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Comparative Analysis of MobileNetV2 and ResNet50 for Cotton Leaf Disease Classification using Deep Learning

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Abstract - Cotton is a vital cash crop in India, especially in Maharashtra, where it contributes significantly to the agricultural economy and textile industry. However, its productivity is frequently threatened by foliar diseases such as cotton leaf curl, bacterial blight, fusarium wilt, powdery mildew, target spot**, and** pest infestations**, which result in severe yield losses. Traditional diagnostic methods based on manual inspection are slow, labor-intensive, and prone to inaccuracies. To address these limitations, this study leverages** deep learning and computer vision **for automated cotton disease detection and classification. A dataset of** 5561 images**, collected from the Akola and Yavatmal districts and supplemented with publicly available samples, was used to train and evaluate convolutional neural network (CNN) models. Two state-of-the-art architectures,** MobileNetV2 **and** ResNet50**, were fine-tuned to classify** seven categories of cotton leaves**, including healthy samples. Experimental results demonstrate that** ResNet50 achieved a test accuracy of 99.3%**, while** MobileNetV2 reached 98.8%**, highlighting their effectiveness in disease recognition. The proposed approach provides a** scalable and efficient solution for early disease detection**, enabling timely decision-making and reducing economic losses in cotton cultivation. This work contributes empirical evidence on CNN-based cotton disease classification, with potential for integration into** precision agriculture systems and mobile applications **for farmer support.**

Keywords - Cotton plant disease, Deep learning, Convolutional neural networks, MobileNetV2, ResNet50, Agricultural AI, Plant pathology.

1. INTRODUCTION

Cotton (Gossypium spp.) is a vital commercial crop and the backbone of India's textile sector, cultivated on nearly 12 million hectares and contributing about 19% of global cotton production. Despite this importance, its productivity is frequently threatened by leaf diseases such as Cotton Leaf Curl Virus (CLCuV), Fusarium Wilt, and Bacterial Blight, which cause significant yield and quality losses. Globally, plant diseases account for annual crop losses exceeding US $60 billion, underscoring the need for reliable and scalable diagnostic solutions.

Conventional disease detection relies on visual inspection, which is slow, subjective, and unsuitable for large-scale monitoring. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have demonstrated strong performance in plant disease classification by learning discriminative features directly from leaf images.

This study compares two widely used CNN architectures — MobileNetV2, a lightweight model optimized for mobile deployment, and ResNet50, a deeper model with strong representational capacity. To the best of our knowledge, limited comparative studies exist for cotton leaf disease classification, and this work contributes empirical insights into balancing accuracy and deployability for precision agriculture.

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2. LITERATURE REVIEW

Recent studies have demonstrated the use of CNN architectures in plant disease classification across crops such as tomato, rice, and maize, with accuracies exceeding 90%. MobileNetV2 has been favored for lightweight applications, while ResNet50 has achieved superior accuracy in deeper feature learning. However, limited work exists comparing these two models specifically for cotton disease classification.

Researchers have explored a variety of approaches to improve the detection, classification, and quantification of plant diseases with high accuracy. Convolutional Neural Networks (CNNs) remain the most widely used, owing to their ability to automatically extract hierarchical features from leaf images. A typical CNN framework includes convolutional layers for feature extraction, pooling operations, and flattening, followed by a Softmax output layer that assigns the probability of disease occurrence. In one study, this design achieved an accuracy of 96.6% after 500 training epochs [1].

For cotton leaf lesions, CNN-based deep learning models such as ResNet50 and GoogleNet were applied, yielding classification accuracies of 89.2% and 86.6%, respectively, on a dataset of 6,659 images containing both healthy and diseased leaves, along with background elements like straw and soil [2]. Another work demonstrated that CNN classifiers could effectively predict cotton diseases using training samples drawn from two categories, highlighting the potential of deep learning for binary classification problems [5].

Further, cotton leaf images representing bacterial blight, healthy, leaf miner, and spider mite were classified from a dataset of 2,400 samples. The researchers applied dropout rates of 0.25 and 0.5 across 50, 100, and 150 epochs, combined with preprocessing steps for noise reduction, and reported an accuracy of 96.4% [6].

Beyond deep learning, traditional machine learning techniques such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have also been investigated. With preprocessing based on K-Means segmentation for background removal and Adaptive Histogram Equalization for feature extraction, these methods achieved classification accuracies of 85%, 70%, and 90%, respectively [7].

Overall, prior research demonstrates the effectiveness of both deep learning and conventional machine learning techniques for cotton disease identification. However, further comparative evaluations of lightweight and deep CNN architectures are still needed to optimize both accuracy and real-world deployability.

3. PROPOSED WORK AND DATASET

The proposed research focuses on developing an automated system for the detection and classification of cotton leaf diseases using Convolutional Neural Networks (CNNs). The process begins with a digitized color image of a cotton leaf, which may be infected or healthy. The user uploads this image to the system, where pre-processing operations such as resizing, normalization, and augmentation are applied to enhance image quality and improve model generalization. The processed images are then passed to the CNN architecture, which automatically extracts discriminative features and performs classification into the respective disease categories. This approach eliminates the need for manual feature engineering and ensures a high level of accuracy and robustness in disease detection.

