Classification and Visualization of Plant Leaf Diseases Using Deep Learning and Image Processing Techniques

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***Abstract*—The early identification of plant diseases plays a crucial role in preventing crop damage and ensuring food security. Deep learning models have been widely used for automated plant disease detection due to their efficiency in image classification tasks. However, many existing models require a large number of parameters, leading to increased computational costs and challenges in real-world deployment. In this study, various deep learning architectures are evaluated on two plant disease datasets: the New Plant Diseases Dataset, which consists of 87,000 images across 38 classes, and the Plant Village Dataset, which contains 70,000 images from nine plant species. Multiple models, including CNN, AlexNet, ResNet, EfficientNet, MobileNetV2, DenseNet121, VGG16, InceptionV3, and VanillaCNN, are tested to compare their performance. On the New Plant Diseases Dataset, CNN achieves an accuracy of 95.94%, while MobileNetV2 attains 92.12%. For the Plant Village Dataset, EfficientNet records the highest accuracy of 99.40%, followed by AlexNet (96.71%) and ResNet50 (96.19%). In contrast, InceptionV3 exhibits significantly lower performance with an accuracy of 18.07%, and DenseNet121 achieves 47%. These results highlight the effectiveness of deep learning models in plant disease classification, with EfficientNet demonstrating superior performance. The findings of this study contribute to the development of efficient plant disease detection systems, which can assist farmers in disease diagnosis and improve agricultural productivity.**

I. Introduction

Plant diseases pose a significant threat to global agriculture, leading to reduced crop yields and economic losses. Early and accurate identification of plant diseases is essential for effective disease management and the prevention of large-scale outbreaks. Traditionally, plant disease detection has relied on visual inspection by farmers and agricultural experts. However, this method is time-consuming, prone to human error, and not always feasible for large-scale farming. With advancements in artificial intelligence, deep learning techniques have been increasingly utilized for plant disease classification due to their ability to analyze complex patterns in images.

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks, making them suitable for plant disease detection. Various deep learning models, including AlexNet, ResNet, EfficientNet, MobileNetV2, DenseNet121, VGG16, InceptionV3, and VanillaCNN, have been developed and applied to plant disease classification. These models differ in architecture, computational efficiency, and accuracy. However, many deep learning models require extensive computational resources, making them challenging to deploy on small-scale agricultural devices or mobile applications.

To address these challenges, this study evaluates multiple deep learning architectures on two widely used plant disease datasets: the New Plant Diseases Dataset, which contains 87,000 images across 38 classes, and the Plant Village Dataset, which consists of 70,000 images from nine plant species. The models are assessed based on their classification accuracy to determine the most effective approach for plant disease identification. The results of this study contribute to the development of more efficient and accurate automated plant disease detection systems, ultimately supporting farmers and agricultural professionals in improving crop health and productivity.

II. Literature Review

The early detection of plant diseases is increasingly critical in the context of global food security and agricultural productivity. Recent advancements in machine learning (ML) and deep learning techniques have demonstrated significant improvements over traditional methods. In this paper [1] (2023) analyzed 48 studies focusing on image-based plant disease detection, emphasizing the superior performance of various deep learning architectures, especially AlexNet when used with Transfer Learning, which achieved the highest accuracy on the PlantVillage dataset. Their findings highlight the potential for integrating these advanced methodologies in real-world agricultural applications, thereby improving disease management practices and enhancing crop yield.

The paper [2] presents a thorough examination of how deep learning techniques are transforming plant disease recognition in agriculture. It discusses various models such as ResNet50, Inception V3, and MobileNet, showcasing their notable accuracy rates ranging from 77.65% to 96.84% depending on the tasks. The review highlights the utilization of the PlantVillage dataset, which contains over 54,309 images of plant leaf diseases, emphasizing the importance of large, diverse datasets for enhancing model performance. Furthermore, it addresses challenges related to model robustness and the need for effective early detection using deep learning methods. This review serves as an essential resource for advancing research in plant disease detection.

The paper [3] by SK Mahmudul Hassan and Arnab Kumar Maji introduces a novel CNN architecture that combines depth-wise separable convolutions and residual connections to enhance plant disease identification. The model was trained and tested on three datasets: the PlantVillage dataset, the Rice disease dataset, and the Cassava dataset. Evaluation metrics included accuracy, precision, recall, and F1-score.

