**Title**  
Plant Disease Detection Using Convolutional Neural Networks: A Comparative Analysis

**Abstract**  
Plant diseases cause significant losses in global crop production, impacting food security and farmers' livelihoods. This project aims to enhance plant disease detection through the use of Convolutional Neural Networks (CNNs). Leveraging a dataset of over 87,000 images, we compared a baseline model (Model 4) from a published study with our custom-designed model (Model 5). Results show improvements in classification performance, with Model 5 achieving an average AUC of 0.99, surpassing the baseline Model 4 (AUC 0.96). This report details the methods, dataset, experimental setup, and results, providing a foundation for further advancements in agricultural disease diagnostics.

**Introduction**  
Plant diseases pose a critical threat to global agriculture, with up to 40% of crop production lost annually. Early and accurate detection can mitigate these losses, reducing pesticide use and improving sustainability. CNNs have emerged as a powerful tool for image-based disease classification. This project builds upon prior work by implementing and evaluating a custom CNN model for multi-class plant disease classification.

**Related Work**  
In recent years, machine learning, particularly deep learning, has emerged as a powerful tool for addressing challenges in plant disease detection. Among the notable contributions, a base model proposed by Islam et al. utilized Convolutional Neural Networks (CNNs) to classify plant diseases using images of diseased and healthy leaves. The model employed a dataset of approximately 13,000 images, covering crops such as maize, peach, grape, potato, and strawberry. Images were preprocessed through resizing, normalization, and augmentation techniques like rotation, flipping, and zooming to enhance the diversity and robustness of the dataset.

The base model's CNN architecture consisted of 8 convolutional layers with ReLU activation, max-pooling, and dropout for regularization. The softmax output layer enabled multi-class classification across several disease categories. The model achieved a remarkable overall accuracy of **94.29%**, with AUC scores close to **1.0** for most classes, demonstrating its high sensitivity and specificity. Notably, the model excelled in identifying diseases in maize and grape crops, achieving validation accuracies of **98.23%** and **98.89%**, respectively.

While this base model set a strong benchmark in plant disease detection, its focus was limited to a specific set of crops and diseases. Building upon this work, our proposed approach aims to enhance classification accuracy further, extend disease coverage, and improve the generalizability of the model to broader datasets and real-world applications.

**Proposed Method**  
Our custom CNN model (Model 5) features enhancements in architecture and preprocessing:

1. **Image PreprocessingPreprocessing**

The preprocessing stage in this project was designed to ensure that the dataset was prepared for optimal performance in training a Convolutional Neural Network (CNN). This step was critical to maintain consistency, enhance generalization, and stabilize the training process.

The first task involved verifying the consistency of image dimensions within the dataset. All images were resized to 256x256 pixels to ensure uniformity. This step is essential because CNNs require fixed input dimensions to process data effectively across layers. Inconsistent image dimensions would lead to errors during training and compromise the integrity of the model's architecture.

Next, the pixel values of the images were normalized by rescaling them to a range between 0 and 1. This was achieved by dividing all pixel intensities by 255. Normalization reduces the variance in input values and prevents large gradient updates during backpropagation, which can destabilize the optimization process. This step ensures a smoother and more efficient convergence during training.

To improve the model's ability to generalize to unseen data, extensive data augmentation techniques were applied to the training dataset. These transformations included random rotations of up to 20 degrees, horizontal and vertical shifts of up to 20% of the image size, zooming by up to 20%, and random horizontal flipping. Additionally, any missing pixels created during these transformations were filled using the nearest available pixel value. Data augmentation artificially increases the diversity of the training dataset, exposing the model to a broader range of image variations. This reduces the likelihood of overfitting by encouraging the model to learn more generalized patterns instead of memorizing specific examples.

For the validation dataset, only rescaling was applied, as this data was intended to evaluate the model's performance on unaltered images. Applying transformations to validation images would introduce inconsistencies and potentially misrepresent the true generalization capabilities of the model.

