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AN AI-DRIVEN APPROACH FOR THE DETECTION AND CLASSIFICATION OF COTTON LEAF DISEASES

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Abstract

Cotton, one of the biggest cash crops, is essential to the textile and agricultural sectors. Cotton, on the other hand, is extremely susceptible to several leaf diseases, which impact production and fiber quality. To help in the effective management and timely treatment of the plant diseases, the information on the presence of the diseases in the early stages of occurrence and the correct time of the occurrence is very important. Traditional diagnosis is usually time-consuming, labor intensive, and is less reliable in the field. For that purpose, the current study proposes a deep learning model (ResNet50) architecture for the automatic detection and classification of cotton leaf disease. The SAR-CLD-2024 cotton leaf dataset, which consists of 2,137 original field photos that were enlarged to about 7,000 images through data augmentation and covers seven classes Bacterial Blight, Curl Virus, Healthy Leaf, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Redding, and Leaf Variegation is used to train and assess the model. The proposed pipeline integrates systematic data cleaning, image preprocessing, augmentation, and transfer learning with fine-tuning of ResNet50's pretrained ImageNet weights to adapt the network to the agricultural. Experimental results show that the proposed model achieves an overall accuracy of 94.60%, with a weighted precision of 93.60%, recall of 92.60%, and F1-score of 93.10% across all seven-disease categories. The results show the classification of cotton leaf disease can be done with reliable and efficient performance by ResNet50, and can be applied to smart agriculture through automatic monitoring of the disease.

1. Introducion

Pakistan is one of the top four countries in the world for cotton production, and the crop is known as "White Gold" since it accounts for around 55% of the nation's export revenue. Cotton production was expected to reach its lowest level in the preceding 20 years in 2020–2021, according to official figures. This results from a lack of technological advancements in disease prevention and seed production. Because it is utilized in so many different businesses worldwide, cotton is a valuable commodity. It can be grown in many countries and is imported and sold as a cash crop due to its diverse uses. However, the existence of pests, viruses, harmful bacteria, etc. has a detrimental effect on cotton production. [1]. About 30% to 40% of the cotton is used domestically in final products, with the remainder being exported as clothing, raw materials, and apparel. In Pakistan, cotton is mostly grown in the following regions: D. G. Khan, Rahim Yar Khan, Khanewal, Sahiwal, Layyah, Dadu, Khairpur, and Nawab Shah [2].

Agriculture plays an important role in a country's food system and in economic development. But diseases of crop plants adversely affect both yields and economic security. Traditional disease identification relies primarily on human labor and considerable experience and expertise is required in the human to accurately identify the type of disease on the leaf. It takes a lot of time and manpower, and it has a high risk of being too subjective and misjudged.. Laboratory methods are time consuming and expensive. In order to confront these shortcomings, researchers have been, on a high level, assessed the automatic identification of leaf diseases with computer vision. [3].

Early disease detection and treatment are further hindered by the lack of access to skilled workers in the majority of rural communities with small-scale activities. As a result, there has been an increasing need to assist farmers in identifying and controlling cotton plant diseases, which require automated, effective, and scalable solutions. AI and ML technologies have significantly changed the landscape of agricultural disease detection, enabling the automation of plant health analysis through image-based approaches in recent years. In the field of Agriculture, deep learning (DL) models, like CNN, have been found to be effective in the plant disease classification, as they have proven to be powerful tools in agriculture for recognizing agricultural images with complex patterns.[4].

This study presents the AI-based image processing system, which can recognize and categorize the cotton leaf diseases utilizing deep learning method. The proposed approach is specifically designed for cotton crop identification of disease with model trained with a dataset include multiple categories of diseases. The system aims to automatically diagnose the disease with high accuracy using the advanced architectures like inception based deep learning models [5].

The primarily objective of this project is to create a dependable and computationally effective tool that can assist farmers in identifying cotton plant illnesses early on, allowing for prompt treatment and improved crop management.. This will minimize crop losses, increase productivity and support the development of sustainable and technology driven agriculture. In this study, automatic cotton leaf disease detection and classification are realized by proposing a deep learning framework based on ResNet50. ResNet50 is a robust CNN architecture that features residual connections to enhance gradient flow and achieve deeper feature learning. The objective of this work is to use data augmentation and transfer learning techniques to classify the cotton leaf photos into seven classes [15].

This paper's remaining sections are structured as follows. Related research on cotton and plant leaf disease detection is reviewed in Section 2. The suggested methodology, which includes the dataset, preprocessing pipeline, and ResNet50-based architecture, is explained in Section 3. In Section 4 the experimental results and comparison analysis are presented and section 5 described the conclusion and future work.

1. Literature Review

Deep learning and traditional machine learning techniques have been investigated in a number of studies to increase the precision and effectiveness of cotton leaf disease diagnosis. [5]. This section reviews representative work spanning classical machine learning pipelines, transfer-learning-based CNN architectures, and hybrid approaches relevant to the proposed framework [5].

