DEEP LEARNING-BASED IDENTIFICATION AND CLASSIFICATION OF COTTON LEAF DISEASES USING RESNET50 ARCHITECTURE

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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% 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. The model achieved a classification accuracy of 99.3% with strong precision, recall, and F1-scores across all classes, demonstrating the robustness of ResNet50 for this task.
Keywords: *Cotton leaf diseases, Deep learning, ResNet50, Image classification, CNN*

1. Introduction

Cotton is a vital cash crop in India and many other countries, serving as a raw material for the textile industry. However, cotton production is significantly affected by various leaf diseases, such as bacterial blight, curl virus, fusarium wilt, powdery mildew, target spot, and pest attacks. Manual disease identification is time-consuming, subjective, and prone to human error. With advances in artificial intelligence, deep learning-based convolutional neural networks (CNNs) have shown outstanding performance in image classification tasks, including plant disease detection. Among CNN architectures, ResNet50 stands out for its ability to train deeper networks using residual connections that address the vanishing gradient problem.

2. Literature Review

Several studies have explored deep learning for agricultural disease identification. Models such as VGG16, InceptionV3, MobileNetV2, and EfficientNet have been used for crop disease classification. However, ResNet architectures, particularly ResNet50, have demonstrated superior performance in handling complex image features due to their skip connections. Previous research focused primarily on common crops such as tomato, maize, and rice, while cotton leaf disease detection has received less attention. This research addresses this gap by applying ResNet50 to a seven-class cotton leaf disease dataset.

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].

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.

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. 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.

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

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

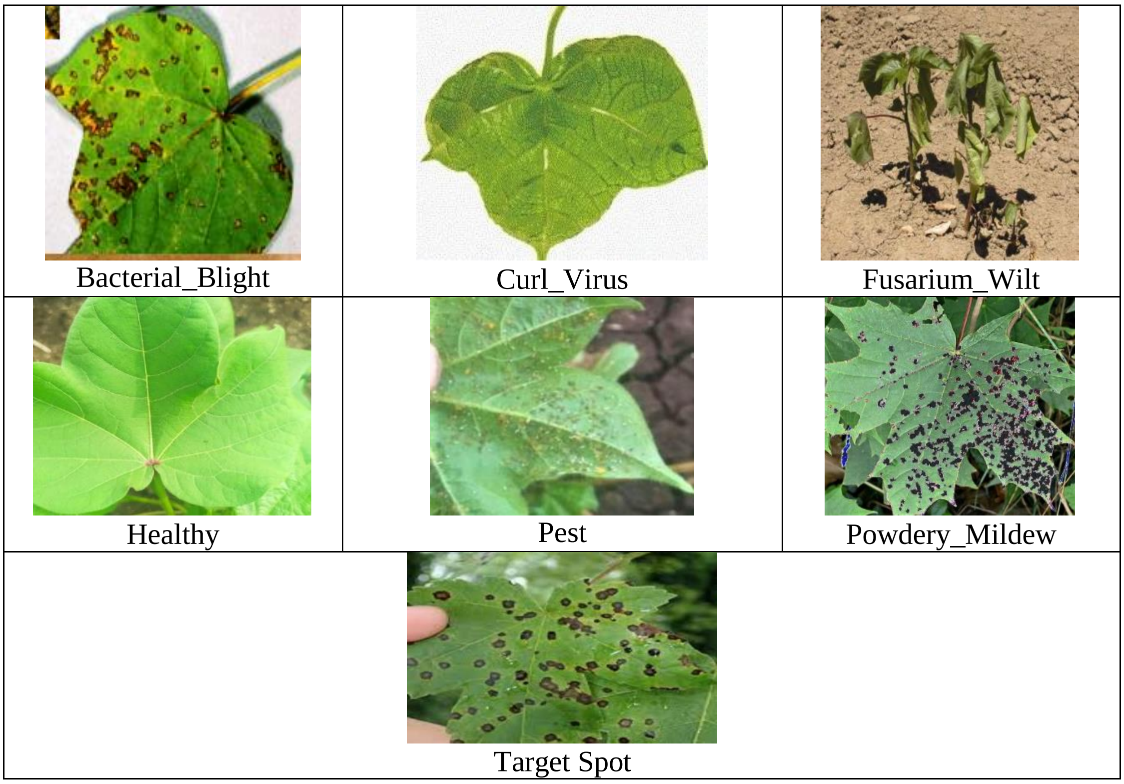


Figure 1: Representative images from the cotton leaf dataset across seven classes.