3.1 Dataset Description

The experimental dataset used in this research comprises a total of 5,561 cotton leaf images, categorized into seven classes: Bacterial Blight, Curl Virus, Fusarium Wilt, Healthy, Pest Damage, Powdery Mildew, and Target Spot. The dataset combines field images collected from Akola and Yavatmal districts (Maharashtra, India) with open-access images from online repositories. All samples were manually verified for quality and labeled accordingly.

The dataset was divided into training , validation , and testing subsets using a fixed random seed (42) to maintain reproducibility. The detailed class-wise distribution is shown in Table 1.

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Class	Train	Validation	Test	Total
Bacterial_Blight	798	99	101	998
Curl_Virus	773	96	98	967
Fusarium_Wilt	775	96	98	969
Healthy	780	97	99	976
Pest	440	55	55	550
Powdery_Mildew	440	55	55	550
Target Spot	440	55	55	550
TOTAL	4446	553	562	5561

Table 1: Distribution of images per class across training, validation, and test splits.

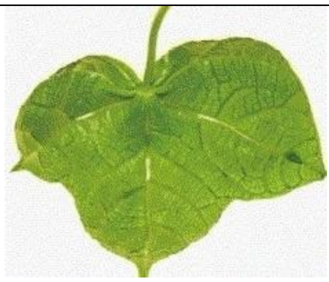
 Bacterial_Blight	 Curl_Virus	 Fusarium_Wilt
 Healthy	 Pest	 Powdery_Mildew
 Target Spot		

Table 2. Sample images from database

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4. METHODOLOGY AND ARCHITECTURE

The proposed system is designed to perform automated identification and classification of cotton leaf diseases using two advanced Convolutional Neural Network (CNN) architectures—MobileNetV2 and ResNet50. Both models are evaluated and compared in terms of classification accuracy, computational efficiency, and suitability for real-time agricultural applications.

4.1 . Methodology Overview

1. **Image Acquisition:**
   High-resolution color images of cotton leaves were captured under natural field conditions from farms located in **Akola and Yavatmal districts, Maharashtra**, and supplemented with publicly available data.
2. **Image Pre-processing:**
   Each image is resized to **224 × 224 pixels** and normalized to the range [0, 1].
   To enhance generalization and reduce overfitting, augmentation techniques such as random flipping, rotation, zooming, and contrast adjustment (±0.1) were applied.
3. **Feature Extraction and Classification:**
   The pre-processed images are fed into the CNN models (MobileNetV2 and ResNet50), which automatically extract hierarchical feature representations.
   A **SoftMax classifier** at the output layer predicts one of the seven classes: Bacterial Blight, Curl Virus, Fusarium Wilt, Healthy, Pest Damage, Powdery Mildew, or Target Spot.

4.2 CNN Model

The CNN architecture employed is based on MobileNetV2, a lightweight yet powerful model pre-trained on the ImageNet dataset. The input images were resized to 224 × 224 pixels, and the model was fine-tuned in two stages using the Adam optimizer (initial learning rate = 1e-3, later reduced to 1e-4). Training was performed with Early Stopping and ReduceLROnPlateau callbacks to optimize convergence and prevent overfitting.

4.2.1 MobileNetV2 Architecture

MobileNetV2 is a lightweight deep CNN optimized for mobile and embedded devices.
It employs depth wise separable convolutions and inverted residual blocks with linear bottlenecks, drastically reducing computational cost while maintaining high accuracy.

Key Components:

- Depth wise and pointwise convolutions for efficient filtering and channel combination.
- Inverted residual blocks that connect thin bottleneck layers.
- ReLU6 activation and Batch Normalization for stability.
- Global Average Pooling followed by a SoftMax layer for final classification.

4.2.2 ResNet50 Architecture

ResNet50 (Residual Network) is a deeper and more complex CNN architecture composed of 50 layers, designed to overcome the vanishing-gradient problem using skip (residual) connections.
These connections allow gradients to flow more effectively during backpropagation, enabling the network to learn very deep representations.

Key Components:

- Convolutional layers with Batch Normalization and ReLU activation.
- Residual blocks that perform identity mapping via shortcut connections.
- Global Average Pooling and fully connected layers followed by a SoftMax output.

