense (Dense)	(None, 256)	47,776,000
dense_1 (Dense)	(None, 38)	9,766

```
Total params: 47,805,158 (182.36 MB)
Trainable params: 47,805,158 (182.36 MB)
Non-trainable params: 0 (0.00 B)
```

Figure 1: Custom CNN model architecture used as a baseline for comparative analysis.

E. Training Configuration

The model was trained using TensorFlow/Keras with the following configuration:

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Evaluation Metric: Accuracy
- Output Activation: Softmax
- Batch Size: 32
- Epochs: 10
- Learning Rate: 0.001

F. Explainability Using Grad-CAM

To improve interpretability, the proposed system integrates Grad-CAM (Gradient-weighted Class Activation Mapping). Grad- CAM highlights the important regions of the input image that contribute most strongly to the model's prediction. In the context of plant disease detection, this helps visualize whether the model is focusing on infected leaf regions such as spots, discoloration, lesions, or damaged areas. The Grad-CAM output is overlaid on the original image and displayed in the web application, making the system more transparent and trustworthy.

G. Web Application Deployment

To make the model practically usable, it is deployed using Streamlit, which provides a lightweight and interactive web interface.

The deployed application allows users to:

- Upload plant leaf images
- View predicted disease class and confidence score
- Inspect top-3 predictions
- Visualize Grad-CAM heatmap

IV. System Design/Architecture

The proposed plant disease detection system is composed of four main modules:

A. Input Module

The input module accepts plant leaf images uploaded by the user through the Streamlit interface.

B. Processing Module

The uploaded image is resized, normalized, and prepared for inference according to the model input format.

C. Prediction Module

The processed image is passed to the MobileNetV2 model, which predicts the disease class and generates confidence scores.

D. Explainability and Output Module

The final module displays the predicted class, confidence score, top-3 predictions, and the Grad-CAM visualization. This modular design improves usability, maintainability, and interpretability of the system.

V. Experimental Setup

The proposed model was developed and tested using Python-based deep learning and computer vision libraries.

A. Software Environment

The following tools and libraries were used in the implementation: Python, TensorFlow / Keras, OpenCV, NumPy, Matplotlib, and Streamlit.

B. Hardware Environment

The model was trained and tested on a personal computing system with moderate hardware resources:

- Intel Core i5 8th Generation Processor
- Intel UHD Graphics 620
- 8 GB RAM
- Windows Operating System

The use of MobileNetV2 makes the model suitable for systems with limited computational capacity.

VI. Results and Discussion

The proposed MobileNetV2-based plant disease detection system was evaluated on a dataset containing 38 classes of plant leaf diseases and healthy leaves. The model demonstrated strong classification performance while maintaining lightweight deployment characteristics.

A. Classification Performance

The trained model achieved satisfactory performance for multi-class plant disease classification. These results indicate that transfer learning with MobileNetV2 is effective for distinguishing between multiple plant disease categories.

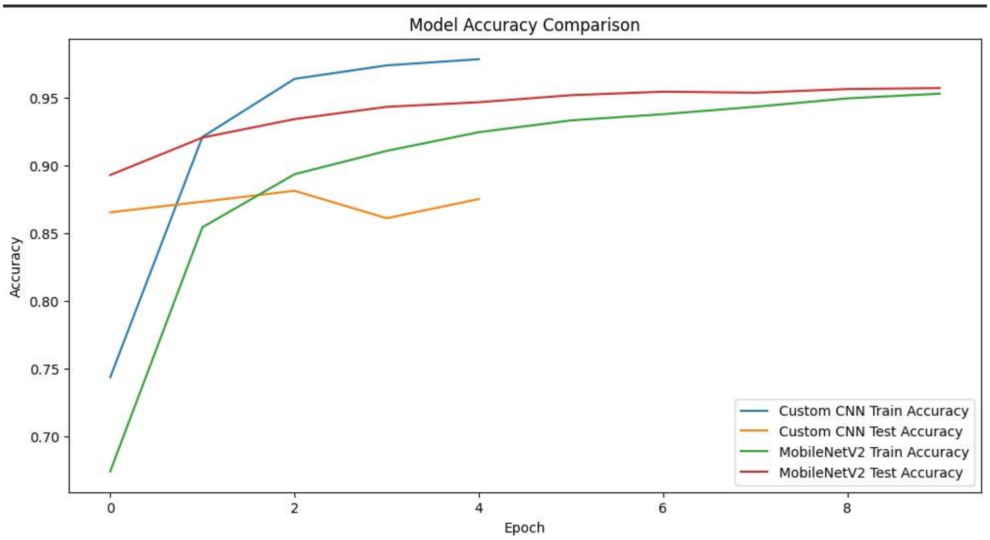

Figure 2: Accuracy comparison between Custom CNN and MobileNetV2 models across training epochs.