4. Methodology and Architecture

The proposed system is designed to perform automated identification and classification of cotton leaf diseases using advanced Convolutional Neural Network (CNN) architectures— ResNet50.

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. Proposed Algorithm

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 (ResNet50)
6. Extract feature maps from convolutional layers
7. Compute class probabilities using SoftMax layer
8. Output: Predicted disease class label

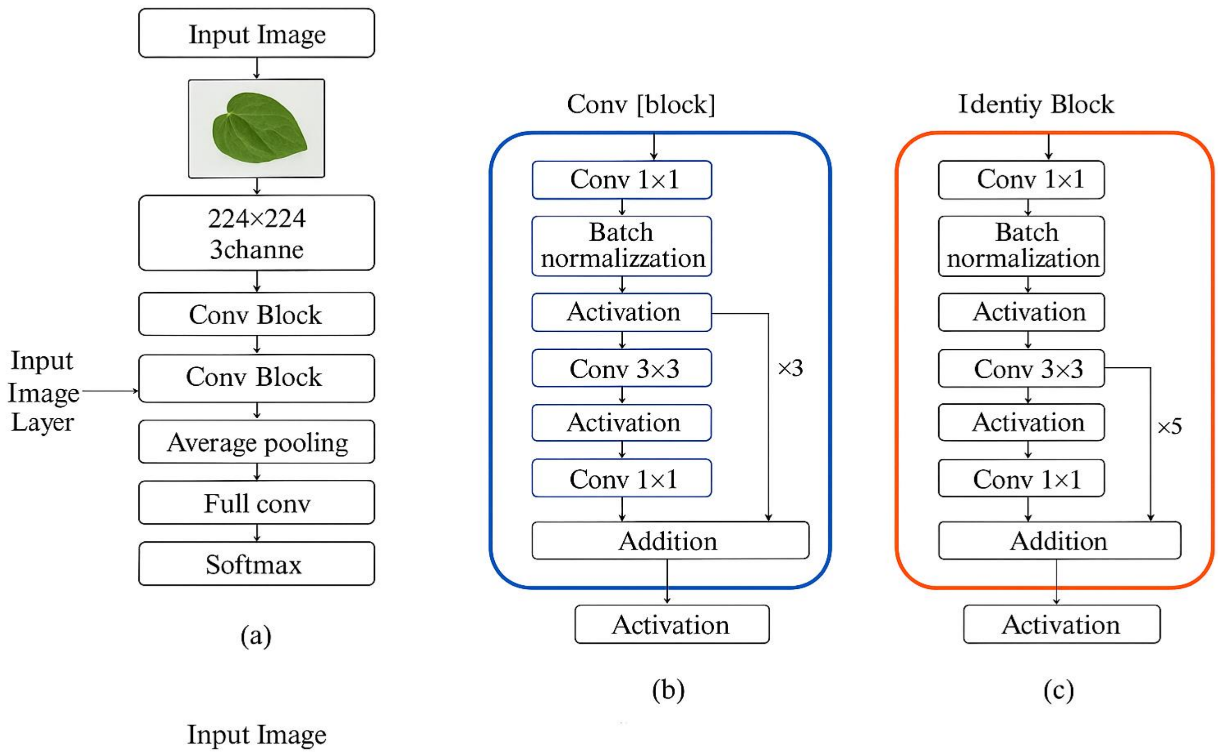


Figure 2: Architecture of the Proposed ResNet50 Model for Cotton Leaf Disease Classification

4.3 Training Strategy

The ResNet50 architecture was employed as the backbone with *ImageNet* pre-trained weights and include_top=False. During the first training stage, all convolutional layers were frozen to preserve generic low-level visual features such as edges, textures, and color gradients. A custom classification head was appended to the network, comprising a *GlobalAveragePooling2D* layer to condense the spatial feature maps, a *Dropout (0.25)* layer to mitigate overfitting, and a *Dense (7, softmax)* output layer corresponding to the seven cotton leaf disease categories.