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4.3. Algorithmic Steps

Algorithm 1: Cotton Leaf Disease Classification Using CNNs

1. Input: Cotton leaf image *I*
2. Resize *I* to (224 × 224 × 3)
3. Normalize pixel values to [0, 1]
4. Apply random augmentations
5. Feed image into CNN model (MobileNetV2 / ResNet50)
6. Extract feature maps from convolutional layers
7. Compute class probabilities using SoftMax layer
8. Output: Predicted disease class label

4.4 Training Configuration

Parameter	**Configuration / Setting**
Framework	TensorFlow 2.20.0 / Keras
Input Image Size	224 × 224 × 3
Optimizer	Adam
Learning Rate	$1\times10^{-3} \rightarrow 1 \times 10^{-4}$ (ReduceLROnPlateau)
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	20 (EarlyStopping at best validation loss)
Callbacks Used	EarlyStopping, ReduceLROnPlateau, ModelCheckpoint
Pretrained Weights	ImageNet
Fine-Tuning Strategy	Unfrozen last 40 layers in stage-2 training
Data Split Ratio	Train 70 % Test 15% Validation 15%
Augmentation	Random flip, rotation, zoom, contrast (±0.1)

Table 3. Training Configuration

5. PERFORMANCE MEASUREMENT

A total of 562 cotton leaf images from the test dataset were used to evaluate the performance of the proposed classification models. The effectiveness of each model is assessed using standard performance metrics such as Classification Accuracy (CA), Precision (Pre), Recall (Rec), and F1-Score (F1). These metrics are derived from the confusion matrix parameters — True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) — as defined below:

A. Classification Accuracy (CA)

$$CA = \frac{TP+TN}{TP+TN+FP+FN}$$

Classification Accuracy measures the overall proportion of correctly classified samples among all test samples.

B. Precision (Pre)

$$Pre = \frac{TP}{TP+FP}$$

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Precision indicates the ratio of
fewer false positives.

C. Recall (Rec)

$$\text{Rec} = \frac{\text{TP}}{\text{TP+FN}}$$

Recall (also known as Sensitivity) measures the ability of the model to correctly identify positive cases.

D. F1-Score (F1)

$$\text{F1} = \frac{2 \times (\text{Pre} \times \text{Rec})}{\text{Pre} + \text{Rec}}$$

The F1-Score is the harmonic mean of Precision and Recall, providing a balanced evaluation of the classifier's accuracy, especially in imbalanced datasets.

6. RESULTS

6.1 MobileNetV2 (Fine-tuned)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bacterial_Blight	1.000	0.947	0.973	151
Curl_Virus	1.000	1.000	1.000	146
Fusarium_Wilt	1.000	1.000	1.000	146
Healthy	1.000	1.000	1.000	147
Pest	0.988	0.976	0.982	83
Powdery_Mildew	1.000	1.000	1.000	83
Target_Spot	0.902	1.000	0.949	83
Accuracy	**0.988**	**0.988**	**0.988**	**839**
Macro Avg	0.984	0.989	0.986	839
Weighted Avg	0.989	0.988	0.988	839

Table 4. MobileNetV2 (Fine-tuned)

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MobileNetV2 achieved 98.8% accuracy. It performed perfectly on Curl Virus, Fusarium Wilt, Healthy, and Powdery Mildew. Slightly lower performance was noted for Target Spot (F1=0.95) and Bacterial Blight (F1=0.97).

6.2 ResNet50 (Baseline)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Bacterial_Blight	1.000	0.980	0.990	151
Curl_Virus	1.000	1.000	1.000	146
Fusarium_Wilt	1.000	1.000	1.000	146
Healthy	0.993	1.000	0.997	147
Pest	1.000	0.964	0.982	83
Powdery_Mildew	1.000	1.000	1.000	83
Target_Spot	0.943	1.000	0.971	83
Accuracy	**0.992**	**0.992**	**0.993**	**839**
Macro Avg	0.991	0.992	0.991	839
Weighted Avg	0.993	0.993	0.993	839

Table 5. ResNet50 (Baseline)

ResNet50 achieved 99.3% accuracy with balanced macro and weighted F1-scores above 0.99. It demonstrated slightly higher accuracy compared to MobileNetV2 but required greater computational resources.

6.3 Comparative Analysis

Model	Test Accuracy	Macro F1	Weighted F1	Notes
MobileNetV2 (fine-tuned)	98.8%	0.986	0.988	Efficient, near-perfect except Target Spot
ResNet50	99.3%	0.991	0.993	Slightly higher accuracy, heavier model

