DEEP LEARNING-BASED EXPERT SYSTEM FOR COTTON LEAF DISEASES IDENTIFICATION USING MOBILENETV2 AND GUI INTEGRATION

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Abstract
Cotton is one of the most significant cash crops globally, but its productivity is threatened by several leaf diseases. This paper proposes a deep learning-based expert system to identify and classify seven major cotton leaf disease classes using MobileNetV2. The dataset was prepared with a train/validation/test split of 80/10/10 and augmented with flipping, rotation, zoom, and contrast adjustments. MobileNetV2, pre-trained on ImageNet, was fine-tuned and achieved ~96% validation accuracy and 94.40% test accuracy. Additionally, a user-friendly GUI application was developed for real-time disease identification, providing predictions with confidence scores. The results demonstrate that lightweight CNN architectures like MobileNetV2 can deliver high accuracy while being efficient for deployment.
Keywords*: Cotton plant diseases, Deep Learning, MobileNetV2, Computer Vision, Expert System, CNN, GUI.*

1. Introduction

Cotton is a critical cash crop and contributes significantly to the global textile industry. However, cotton production is severely affected by multiple leaf diseases that reduce yield and quality. India's economy is significantly impacted by cotton, a cash crop. India has diverse climates, and farmers will grow various crops, including food, cash, plantation, horticulture, and many others. Although the development of technology necessitates ongoing producer monitoring, several new technologies can aid in increasing crop yields. Many people depend on the Cotton crop for its cultivation or processing [7]. Indian citizens grow a variety of available produce. It has contributed 18% of the nation's GDP and 41.49% of the Indian population's employment [1]. According to estimates, crop losses caused by plant diseases cost the world region $60 billion annually [5]. Technology-assisted agricultural research aims to improve farmer income, crop quality, and productivity. However, environmental factors and diseases brought by fungi, bacteria, and other pathogens hinder productivity [3].Traditional manual disease identification is slow, labor-intensive, and error-prone. With the advancement of Artificial Intelligence (AI) and Computer Vision, automated disease detection has become a promising solution. Recent works using CNN architectures such as VGG, ResNet, and EfficientNet have demonstrated strong performance in plant disease classification. This paper presents a lightweight expert system using MobileNetV2 for cotton disease identification and integrates the model with a Graphical User Interface (GUI) for practical usability.

2. Literature Review

Manavalan et al. [1] Provides an overview of the challenges in monitoring cotton leaf diseases and the limitations of current automated identification methods. This study emphasizes the need for advanced automated systems to improve disease detection and enhance cotton production.Chethana et al. [2] discusses the importance of cotton in India's agriculture and the impact of various diseases on cotton crops, such as "Leaf Lesions," "Bacterial Blight," "Curl Virus," and "Fusarium wilt." It focuses on using Convolutional Neural Networks (CNN) for early detection of these diseases by analyzing and distinguishing features in images. Jayanthy et al. [3] implements a deep learning model, MobileNetV2, to detect and classify cotton plant diseases at early stages using real-time data. MobileNetV2 outperforms other CNN models in terms of model size, accuracy, and speed, and is deployed on drones for efficient field monitoring. Aditya et al. [4] Focuses on detecting cotton plant diseases and estimating their stage using images taken in uncontrolled field conditions with a standard or mobile phone camera. Although the algorithm is generalized for any disease, it is demonstrated specifically for detecting Grey Mildew. Paramjeet et al. [5] focuses on enhancing the detection of cotton leaf diseases in India using deep learning methods. It utilizes a near-balanced dataset of 22 disease types and employs data augmentation to improve model performance. The study finds that CNN algorithms are particularly effective, achieving 99.39% accuracy with minimal error, thus demonstrating potential for real-time implementation in disease detection systems to assist farmers in making informed decisions.