The proposed model achieved impressive accuracies of 99.39% on the PlantVillage dataset, 99.66% on the Rice dataset, and 76.59% on the Cassava dataset, while also significantly reducing the number of parameters compared to conventional models. This efficiency not only improves training time but also enhances the model's practical applicability in real-world agricultural settings.

III. Methodology

A. Dataset Description

In this study, two datasets were utilized: the New Plant Diseases Dataset and the Plant Village Dataset (Updated). The New Plant Diseases Dataset, consisting of 87,000 images, is categorized into 38 distinct classes, representing 14 different crop species affected by various diseases or remaining in a healthy state. This dataset provides a diverse collection of plant conditions, making it highly valuable for developing models aimed at plant disease detection and classification.

Additionally, the Plant Village Dataset (Updated) was employed, comprising 70,000 high-quality images of diseased and healthy plant leaves from nine different species. This dataset is widely used in machine learning research, particularly in agricultural diagnostics, due to its comprehensive representation of plant health conditions.

By utilizing these two datasets, a more robust and accurate approach to plant disease classification was developed, contributing to advancements in automated agricultural disease detection and crop management strategies.

B. Image Pre-Processing

1) **Image Loading:** Images were loaded from the dataset directory using with inferred labels.
2) **Resizing:** All images were resized to `128 × 128` pixels to maintain uniformity and reduce computational complexity.
3) **Normalization:** Pixel values were scaled to the range [0,1] to improve model convergence and stability.
4) **Shuffling:** Images were shuffled to ensure randomness and reduce model bias during training.
5) **Data Augmentation:** Techniques such as random rotation, flipping, and zooming were applied to artificially expand the dataset and improve generalization.

C. Pretrained Model Architecture

Deep learning models have been widely adopted for plant disease classification due to their ability to automatically extract complex features from images. Pre-trained architectures leverage transfer learning by utilizing weights from large-scale datasets like ImageNet, enabling efficient and accurate classification. The key models used are described below.

- **Convolutional Neural Network (CNN):** A custom CNN was designed with multiple convolutional layers for feature extraction, followed by fully connected layers for classification. This architecture was tailored for image recognition tasks and optimized for plant disease detection.
- **AlexNet:** A deep CNN architecture featuring five convolutional layers and three fully connected layers. It utilizes ReLU activation for faster training and dropout to prevent overfitting, making it effective for large-scale image classification tasks.
- **EfficientNet:** A model optimized for both accuracy and efficiency using a compound scaling method. It balances network depth, width, and resolution, making it computationally efficient while maintaining high performance across different datasets.
- **ResNet (Residual Networks):** This architecture introduces skip connections to allow deeper networks to train effectively by mitigating the vanishing gradient problem. It is widely used for feature extraction due to its ability to retain information across multiple layers.
- **MobileNetV2:** A lightweight model designed for mobile and embedded vision applications. It employs depthwise separable convolutions and an inverted residual structure

to reduce computational complexity while maintaining high classification performance.

- **DenseNet121:** A model that enhances feature propagation by connecting each layer to every other layer in a feed-forward fashion. This structure reduces redundant computations and improves gradient flow, resulting in more efficient learning.
- **VGG16:** A deep CNN with a uniform structure of convolutional layers followed by fully connected layers. It is known for its simplicity and ability to extract hierarchical features, making it suitable for various image recognition tasks.
- **InceptionV3:** An advanced architecture designed to optimize computational efficiency by using factorized convolutions. It includes multiple convolutional filter sizes within each module, allowing it to capture information at different scales.
- **Vanilla CNN:** A basic CNN architecture trained from scratch with multiple convolutional layers followed by fully connected layers. It serves as a baseline model for comparison with more complex pre-trained architectures.

D. Result and Discussion

The table compares the accuracy of different deep learning models on two plant disease datasets. The performance of various deep learning models on the New Plant Diseases Dataset and the Plant Village Dataset is presented in Table I. The results demonstrate significant variations in accuracy across models and datasets, highlighting the importance of architecture selection for plant disease classification tasks.