Table 6. Comparative Analysis of MobileNetV2 (fine-tuned) and ResNet50

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6.4 Visual Comparison

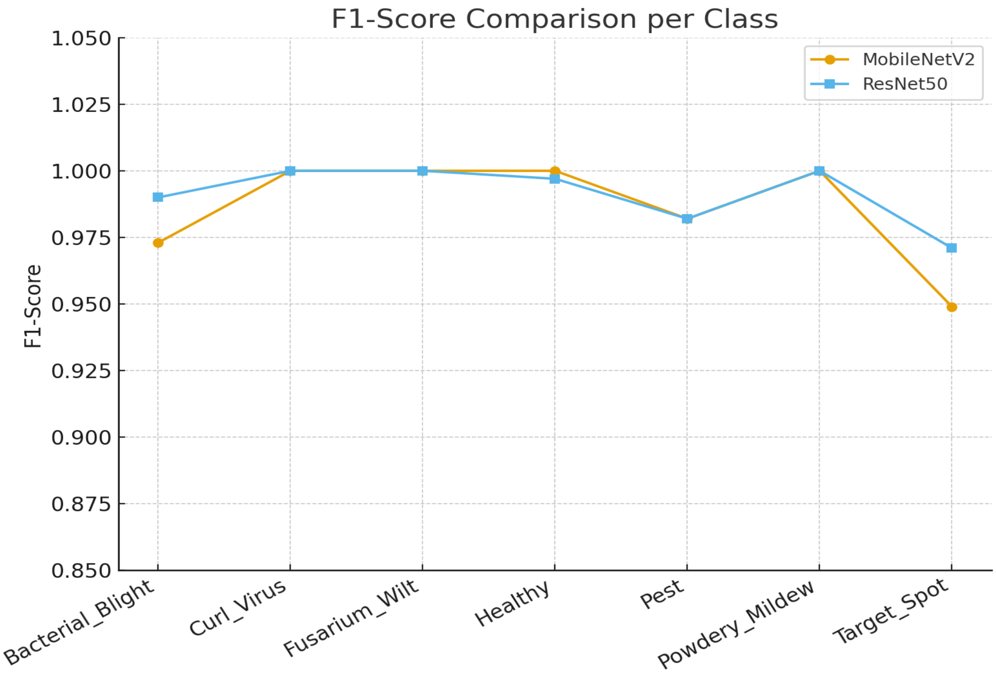

Figure 1. Illustrates the F1-Score comparison per class between MobileNetV2 and ResNet50.

6.5 Training and Evaluation Plots

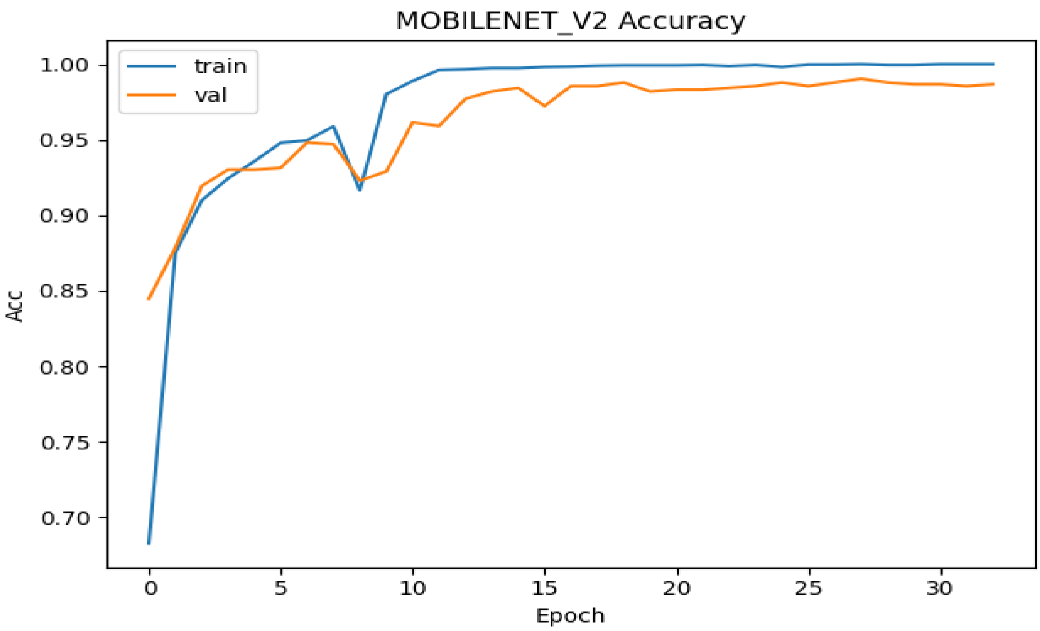

Fig 2 MobileNetV2 Accuracy.

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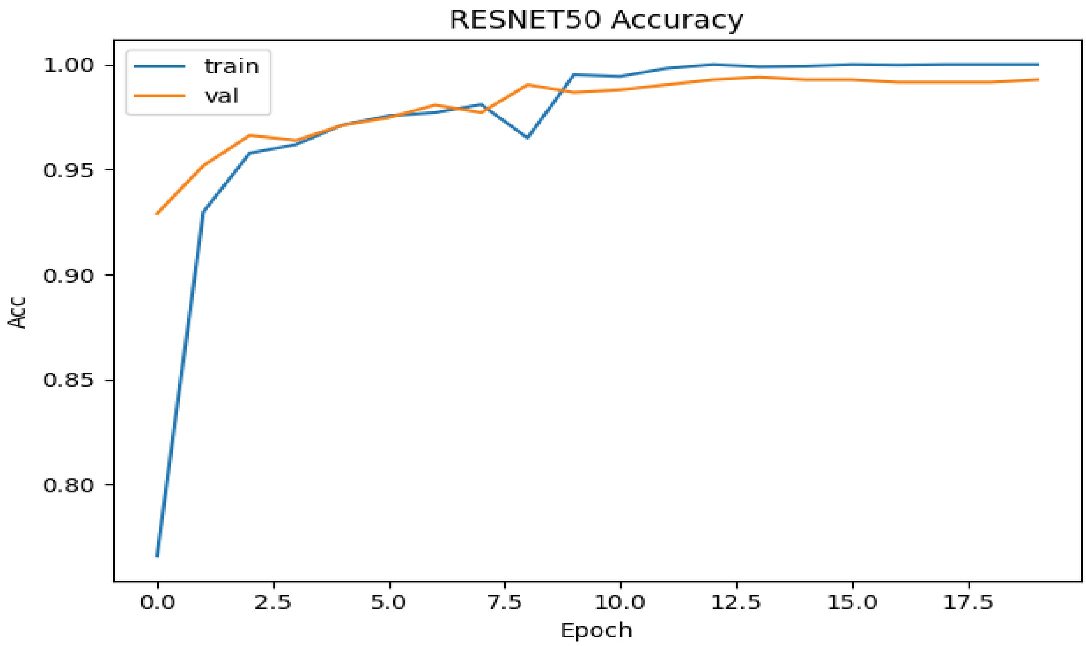