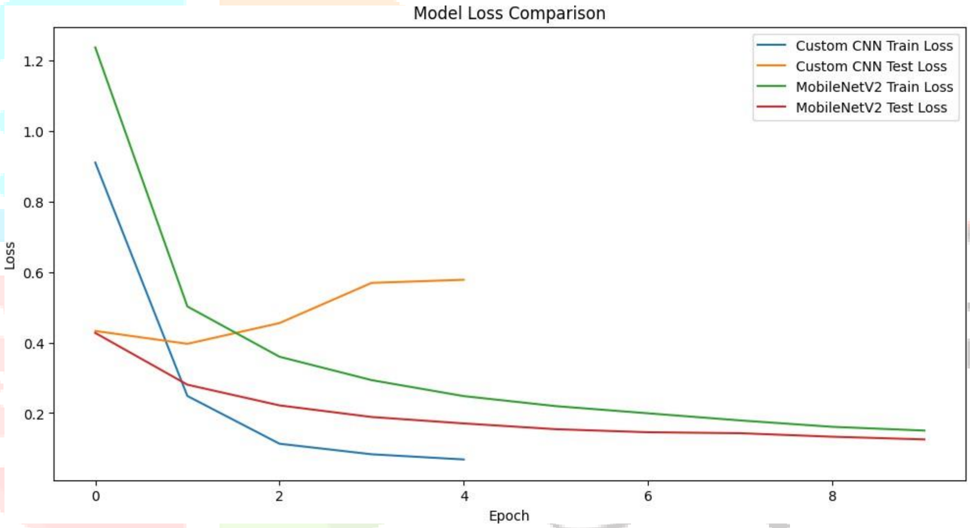

Figure 3: Loss comparison between Custom CNN and MobileNetV2 models across training epochs.

B. Top-3 Prediction Analysis

In addition to the top-1 predicted class, the system also displays the top-3 most probable disease classes. This improves usability by allowing users to inspect alternate predictions, especially when multiple diseases have visually similar symptoms. The top-3 output enhances practical decision-making and makes the system more informative for end users.

C. Grad-CAM Visualization

The Grad-CAM visualizations showed that the model focuses primarily on the diseased portions of the leaf, such as spots, lesions, discoloration, and damaged areas. This suggests that the model learns meaningful disease-specific visual patterns rather than relying on irrelevant background features. The integration of Grad-CAM improves the interpretability and reliability of the system.

