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AI-DRIVEN CROP DISEASE PREDICTION AND MANAGEMENT SYSTEM

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ABSTRACT :

Rice is a vital cereal crop and a staple food for a large portion of the global population. However, its cultivation is frequently threatened by leaf diseases such as bacterial blight, brown spot, and leaf smut. Manual disease detection methods are not scalable and often lack reliability. This paper presents a comparative study of three prominent Convolutional Neural Network (CNN) models—MobileNetV2, ResNet-50, and VGG19—for rice leaf disease classification using image analysis. All models were trained using the same dataset from Kaggle, with identical preprocessing and evaluation protocols to ensure fair comparison. The results show that while ResNet-50 achieved the highest validation accuracy (~96.3%), MobileNetV2 provided the best trade-off between performance and computational efficiency. This study highlights the strengths and limitations of each model, offering insights for developing scalable and accurate disease detection systems in agriculture.

KEYWORDS: CNN, MobileNetV2, ResNet-50, VGG19, Rice Leaf Disease, Image Classification, Deep Learning.

I. INTRODUCTION

Paddy Plant diseases significantly affect crop yields, threatening food security and farmer livelihoods. Traditional manual methods of identifying these diseases are error-prone and time-consuming. With the advent of deep learning, Convolutional Neural Networks (CNNs) have emerged as powerful tools for image-based plant disease detection. This study aims to compare the performance of three widely used CNN architectures—MobileNetV2, ResNet-50, and VGG19—on the task of classifying rice paddy leaf diseases.

II. RELATED WORK

Numerous studies have employed CNNs for plant disease classification. Ferentinos (2018) demonstrated high accuracy using CNNs across multiple crop types. Sandler et al. (2018) proposed MobileNetV2 for efficient deep learning on mobile devices. He et al. (2016) introduced ResNet-50, which addressed vanishing gradient problems in deep networks. Simonyan and Zisserman (2014) developed VGG19, known for its simplicity and depth. Our work builds on these foundations by offering a side-by-side comparison of these models on the same dataset.

III. METHODOLOGY

- **A.** Dataset: The dataset used is publicly available on Kaggle, containing images of healthy and diseased rice leaves categorized into Bacterial Blight, Brown Spot, and Leaf Smut. The images were stored in Google Drive and accessed using Google Colab.

- **B.** Preprocessing: Image resizing to 224x224 pixels, normalization (rescaling pixel values to [0,1]), data augmentation: rotation, flipping, brightness variation, and zoom, and 80% for training, 20% for validation.

- **C.** Model Architecture and Training: Each model was initialized with pretrained ImageNet weights. The top layers were replaced with a GlobalAveragePooling2D layer, a fully connected layer of 512 or 1024 units, and a final softmax layer for classification. Early stopping and model checkpointing were used to preserve the best models.

- **D.** Training Configuration: Optimizer: Adam, Loss: Categorical Crossentropy, Epochs: 5 (ResNet-50 optimized for fewer epochs), Batch size: 32.

IV. PROPOSED ALGORITHM

Input: Raw image dataset of paddy leaves (Bacterial Leaf Blight, Brown Spot, Leaf Smut)
Output: Predicted disease label for each image (one of the three classes)

Step 1: Import Libraries and Tools

- Import necessary libraries: TensorFlow, Keras, NumPy, Matplotlib, and Scikit-learn.
- Mount Google Drive to access the dataset.

Step 2: Dataset Preparation

- Load dataset from Google Drive.
- Resize all images to 224x224 pixels.
- Apply data augmentation (rotation, zoom, flipping, brightness) to increase training robustness.
- Normalize pixel values to [0, 1].
- Split dataset into training (80%) and validation (20%) sets.

Step 3: Model Selection and Initialization

- Choose one of the three CNN architectures: MobileNetV2, ResNet-50, or VGG19.
- Load the selected model with pretrained ImageNet weights.
- Freeze base layers to retain learned features.
- Add custom top layers:
    - GlobalAveragePooling2D
    - Dense(512) with ReLU activation
    - Dropout(0.3) for regularization
    - Final Dense(3) layer with softmax activation for 3-class classification.

Step 4: Compile the Model

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Evaluation Metric: Accuracy

Step 5: Train the Model

- Train for 5 epochs using early stopping and model checkpoint callbacks.
- Monitor validation loss to avoid overfitting.