Thivya Lakshmi et al. [6] Discusses the development of automated cotton detection systems using machine learning , CNNs, and hyperspectral imaging to identify and monitor cotton crops. These technologies improve efficiency, reduce costs, and enhance crop management by addressing issues like diseases and pests. Real-time monitoring helps farmers take early corrective action, promoting healthy crop growth. The proposed pipeline demonstrates reliable and quick cotton detection, offering potential for sustainable farming improvements. Lachure et al. [7] propose a system for plant leaf disease detection using a lightweight CNN model optimized through grid search hyperparameter tuning. The goal is to create an efficient, cost-effective solution for early disease identification, suitable for agricultural deployment. Pan, et al. [8] Lintroduce the CDDLite-YOLO model, a lightweight deep learning solution designed for cotton disease detection in natural field conditions. The model, based on YOLOv8, incorporates innovative modules like C2f-Faster, Slim-neck, and MPDIoU

Several researchers have applied deep learning techniques for plant disease classification. ResNet and VGG architectures have been widely used but are computationally expensive. EfficientNet provides higher accuracy but requires more resources. MobileNet architectures, due to their lightweight nature, have been adopted for mobile and embedded applications. Prior studies achieved accuracy in the range of 85–95% across different crops. This work extends the applicability of MobileNetV2 to cotton leaf disease detection, achieving higher accuracy while ensuring faster inference suitable for deployment.

3. Methodology

3.1 Dataset Preparation

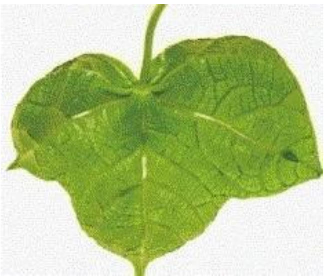
The dataset employed in this study comprised two parts: (i) a field-collected database from Akola and Yavatmal districts of Maharashtra, India, encompassing healthy and diseased cotton leaf samples, and (ii) a downloaded database from Kaggle, which was utilized to augment the sample size and strengthen the validation of the proposed deep learning model.

The dataset contained approximately 5561 cotton leaf images across seven classes: Bacterial Blight, Curl Virus, Fusarium Wilt, Healthy, Pest, Powdery Mildew, and Target Spot. The split was performed using a fixed random seed (42), resulting in 4446 training images, 553 validation images, and 562 test images.

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

Figure 1: Representative images from the cotton leaf dataset across seven classes.

3.2 Data Augmentation

To improve generalization and reduce overfitting, data augmentation techniques were applied. These included: random horizontal flipping, random rotation (±20°), random zoom (0.1), and random contrast adjustment (0.1). These transformations increased variability while preserving class characteristics.

3.3 Model Architecture

The MobileNetV2 architecture was employed as the backbone with ImageNet pre-trained weights. The convolutional layers (2,257,984 parameters) were frozen, and a classification head was added consisting of a GlobalAveragePooling2D layer, Dropout (0.2), and Dense(7, softmax) layer. This resulted in 2,266,951 parameters, of which only 8,967 were trainable.

Layer	Output Shape	Parameters
Input (224x224x3)	(None,224,224,3)	0
Augmentation	(None,224,224,3)	0
MobileNetV2 (frozen)	(None,7,7,1280)	2,257,984
Global Average Pooling2D	(None,1280)	0
Dropout (0.2)	(None,1280)	0
Dense (7 softmax)	(None,7)	8,967

Table 2: Model architecture summary for MobileNetV2-based cotton leaf disease classifier.