The Vanilla CNN, a custom-designed architecture, achieved high accuracy on both datasets (95.94% and 95.69%, respectively), indicating its effectiveness as a baseline model. AlexNet performed comparably well, particularly on the Plant Village Dataset (96.71%), which aligns with findings from the literature review where AlexNet was noted for its strong performance with transfer learning.

EfficientNet exhibited exceptional accuracy (99.40%) on the Plant Village Dataset but performed poorly (4.44%) on the New Plant Diseases Dataset. This discrepancy may be attributed to differences in dataset characteristics or the model's sensitivity to specific image features. ResNet architectures, including ResNet and ResNet50, demonstrated consistently high performance (99.07% and 96.19%, respectively), supporting their reputation for robust feature extraction through skip connections.

MobileNetV2, designed for lightweight applications, achieved moderate accuracy (92.12%) on the New Plant Diseases Dataset, suggesting a trade-off between computational efficiency and performance. In contrast, DenseNet121 and InceptionV3 underperformed on the Plant Village Dataset (47.00% and 18.07%, respectively), possibly due to challenges in adapting their complex architectures to the specific features of plant disease images.

The superior performance of certain models, such as EfficientNet and ResNet, can be linked to their advanced architectural designs, which optimize feature extraction and computational efficiency. Conversely, the poor performance of InceptionV3 may reflect its incompatibility with the dataset's characteristics or insufficient tuning of its factorized convolutions.

These findings underscore the necessity of dataset-specific model evaluation, as emphasized in the study's methodology. The results contribute to the broader goal of developing efficient and accurate plant disease detection systems, as discussed in the conclusion, while also highlighting opportunities for future improvements in model robustness and generalizability.

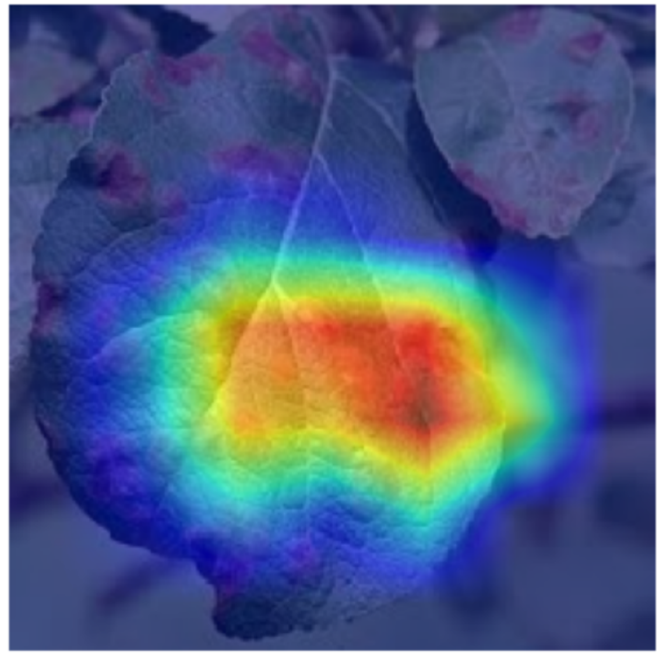

Fig. 1. Gradcam Visualization

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT MODELS ON PLANT DISEASE DATASETS

Model	New Plant Diseases Dataset (%)	Plant Village Dataset (%)
Vanilla CNN	95.94	95.69
AlexNet	93.74	96.71
EfficientNet	4.44	99.40
ResNet	99.07	–
ResNet50	–	96.19
MobileNetV2	92.12	–
DenseNet121	–	47.00
VGG16	–	95.46
InceptionV3	–	18.07

IV. EXPLAINABLE AI

To enhance the interpretability of our deep learning model, we incorporated Explainable AI (XAI) techniques to visualize its decision-making process. Deep learning models are often considered "black boxes," making it challenging to understand the reasoning behind their predictions. To address this, we utilized Class Activation Mapping (CAM)-based techniques to