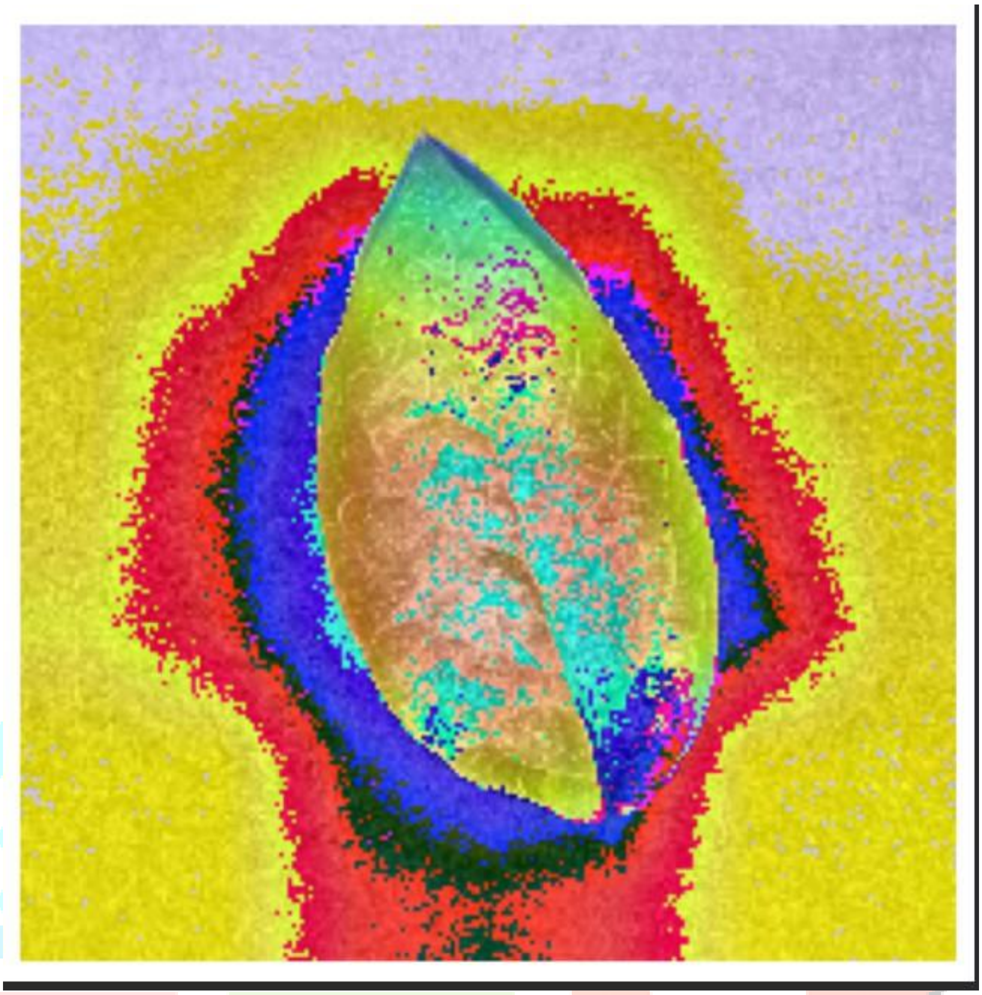

Figure 4: Grad-CAM visualization showing the regions influencing the disease prediction.

D. Discussion

The proposed approach demonstrates that lightweight deep learning models can achieve high classification performance while remaining suitable for real-time deployment. Compared to heavier CNN architectures, MobileNetV2 offers lower computational cost, faster inference speed, smaller model size, and better suitability for web/mobile deployment.

However, the system may still face challenges in real-world conditions due to background clutter, poor image quality, varying illumination, and similar disease symptoms across different classes. Despite these limitations, the proposed model provides a practical and efficient solution for plant disease diagnosis.

VII. Conclusion

In this paper, a deep learning-based plant disease detection system was proposed using MobileNetV2 and transfer learning. The model was trained to classify plant leaf images into 38 disease classes, providing an efficient solution for automated plant disease diagnosis. To enhance usability, the trained model was deployed as a Streamlit web application, enabling users to upload leaf images and receive real-time predictions. Additionally, Grad-CAM was incorporated to provide visual interpretability and improve transparency in model decision-making. The results demonstrate that the proposed system is both accurate and computationally efficient, making it suitable for lightweight agricultural applications. The developed system can assist farmers, researchers, and agricultural practitioners in early disease identification and crop health monitoring.

VIII. Future Work

The proposed work can be further extended in several directions:

- Deployment as a mobile application
- Support for real-world field images
- Integration of disease treatment recommendations
- Inclusion of regional language support
- Expansion to additional crops and diseases
- Optimization for edge and embedded devices

These enhancements can improve the practical impact and scalability of the system.

Acknowledgment

References

[1] P. Mohanty, D. P. Hughes, and M. Salathe´, ”Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, pp. 1-10, 2016.

[2] Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, ”MobileNetV2: Inverted residuals and linear bottlenecks,” in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), 2018, pp. 4510-4520.

[3] R. Selvaraju et al., ”Grad-CAM: Visual explanations from deep networks via gradient-based localization,” in Proc. IEEE Int. Conf. Computer Vision (ICCV), 2017, pp. 618-626.

[4] P. Hughes and M. Salathe´, ”An open access repository of images on plant health to enable the development of mobile disease diagnostics,” arXiv preprint arXiv:1511.08060, 2015.

[5] P. Ferentinos, ”Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018.

[6] Too. L. Yujian, S. Njuki, and L. Yingchun, ”A comparative study of fine-tuning deep learning models for plant disease identi- fication,” Computers and Electronics in Agriculture, vol. 161, pp. 272-279, 2019.

[7] Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, ”Deep neural networks based recognition of plant diseases by leaf image classification,” Computational Intelligence and Neuroscience, vol. 2016, pp. 1-11, 2016.

[8] Howard et al., ”MobileNets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.

[9] Chollet, ”Xception: Deep learning with depthwise separable convolutions,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2017, pp. 1251-1258.

[10] TensorFlow, ”TensorFlow: An end-to-end open-source machine learning platform.” [Online]. Available: https://www.tensorflow.org