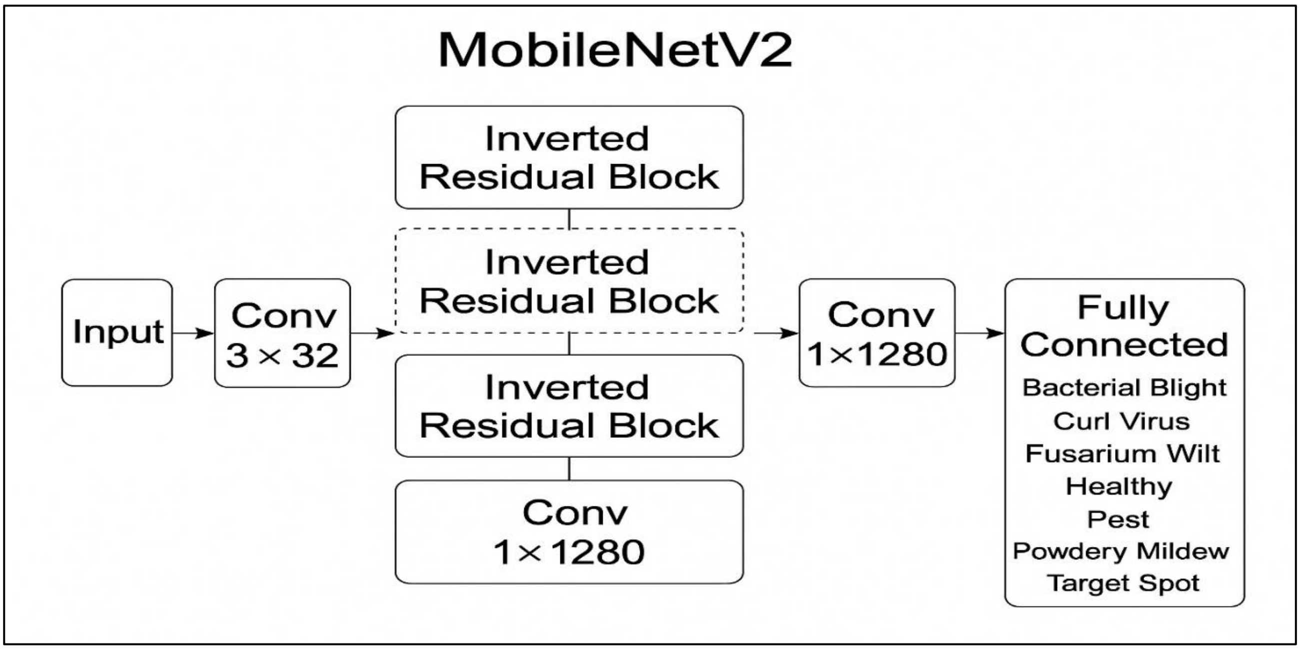


Figure 2: Block diagram of MobileNetV2 architecture used for classification of cotton leaf diseases.

3.4 Proposed Algorithm

The proposed CottonLeafVision algorithm is based on MobileNetV2 with a two-stage transfer learning and fine-tuning strategy. The algorithmic flow is summarized in Algorithm 1.

Algorithm 1: CottonLeafVision (MobileNetV2-based Cotton Leaf Disease Classifier)

Inputs: Image I of a cotton leaf (RGB).

Outputs: Predicted class ŷ ∈ {Bacterial Blight, Curl Virus, Fusarium Wilt, Healthy, Pest, Powdery Mildew, Target Spot} with confidence scores.

1. Split dataset into training, validation, and test sets (seed=42).
2. Preprocess images: resize to 224×224, normalize pixel values, and augment (flip, rotation, zoom, contrast).
3. Initialize MobileNetV2 (pretrained on ImageNet) as backbone.
4. Add classification head: Global Average Pooling → Dropout → Dense(7, softmax).
5. Stage-1 training: freeze backbone, train head using Adam (lr=1e-3).
6. Stage-2 fine-tuning: unfreeze last ~40 layers, train with reduced learning rate (1e-4).
7. Apply callbacks: EarlyStopping, ReduceLROnPlateau, ModelCheckpoint.
8. For inference: preprocess new image, compute probabilities p, and assign ŷ = argmax(p).

This strategy allows the network to leverage pre-trained generic features while adapting to cotton-specific patterns, resulting in a final test accuracy of 94.40%.

3.4 Training Strategy

The model was trained using the Adam optimizer with an initial learning rate of 1e-3, reduced to 1e-4 during fine-tuning. Callbacks included EarlyStopping (patience=5), ReduceLROnPlateau (factor=0.5), and ModelCheckpoint. Training was performed for a maximum of 30 epochs with batch size 32, converging around epoch 13.