Fig 3. ResNet50 Accuracy

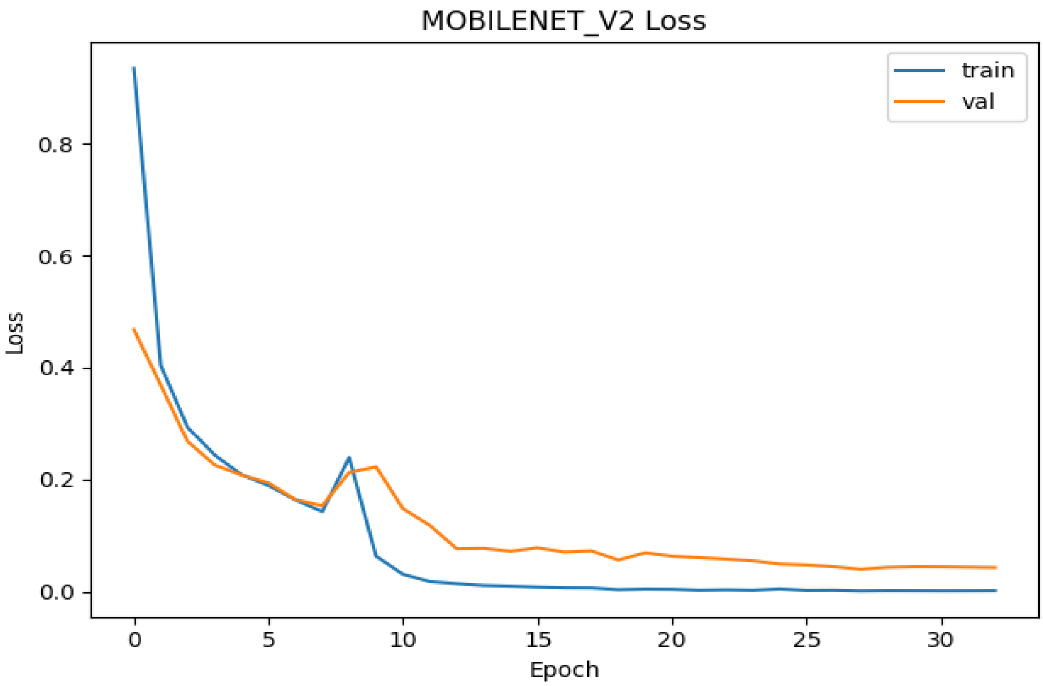

Fig 4. MobileNetV2 Loss

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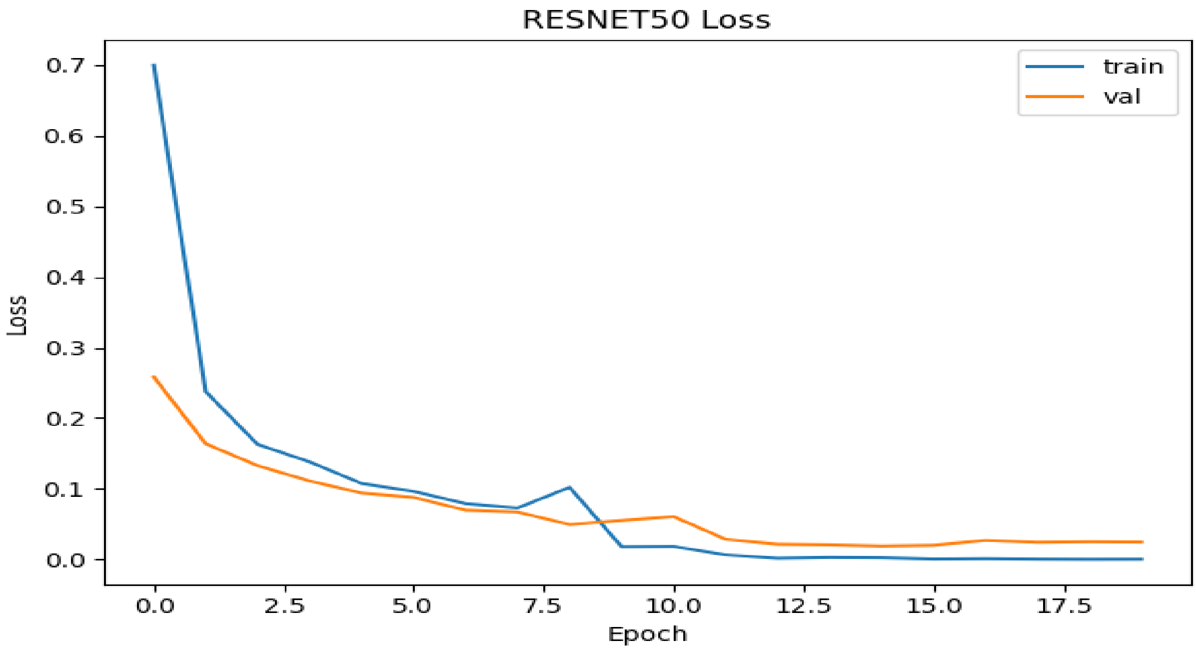