Finally, the preprocessing stage included visual validation of the augmented images. By displaying both the original and augmented versions side by side, it was possible to confirm that the transformations were realistic and retained the essential characteristics of the original images. This visualization step also ensured that the augmentation did not introduce artifacts or distortions that could negatively impact model performance.

In summary, the preprocessing pipeline was carefully designed to balance the need for data consistency, augmentation for improved generalization, and efficient preparation for training the CNN. These steps laid the foundation for building a robust model capable of accurate classification across a diverse set of plant disease images.

1. **Improved Model Architecture**

The improved model builds upon the base CNN architecture by introducing a series of enhancements designed to improve feature extraction, stabilize training, and enhance generalization. The architecture consists of four convolutional blocks, each followed by batch normalization and max pooling layers. These blocks progressively increase the number of filters, starting with 32 in the first block and reaching 256 in the final block. The use of batch normalization within each block plays a crucial role in accelerating training by normalizing the activations, thereby reducing internal covariate shifts and ensuring stable convergence. Additionally, all convolutional layers utilize ReLU (Rectified Linear Unit) activation to introduce non-linearity, enabling the model to learn complex patterns within the input data.

One of the key innovations in the improved model is the replacement of the flattening layer with a global average pooling layer. Unlike traditional flattening, which converts feature maps into a single vector, global average pooling computes the average of each feature map, significantly reducing the number of trainable parameters. This approach not only minimizes the risk of overfitting but also encourages the model to focus on the most globally significant features, which is particularly beneficial for tasks like plant disease classification.

The fully connected layers in the improved model have been expanded to include two dense layers with 512 and 256 units, respectively. Each dense layer is followed by dropout regularization, with rates of 50% and 30%, to mitigate overfitting. These layers allow the model to learn complex feature representations by combining the high-level features extracted by the convolutional blocks. The final output layer employs a softmax activation function, providing probabilities for each of the 38 plant disease classes.

By increasing the depth of the convolutional blocks and introducing additional regularization techniques, the improved model is expected to outperform the base model. The inclusion of a fourth convolutional block with 256 filters enables the model to capture more nuanced and hierarchical features, which are essential for distinguishing subtle differences between disease categories. Batch normalization further stabilizes the learning process, while global average pooling ensures a focus on the most salient features. These enhancements are particularly important given the diversity and complexity of the dataset, which includes variations in plant species, lighting conditions, and disease symptoms.

In conclusion, the architectural modifications in the improved model address several limitations of the base model. The deeper network, combined with advanced regularization and pooling techniques, ensures a more robust and generalizable model, capable of achieving superior classification performance on the challenging task of plant disease detection.

1. **Training**: The model was trained with a batch size of 32 and Adam optimizer (learning rate: 0.001). Categorical cross-entropy was used as the loss function.

**Dataset and Benchmark**  
The dataset comprises 87,000 labeled images of healthy and diseased plant leaves spanning 38 classes. Images were split into training (80%) and testing (20%) sets. Performance was benchmarked against Model 4 from the baseline study, which achieved an AUC of 0.96 using a similar dataset.

**Experimental Results**  
Model 5 demonstrated superior performance compared to the baseline Model 4:

* **AUC**: Model 5 achieved an average AUC of 0.99, significantly improving upon Model 4's AUC of 0.96 (Figures 1 and 2).
* **Confusion Matrix**: High true positive rates and minimal false positives were observed for all classes (Figure 3).
* **Classification Report**: Model 5 achieved precision, recall, and F1-scores above 0.95 for most classes, outperforming Model 4 in key metrics (Figures 4 and 5).
* **ROC Curves**: The ROC curve for Model 5 indicates better sensitivity and specificity across most classes compared to Model 4 (Figures 1 and 2).

**Conclusions and Future Work**  
This study highlights the potential of enhanced CNN architectures for plant disease detection. By improving AUC and accuracy, Model 5 offers a reliable tool for farmers and agricultural professionals. Future work includes integrating this model into mobile applications for real-time disease diagnostics and expanding the dataset to include more diverse crops and conditions.

**References**

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2. FAO. "Plant Production and Protection Division."
3. Kaggle. "Plant Disease Dataset." [Link](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset/data)