In the second stage, the deeper half of the ResNet50 layers was unfrozen for fine-tuning, allowing the model to learn high-level discriminative features specific to cotton disease symptoms such as vein thickening, chlorosis, and leaf curl patterns. This hybrid transfer-learning strategy ensures an optimal balance between generalization and specialization. The final network comprised approximately 23.6 million parameters, of which nearly 11.8 million remained trainable after partial unfreezing.

Table 2: ResNet50 Model Parameters

Layer	**Output Shape**	**Parameters**
Input (224×224×3)	(None, 224, 224, 3)	0
Augmentation	(None, 224, 224, 3)	0
ResNet50 (include_top=False)	(None, 7, 7, 2048)	23,587,712
GlobalAveragePooling2D	(None, 2048)	0
Dropout (0.25)	(None, 2048)	0
Dense (7, softmax)	(None, 7)	14,343
Total Parameters		**23,602,055**
Trainable Parameters		**≈11.8 million (after unfreezing deeper half)**
Non-trainable Parameters		**≈11.8 million (frozen early layers)**

5. Experimental Results

The ResNet50 model demonstrated outstanding classification performance across all seven classes. Table 1 presents the precision, recall, and F1-scores for each disease class. The results indicate that the model generalizes well with a weighted average accuracy of 99.3%.