Step 6: Evaluate the Model

- Load best model weights from checkpoint.
- Predict on validation dataset.
- Generate confusion matrix and classification report.
- Visualize training accuracy and loss curves.

Step 7: Compare Models

- Repeat Steps 3–6 for all three models.
- Compare performance metrics: validation accuracy, training time, model size.

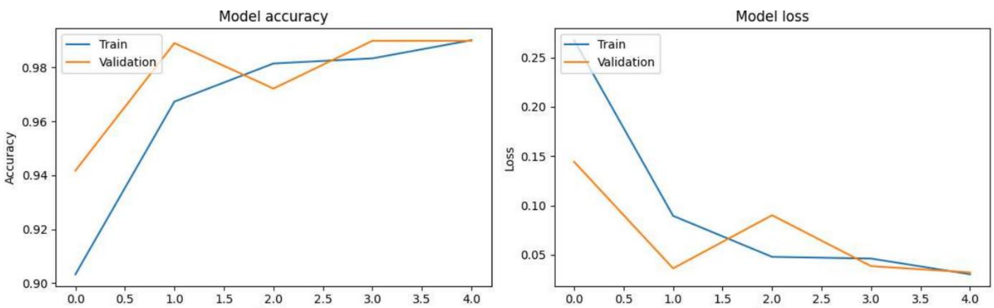
Step 8: Recommend Best Model

- Based on accuracy and efficiency, recommend:
    - ResNet-50 for best accuracy,
    - MobileNetV2 for mobile deployment,
    - VGG19 for deeper feature analysis.

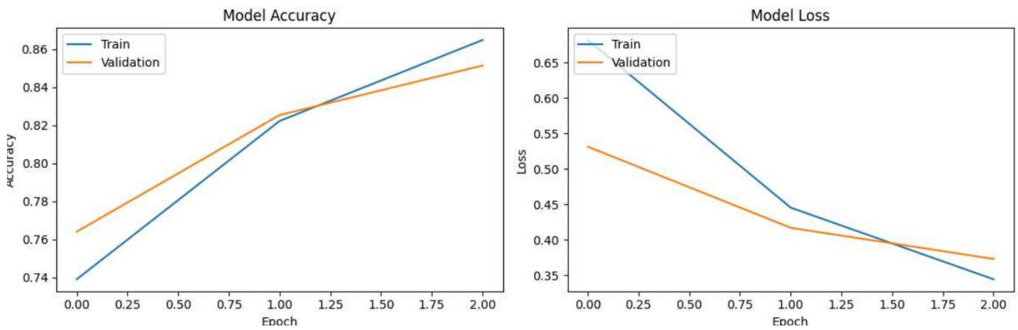
V. RESULTS

Resnet-50

MobileNetV-2



VGG19



VI. RESULTS AND DISCUSSION

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Remarks
MobileNetV2	~98.0%	~95.0%	Low	Stable	Fast and lightweight
ResNet-50	98.7%	96.3%	0.034	0.072	Highest accuracy, slower inference
VGG19	98.3%	94.5%	0.054	0.186	Deepest model, risk of overfitting

A. Accuracy Comparison: ResNet-50 consistently achieved the highest accuracy (~96.3%), followed by MobileNetV2 (~95%) and VGG19 (~94%).

B. Performance Trade-offs: MobileNetV2 had the fastest training time and smallest model size, making it ideal for mobile deployment.

C. Practical Considerations: For applications in the field, especially using mobile devices, MobileNetV2 is preferred. For server-side inference with no resource constraint, ResNet-50 offers the best results.

VII. CONCLUSION

This paper presented a comparative analysis of MobileNetV2, ResNet-50, and VGG19 for paddy leaf disease classification. While ResNet-50 offered the best accuracy, MobileNetV2 struck a balance between accuracy and efficiency. VGG19, though accurate, is better suited for high-performance computing environments. Future work includes integrating IoT-based sensor data and deploying the best-performing model on edge devices for real-time disease monitoring.

VIII. REFERENCES

[1] S. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, 2018.
[2] M. Sandler, et al., "MobileNetV2: Inverted Residuals and Linear Bottlenecks," CVPR, 2018.
[3] K. He, X. Zhang, S. Ren, J. Sun, "Deep Residual Learning for Image Recognition," CVPR, 2016.
[4] K. Simonyan, A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," arXiv, 2014.
[5] Nirmal Sankalana, "Rice Leaf Disease Dataset," Kaggle, 2023.