Kumar, Rahul, et al. [6] presented machine learning based defect recognition of cotton leaf diseases using image analysis techniques. In this paper, the dataset used was the cotton diseases from Kaggel and various models were used, one of which was the Random Forest Model, another was Support Vector Machine, Multi-class SVM, and one was Ensemble learning using the algorithm of Random Forest and Decision Tree. The models were trained to categorize cotton leaves into two groups: healthy and diseased. The experiment outcome has shown that the proposed system was successful with a classification accuracy of 94.5%, in the process of leaf disease identification. This strategy emphasizes how crucial it is to use machine-learning techniques as part of a multifaceted strategy to enable prompt and accurate identification of cotton disease in order to increase the amount and quality of cotton [15].

Caldeira et al. [7] explored the deep learning model of GoogleNet and ResNet50 by fine-tuning for cotton disease detection using field-collected images of cotton leaves. Their results revealed that ResNet50 was more accurate than GoogleNet (89.2% vs 86.6%) highlighting the benefits of the deeper residual network architectures in learning more subtle texture and color variations on cotton leaves related to disease[16].

It is observed that Ganesh et al. [8] have used hand crafted color and texture features from the cotton leaf images for classification, with classification accuracy of 92.5% using Random Forest classification. These classical feature-engineering pipelines are effective and depend on the lighting conditions, background noise, and leaf orientation, but lack a more robust generalization to unseen field conditions than end-to-end deep learning models. Another deep learning model proposed by Suryawanshi, Varun, et al. [8] presented to identify cotton leaf disease using a test dataset that included images of both infected and normal leaves. Transfer learning model and image augmentation were used to enhance performance and generalization capabilities[18]. It had a classification of above 90% and was able to be used broadly to detect a variety of cotton leaf diseases. In addition, the model was integrated with a live web and mobile platform that enabled farmers to upload images to be predicted on-the-go[18]. The paper has presented a scalable, cost-effective, and automated approach to early detection of diseases and suggested how to enhance the approach in future, leveraging the IoT-based monitoring as well as increased number of data sets [15][19].

2. Proposed Methodology

The proposed cotton leaf disease classification pipeline is described as follows, cotton leaf image acquisition, data cleaning, image pre-processing and image augmentation, train and test data splitting, transfer-learning based model generation and training process using ResNet50 model, and model evaluation using the standard classification performance measures. The entire proposed method from raw cotton leaf image data to final evaluation is shown in Figure 1.

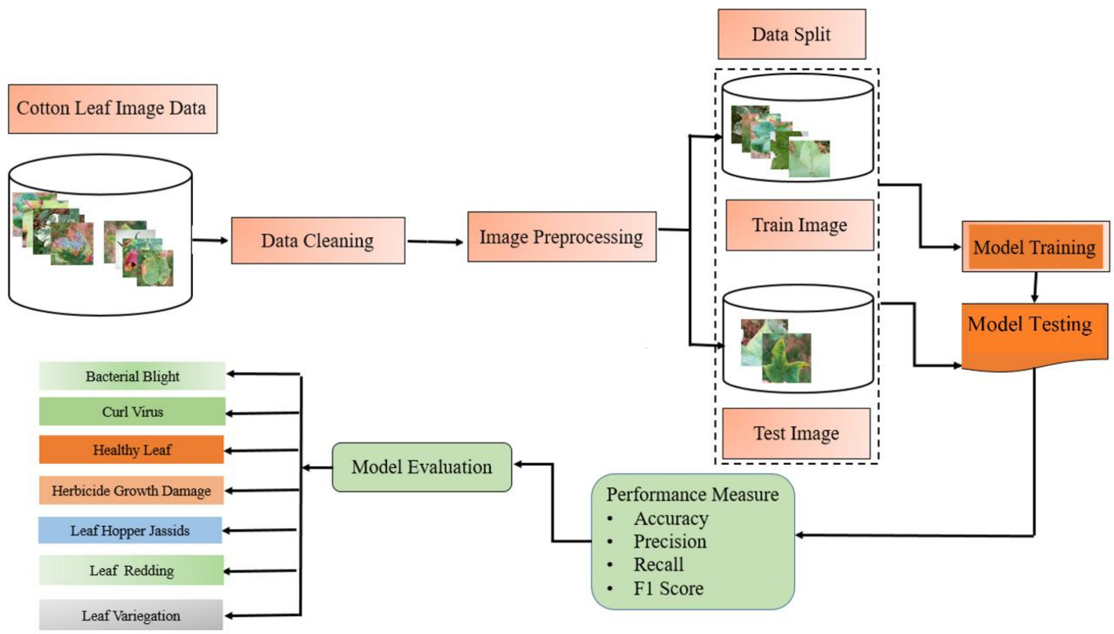

Figure 1: Proposed methodology pipeline for cotton leaf disease

2.1 . Dataset Preparation

The suggested model is implemented and tested on a set of cotton leaf disease images from the SAR-CLD-2024 dataset consisting of 2,137 images of cotton leaves were collected in the field. Seven classes covering both disease and non-disease conditions from cotton fields are represented in the data set, these being: Bacterial Blight, Curl Virus, Healthy Leaf, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Redding, and Leaf Variegation. Additional to this from a practical perspective, it is also important to include a Healthy Leaf class along with a Herbicide Growth Damage class because a farm wishing to distinguish between the two may end up with unnecessary fungicide or pesticide treatments if they mistook leaf discoloration caused by herbicides for disease symptoms.