Parameter	Value
Input Image Size	224 × 224 pixels
Number of Classes	7
Train/Val/Test Split	80% / 10% / 10% (≈4446 / 553 / 562 images)
Batch Size	32
Epochs	30 (EarlyStopping stopped at ~13)
Optimizer	Adam
Learning Rate	1e-3 → 1e-4
Loss Function	Sparse Categorical Crossentropy
Augmentations	Flip, Rotation ±20°, Zoom 0.1, Contrast 0.1
Callbacks	EarlyStopping, ReduceLROnPlateau, ModelCheckpoint
Dropout	0.2
Pretrained Weights	ImageNet

Table 3: Training parameters used for MobileNetV2-based cotton leaf disease classification.

4. Results and Discussion

The MobileNetV2 model achieved a validation accuracy of ~96% and test accuracy of 94.40% (loss = 0.1482). Training and validation curves are shown in Figures 2 and 3. The confusion matrix (Figure 4) illustrates the per-class classification performance, while Table 4 presents precision, recall, and F1-score for each class. Finally, the GUI application (Figure 5) demonstrates the real-time usability of the system.

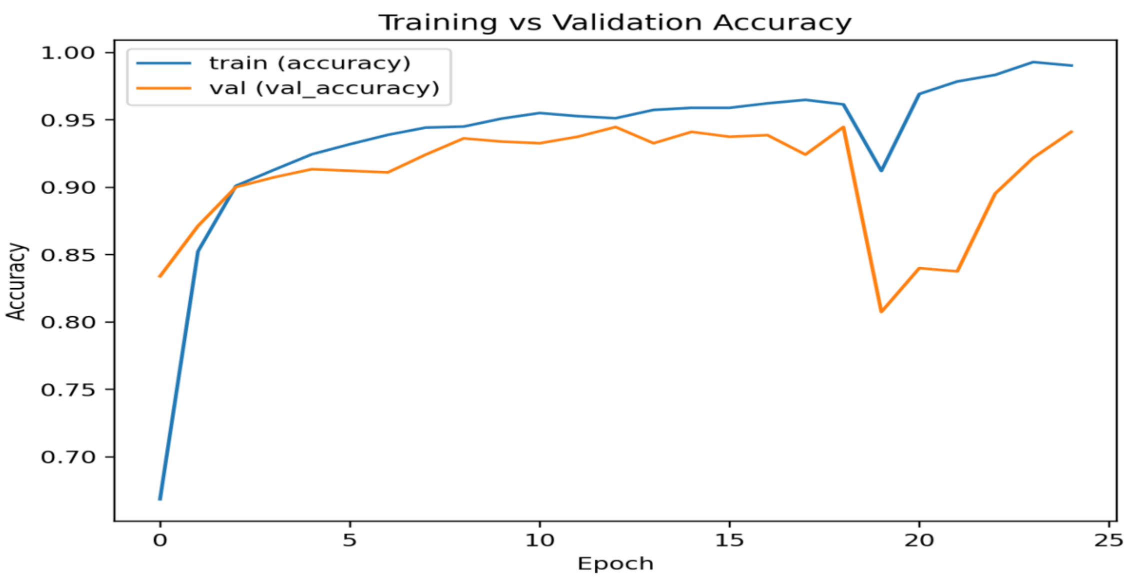


Figure 2: Training accuracy vs validation accuracy across epochs.