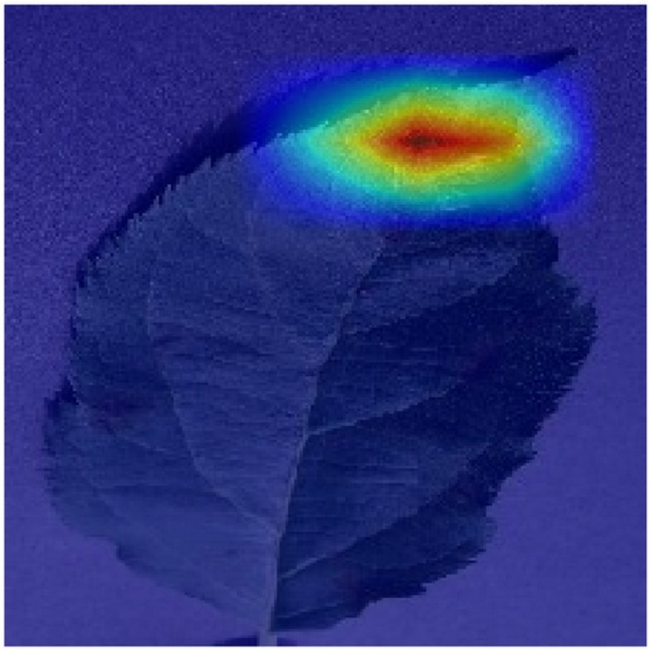

Fig. 2. Gradcam Visualization

generate heatmaps, highlighting the most influential regions in an image that contributed to the classification decision.

Specifically, we implemented Grad-CAM, a widely used XAI method that extracts relevant features from the model's last convolutional layer. The resulting heatmaps overlay the original leaf images, visually indicating the areas the model focused on during classification. In these images, (figure 1,2 red and yellow regions represent areas of high attention, often corresponding to diseased regions. Green areas indicate moderate attention, potentially marking early signs of infection, while blue regions signify low attention, typically associated with healthy parts of the leaf.

These heatmaps provide valuable insights into the model's decision-making process, enhancing transparency and interpretability in AI-driven plant disease detection.

V. Data Visualization

To analyze and interpret the model's predictions, we employed a visualization technique called Grad-CAM (Gradient-weighted Class Activation Mapping). This method allows us to identify the regions in the image that most influence the model's decision by highlighting the areas of the image that are most relevant to the predicted class.

We used the ResNet50 model pre-trained on ImageNet as the base model for this task. The process for generating the visualizations is as follows:

1) **Image Preprocessing:** An image from the dataset was selected, resized to a target size of 224×224, and converted into an array suitable for the model. The image was then preprocessed using the ResNet50 preprocessing function, which adjusts the pixel values in the image to match the format used during training.
2) **Model Prediction:** The image was passed through the ResNet50 model to obtain the prediction for the class of the plant disease. The predicted class was identified by finding the index with the highest output probability.
3) **Gradient Calculation:** To identify which regions of the image contributed most to the prediction, we extracted the output of the last convolutional layer in the ResNet50 model. Using a GradientTape in TensorFlow, we computed the gradients of the predicted class with respect to the output feature map of the last convolutional layer.
4) **Feature Map and Gradient Weighting:** The gradients were pooled (averaged) across spatial dimensions, and each feature map was weighted by the corresponding gradient value. This gives us a heatmap that highlights the areas in the image that contributed most to the model's decision.
5) **Heatmap Generation:** The weighted feature maps were averaged across all channels to generate a final heatmap. This heatmap was then normalized to a range between 0 and 1, and resized to match the original image dimensions. The heatmap was overlaid on the original image to visualize the areas most relevant to the model's classification.
6) **Final Visualization:** The final visualization was created by superimposing the heatmap on top of the original image, allowing us to see which parts of the plant were most associated with the predicted disease class. The heatmap was displayed using a jet color map to indicate the intensity of relevance from low (blue) to high (red).

Figure 1 and 2 shows an example of a heatmap generated for a plant disease image. The red regions indicate areas of the plant most strongly associated with the predicted class.