Fig 5. ResNet50 Loss

6.6 Confusion Matrices

Figure 6 and Figure 7 present the confusion matrices for MobileNetV2 and ResNet50, respectively.

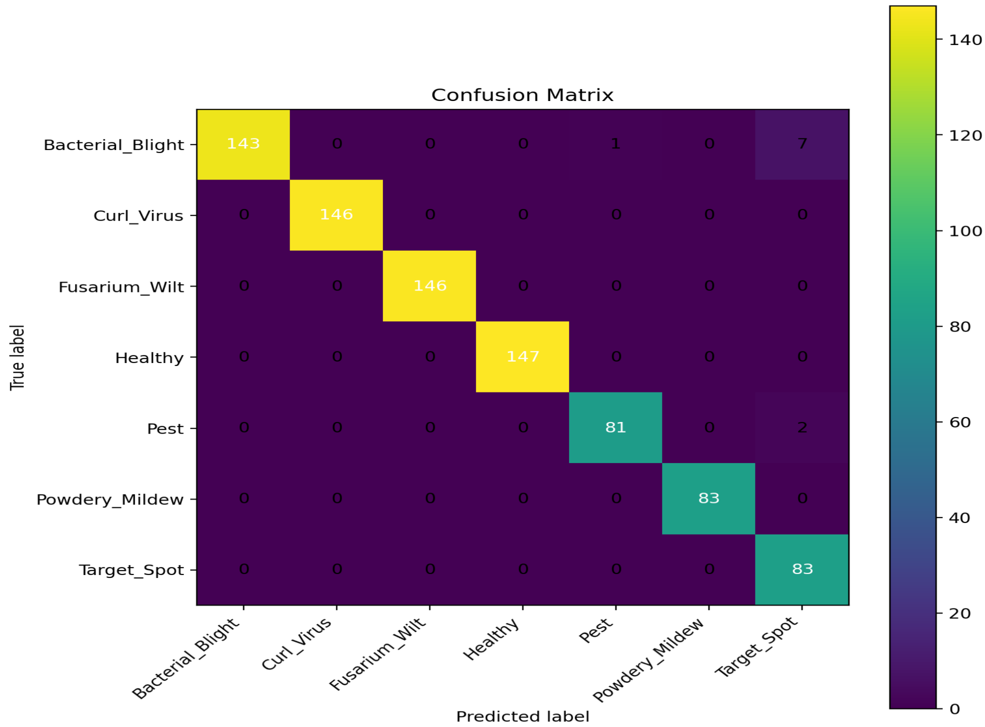

Fig 6. Confusion Matrix MobileNetV2

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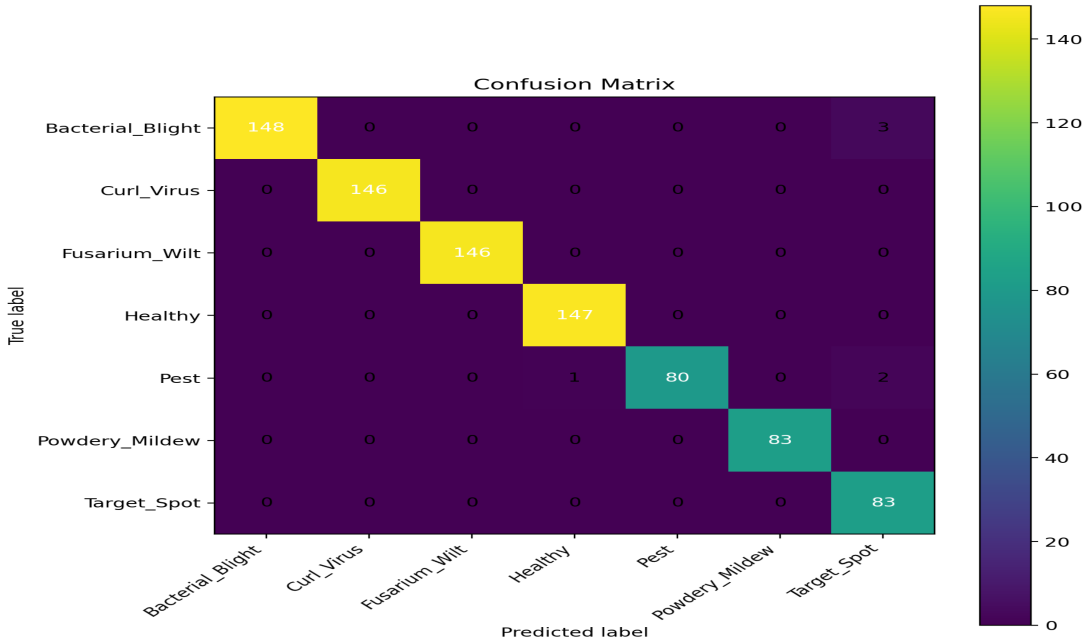