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

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

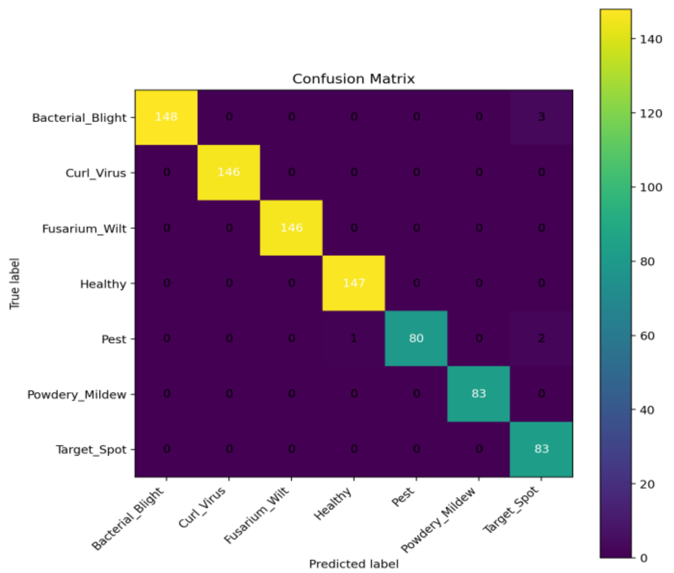
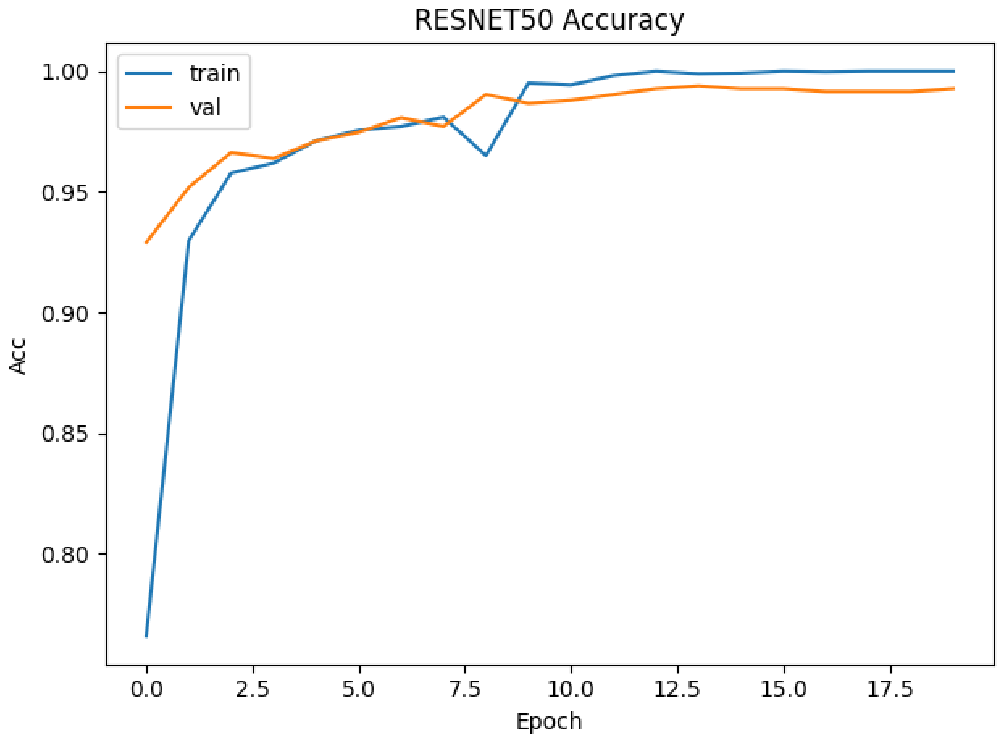
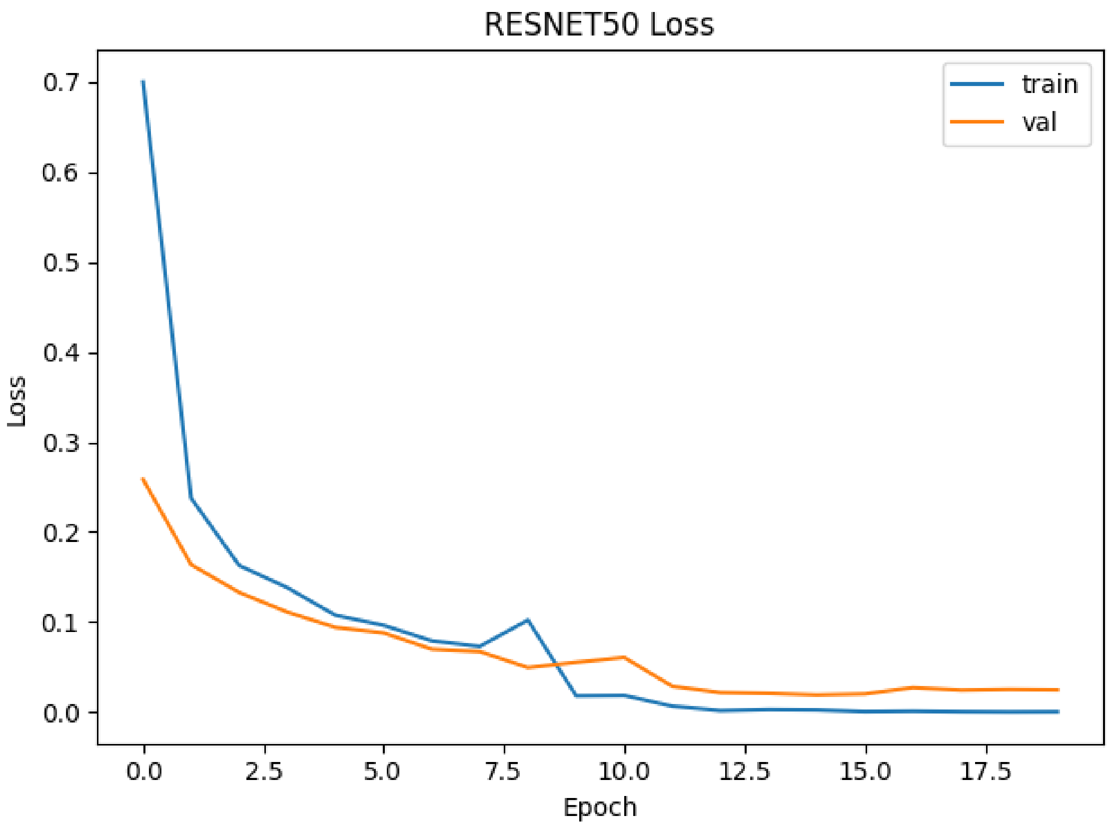