VI. Future Scope

In the future, plant disease detection using deep learning can be improved in several ways:

- Lightweight models – Developing more efficient models that require less computational power, making them suitable for mobile applications and real-time use in farms.
- Larger and diverse datasets – Expanding datasets to include more plant species, different disease stages, and images taken in real-world conditions to improve model accuracy.
- Integration with IoT devices – Combining deep learning models with smart farming devices like drones and sensors to provide real-time disease monitoring.
- Multi-disease detection – Training models to detect multiple plant diseases in a single image for more comprehensive plant health analysis.
- Disease progression prediction – Developing AI systems that not only detect diseases but also predict their progression, helping farmers take preventive measures.
- Cross-regional generalization – Improving model adaptability so that it works effectively across different climates, lighting conditions, and agricultural environments.

VII. References

In this section, we discuss relevant literature and previous research that has informed and guided the methodology and approach used in this paper. These studies are primarily focused on plant disease classification, image processing techniques, and the application of deep learning models such as convolutional neural networks (CNNs) and their visualization.

1) **Pandey, V., Tripathi, U., Singh, V. K., Gaur, Y. S., Gupta, D. (Year).** Survey of Accuracy Prediction on the PlantVillage Dataset using different ML techniques. *EAI Endorsed Transactions on Internet of Things.*
This paper surveys various machine learning techniques applied to the PlantVillage dataset for plant disease prediction and accuracy evaluation. It provides a comprehensive comparison of different methods and their effectiveness in real-world agricultural scenarios.
2) **Li, L., Zhang, S., Wang, B. (Year).** Plant Disease Detection and Classification by Deep Learning—A Review. *Journal Name*.
This review paper discusses the application of deep learning techniques in plant disease detection and classification. It outlines the advancements in the field and highlights challenges and trends in using deep learning for plant disease recognition and feature extraction. It also discusses the role of automated systems in improving agricultural practices and disease management.

VIII. Links to Our Machine Learning Tool

In this section, we provide direct links to the machine learning tool developed for plant disease classification. This tool forms the core of the research presented in this paper and includes everything needed for accurate plant disease detection, including the source code, pre-trained models, and supporting resources.

GitHub Repository:
https://github.com/FaizaM07/Machine-Learning-Project
The source code for the machine learning tool is available on GitHub. This repository contains code for data preprocessing, model training, and evaluation. The tool is designed with deep learning techniques to accurately classify plant diseases. We encourage you to explore the repository, contribute, or use it as a foundation for your own projects.

Hugging Face Model:
https://huggingface.co/nstuli/Plant_disease_machine_learning
Previous Version for plant disease classification are hosted on Hugging Face. These models are ready to be used for inference and can be fine-tuned for your specific dataset. You can easily integrate them into your workflow for efficient and reliable disease detection.

For further information, feel free to explore the detailed documentation and setup instructions included in the GitHub repository. Contributions, suggestions, and feedback are always welcome!

IX. Conclusion

In this study, the proposed model not only achieves high accuracy in identifying plant diseases but also enhances interpretability through explainability techniques. By integrating XAI, the model addresses the common issue of deep learning being treated as a "black box," providing transparency and insights into the key features influencing classification. This interpretability allows farmers and agricultural experts to better trust and understand the model's decision-making process.

The results demonstrate that combining deep learning with explainability techniques significantly improves plant disease detection by delivering precise and reliable predictions. The model's strong performance suggests that AI-driven plant health monitoring has the potential to reduce crop losses and enhance agricultural productivity. Additionally, the use of a diverse dataset improves generalizability, making the model adaptable to different plant species and varying environmental conditions.

Future work can focus on expanding the dataset to include more real-world variations, further refining model robustness, and exploring lightweight architectures for deployment in resource-constrained environments.

Overall, this study contributes to the growing field of AI in agriculture by showcasing the effectiveness of deep learning in plant disease detection while ensuring transparency through explainability techniques. The findings pave the way for future advancements in AI-driven agricultural solutions, promoting both accuracy and interpretability in real-world applications.

[1] V. Pandey, U. Tripathi, V. K. Singh, Y. S. Gaur, and D. Gupta, "Survey of accuracy prediction on the plantvillage dataset using different ml techniques," *EAI Endorsed Transactions on Internet of Things*, vol. 10, pp. 1–14, 2024.

[2] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—a review," *IEEE Access*, vol. 9, pp. 56 683–56 698, 2021.
[3] S. M. Hassan and A. K. Maji, "Plant disease identification using a novel convolutional neural network," *IEEE access*, vol. 10, pp. 5390–5401, 2022.