Fig 7. ResNet Confusion Matrix

6.7 Overall Metrics Summary

Figure 8 compares overall Accuracy, Macro F1, and Weighted F1 between MobileNetV2 and ResNet50. ResNet50 achieves slightly higher scores across all metrics, while MobileNetV2 remains highly competitive

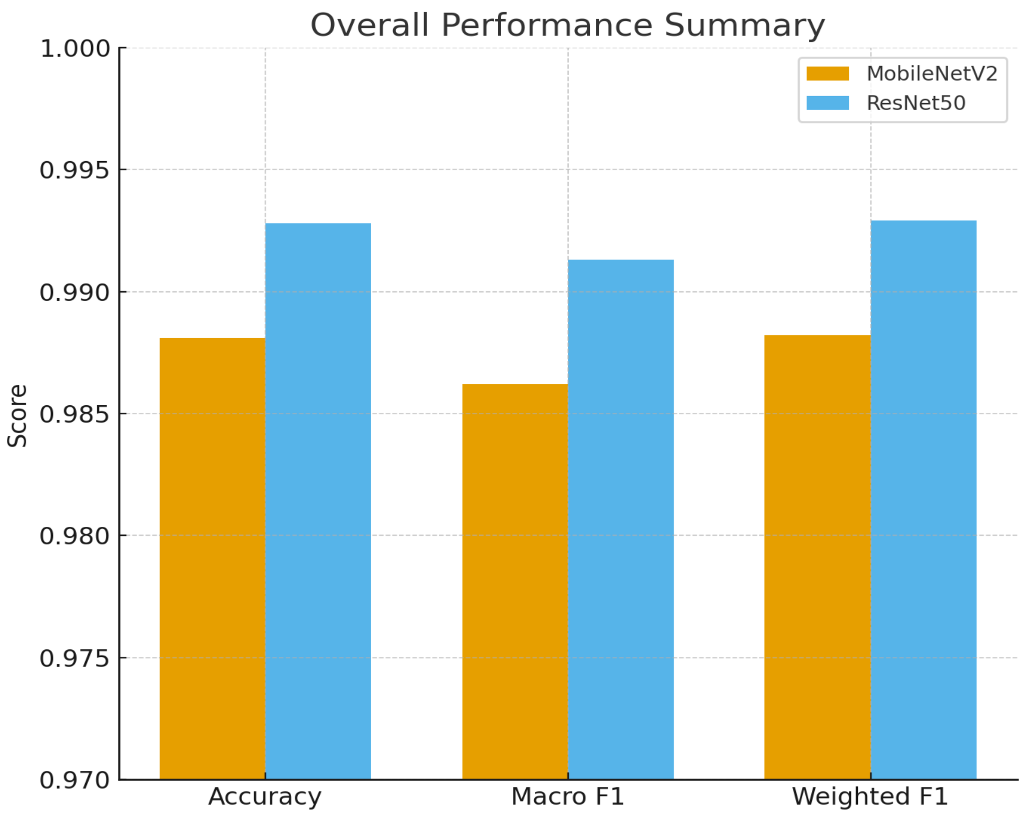

Fig 8. Overall Performance

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7. DISCUSSION

The comparative analysis indicates that while ResNet50 achieves marginally higher accuracy, MobileNetV2 demonstrates comparable performance with significantly fewer parameters, making it suitable for mobile and edge applications. The trade-off between accuracy and computational efficiency highlights different use-case scenarios.

9. CONCLUSION AND FUTURE WORK

This research establishes that ResNet50 outperforms MobileNetV2 slightly in cotton leaf disease classification, achieving 99.3% accuracy compared to MobileNetV2's 98.8%. However, MobileNetV2's lightweight nature makes it preferable for real-time, on-field applications. Future work will involve expanding the dataset, exploring architectures such as EfficientNet and DenseNet, and developing mobile/web-based expert systems for farmers.

REFERENCES

[1] Patil, B. V., & Patil, P. S. (2021). Computational method for Cotton Plant disease detection of crop management using deep learning and internet of things platforms. In Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2020 (pp. 875-885). Springer Singapore.

[2] Caldeira, R. F., Santiago, W. E., & Teruel, B. (2021). Identification of cotton leaf lesions using deep learning techniques. Sensors, 21(9), 3169.