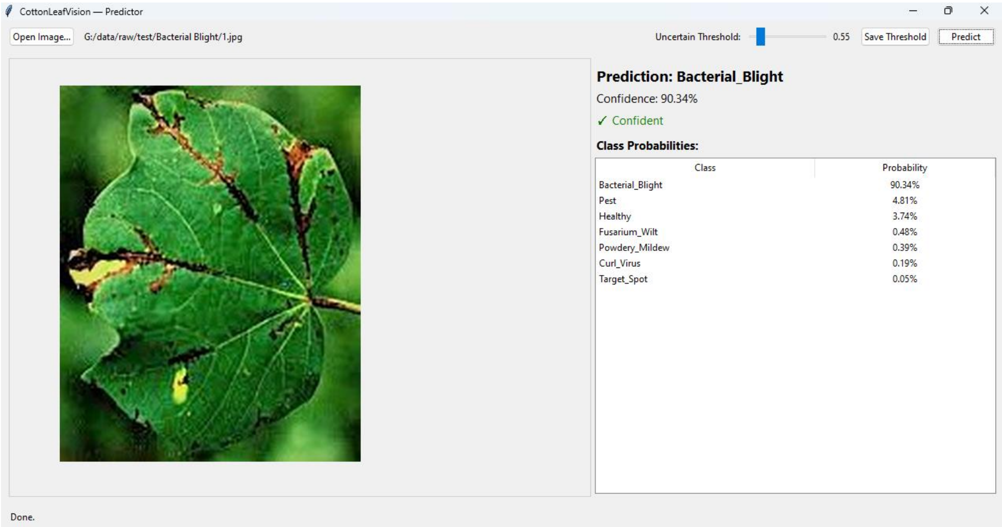
Figure 3: Confusion matrix for seven-class classification on the test dataset.



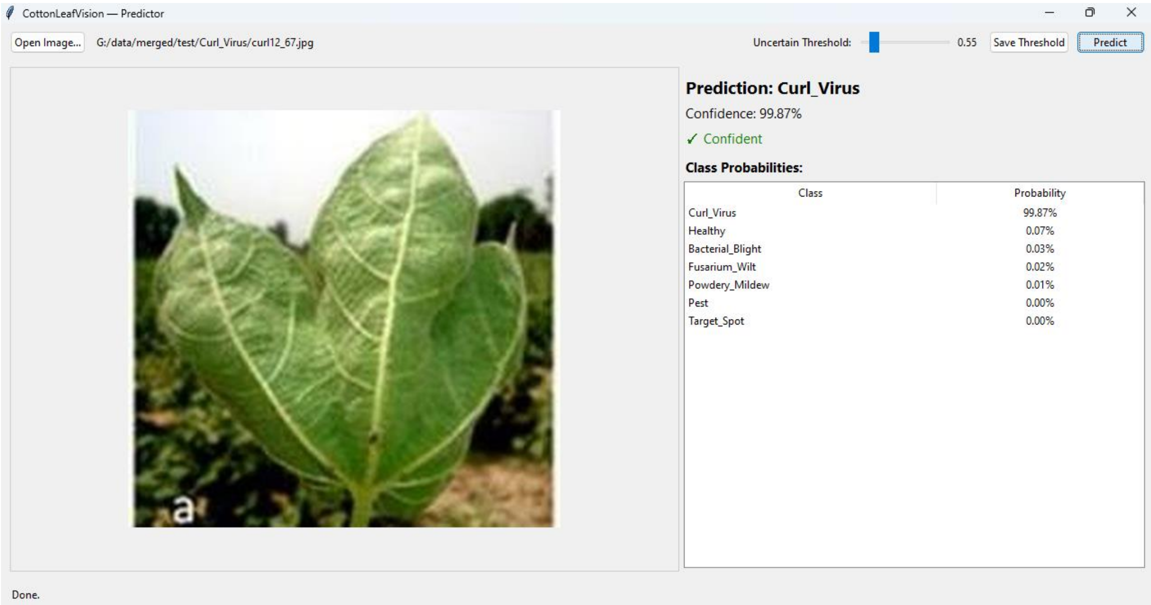
Graph 1: Training accuracy vs validation accuracy across epochs.