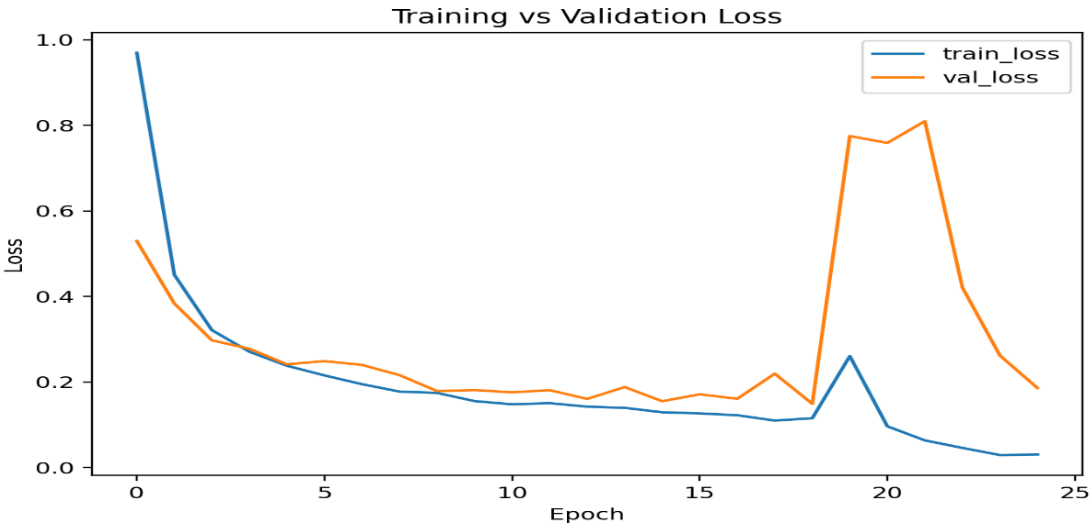


Figure 3: Training loss vs validation loss across epochs.

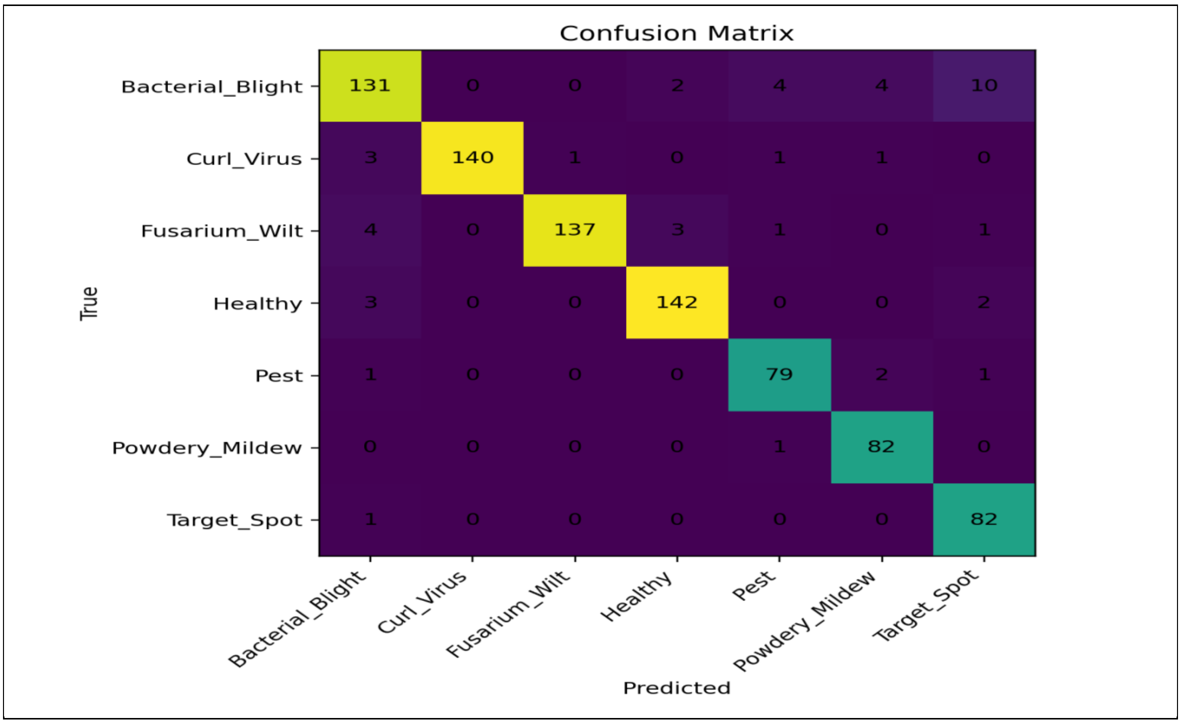
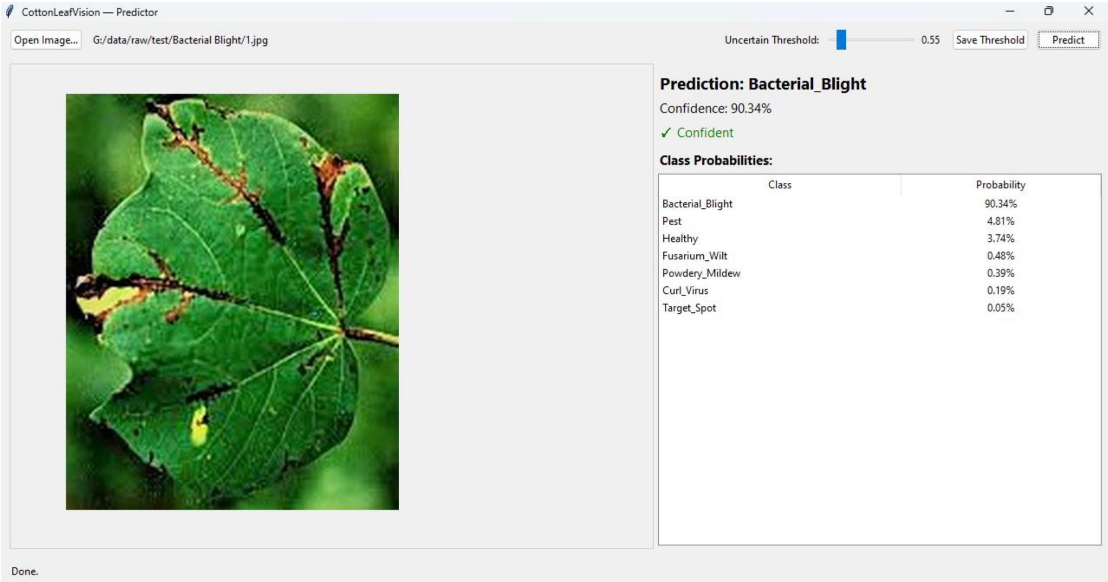