[3] Tanwar, P., Shah, R., Shah, J., & Lokhande, U. (2022). Cotton Price Prediction and Cotton Disease Detection Using Machine Learning. In Intelligent Data Communication Technologies and Internet of Things: Proceedings of ICICI 2021 (pp. 115-128). Singapore: Springer Nature Singapore.

[4] Jenifa, A., Ramalakshmi, R., & Ramachandran, V. (2019, December). Cotton leaf disease classification using deep convolution neural network for sustainable cotton production. In 2019 IEEE international conference on clean energy and energy efficient electronics circuit for sustainable development (INCCES) (pp. 1- 3). IEEE.

[5] Saha, P., & Nachappa, M. N. Cotton Plant Disease Prediction Using Deep Learning.

[6] Zekiwos, M., & Bruck, A. (2021). Deep learning-based image processing for cotton leaf disease and pest diagnosis. Journal of Electrical and Computer Engineering, 2021, 1-10.

[7] Tripathy, S. (2021, November). Detection of cotton leaf disease using image processing techniques. In Journal of Physics: Conference Series (Vol. 2062, No. 1, p. 012009). IOP Publishing.

[8] Kalaiselvi, T., & Narmatha, V. (2023). Cotton Crop Disease Detection Using FRCM Segmentation and Convolution Neural Network Classifier. In Computational Vision and Bio-Inspired Computing: Proceedings of ICCVBIC 2022 (pp. 557-577). Singapore: Springer Nature Singapore.

[9] Dubey, Yogita K., Milind M. Mushrif, and Sonam Tiple. "Superpixel based roughness measure for cotton leaf diseases detection and classification." In 2018 4th International Conference on Recent Advances in Information Technology (RAIT), pp. 1-5. IEEE, 2018.

[10] Dhinesh, E., and A. Jagan. "Detection of Leaf Disease Using Principal Component Analysis and Linear Support Vector Machine." In 2019 11th International Conference on Advanced Computing (ICoAC), pp. 350-355. IEEE, 2019.

[11] Khirade, Sachin D., and A. B. Patil. "Plant disease detection using image processing." In 2015 International conference on computing communication control and automation, pp. 768- 771. IEEE, 2015.

[12] Rothe, P. R., and R. V. Kshirsagar. "Cotton leaf disease identification using pattern recognition techniques." In 2015 International Conference on Pervasive Computing (ICPC), pp. 1-6. IEEE, 2015.

[13] Devaraj, Abirami, Karunya Rathan, Sarvepalli Jaahnavi, and K. Indira. "Identification of Plant Disease using Image Processing Technique." In 2019 International Conference on Communication and Signal Processing (ICCSP), pp. 0749-0753. IEEE, 2019.

[14] Gupta, Vishal Mani Tiwari&Tarun. "An Exploration on the Identification of Plant Leaf Diseases using Image Processing Approach." (2016).

[15] Zhang SW, Shang YJ, Wang L. Plant disease recognition based on plant leaf image. J. Anim. Plant Sci. 2015 Jan 1; 25(3):42-5.

[16] Hang J, Zhang D, Chen P, Zhang J, Wang B. Classification of Plant Leaf Diseases Based on Improved Convolutional Neural Network. Sensors. 2019 Jan; 19(19):4161.

[17] Caldeira, R. F., Santiago, W. E., & Teruel, B. (2021). Identification of cotton leaf lesions using deep learning techniques. Sensors, 21(9), 3169.

[18] Tanwar, P., Shah, R., Shah, J., & Lokhande, U. (2022). Cotton Price Prediction and Cotton Disease Detection Using Machine Learning. In Intelligent Data Communication Technologies and Internet of Things: Proceedings of ICICI 2021 (pp. 115-128). Singapore: Springer Nature Singapore.

[19] Jenifa, A., Ramalakshmi, R., & Ramachandran, V. (2019, December). Cotton leaf disease classification using deep convolution neural network for sustainable cotton production. In 2019 IEEE international conference on clean energy and energy efficient electronics circuit for sustainable development (INCCES) (pp. 1- 3). IEEE.

[20] Saha, P., & Nachappa, M. N. Cotton Plant Disease Prediction Using Deep Learning.

[21] Zekiwos, M., & Bruck, A. (2021). Deep learning-based image processing for cotton leaf disease and pest diagnosis. Journal of Electrical and Computer Engineering, 2021, 1-10.

[22] Tripathy, S. (2021, November). Detection of cotton leaf disease using image processing techniques. In Journal of Physics: Conference Series (Vol. 2062, No. 1, p. 012009). IOP Publishing.

[23] Appalanaidu, Majji V., and G. Kumaravelan. "Plant leaf disease detection and classification using machine learning approaches: a review." Innovations in computer science and engineering: Proceedings of 8th ICICSE (2021): 515-525.

[24] Gosai, Dhruvi, et al. "Plant disease detection and classification using machine learning algorithm." 2022 International Conference for Advancement in Technology (ICONAT). IEEE, 2022.

[25] Demilie, Wubetu Barud. "Plant disease detection and classification techniques: a comparative study of the performances." Journal of Big Data 11.1 (2024): 5.