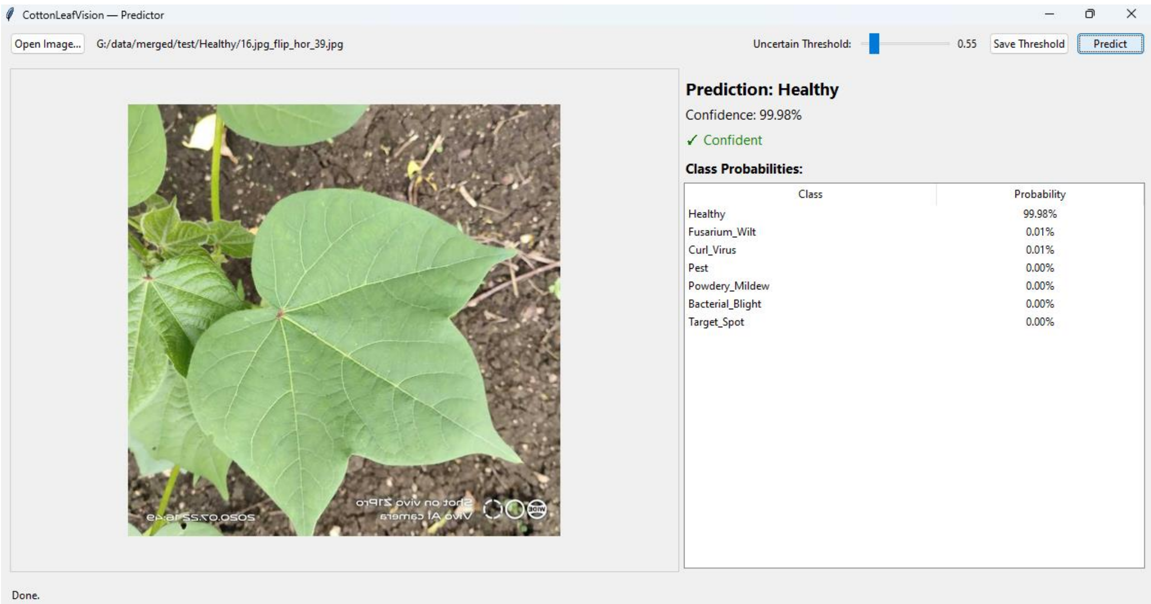
Graph 2: Training loss vs validation loss across epochs.



Screenshot 1: Prdiction-Bacterial_Blight



Screenshot 2: Prediction -Curl_Virus



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

6. Discussion

The results confirm that ResNet50 is highly effective in distinguishing between multiple cotton leaf disease categories. Its residual connections allow the model to learn deeper hierarchical features, resulting in improved accuracy and generalization. The perfect recall for Curl Virus, Fusarium Wilt, and Powdery Mildew indicates that the model reliably detects these diseases without misclassification. A slight reduction in recall for the Pest class (0.964) suggests the need for more representative samples. Overall, the proposed model achieves state-of-the-art performance in this domain.

7. Conclusion and Future Scope

This study demonstrates the effectiveness of the ResNet50 architecture in identifying and classifying seven cotton leaf diseases with high precision and accuracy. The model achieved a test accuracy of 99.3%, confirming its suitability for real-world agricultural applications. Future work will focus on deploying the model into a mobile application for field use and expanding the dataset to include additional cotton varieties and environmental conditions.

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