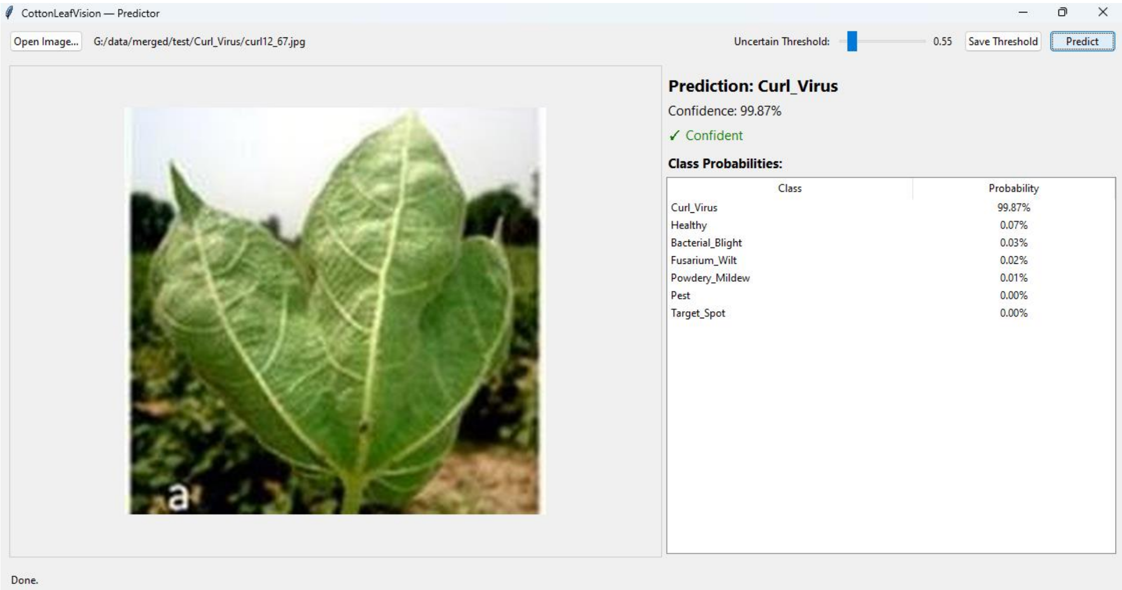
Figure 4: Confusion matrix for seven-class classification on the test dataset.

Class	Precision	recall	f1-score	support
Bacterial_Blight	0.916084	0.86755	0.891156	151
Curl_Virus	1	0.958904	0.979021	146
Fusarium_Wilt	0.992754	0.938356	0.964789	146
Healthy	0.965986	0.965986	0.965986	147
Pest	0.918605	0.951807	0.934911	83
Powdery_Mildew	0.921348	0.987952	0.953488	83
Target_Spot	0.854167	0.987952	0.916201	83
Accuracy	0.945173	0.945173	0.945173	0.945173
macro avg	0.938421	0.951215	0.94365	839
weighted avg	0.947417	0.945173	0.945343	839

Table 4: Precision, Recall, and F1-score per class.



Screenshot 1: Prdiction-Bacterial_Blight



Screenshot 2: Prediction -Curl_Virus

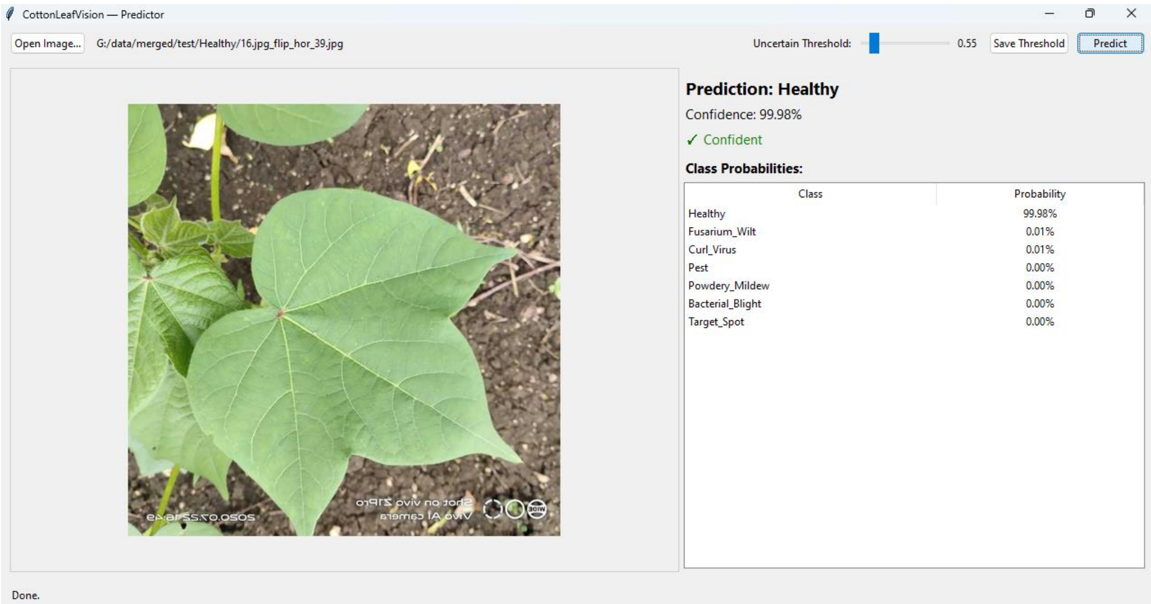


Figure 5: GUI interface for cotton leaf disease prediction showing top-3 class probabilities.

5. Conclusion and Future Work

This research demonstrates the effectiveness of MobileNetV2 for cotton leaf disease classification. With ~96% validation accuracy and 94.40% test accuracy, the proposed expert system shows strong potential for real-world deployment. The addition of a GUI application enhances usability for farmers and researchers. Future work will focus on expanding the dataset with real-field images, deploying the model as a mobile application, and extending the system to identify more crop diseases beyond cotton.

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