The dataset was augmented to about 7000 images by applying data transformation methods such as horizontal flips, rotation, brightness changes, and zooming to address the small size of the original dataset and improved the model's capability to generalize to out-of-sample field conditions. This is presented in Figure 2, which displays typical images of each category (original and rotated, original and brightness adjusted, original and zoomed) in the seven classes.

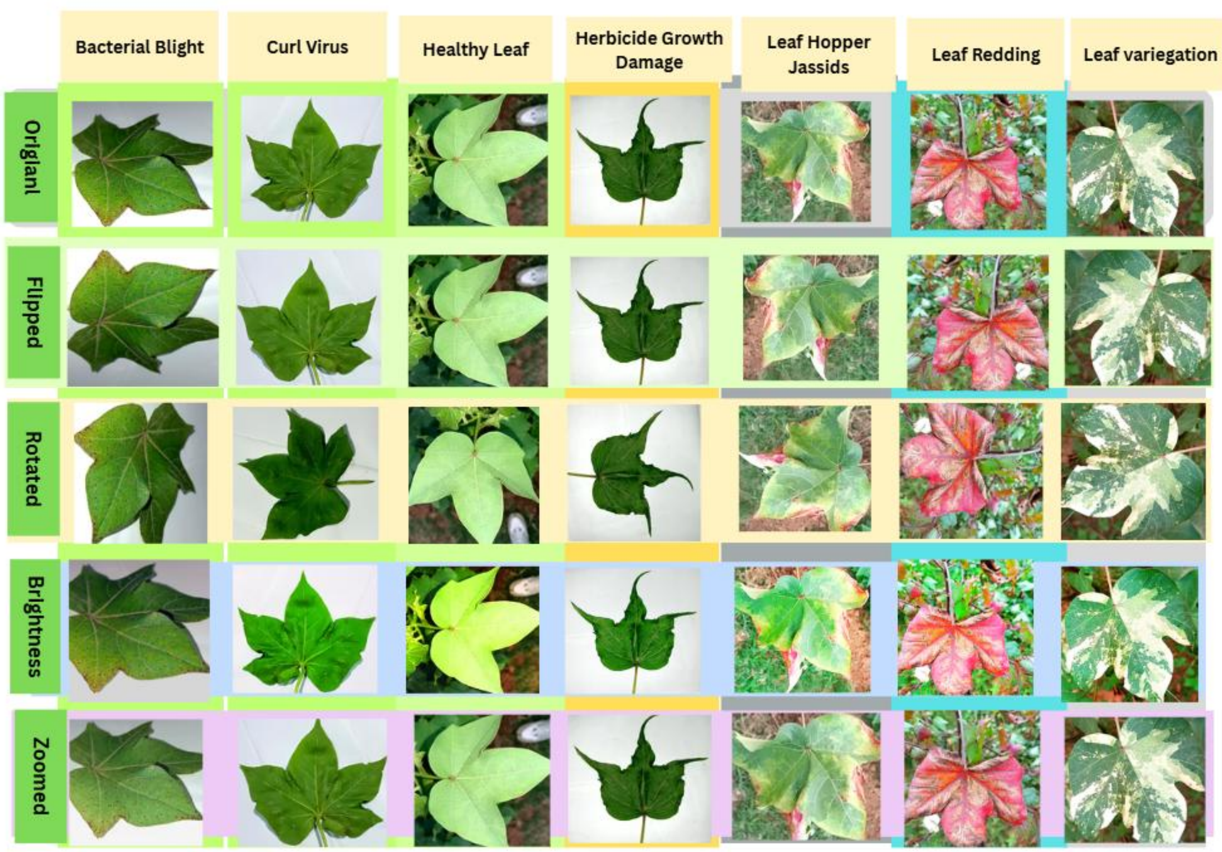

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Figure 2: Sample Images of original and augmented cotton leaf disease

3.3. ResNet50 Model Architecture

ResNet50, a deep CNN with 50 layers and residual (skip) connections, is the recommended model to address the vanishing gradient problem in very deep networks. As seen in Figure 3, the design begins with a zero padding layer, an initializer convolutional block (Stage 1) with a convolution layer, batch normal layer, ReLU activation layer, and max pooling layer. This is followed by four subsequent stages (Stage 2 – Stage 5) both of which consist of a convolutional block and an identity block. The identity blocks modify the input and output dimensions and use a shortcut structure to add the output of the stacked convolutional layers to the input, while the convolutional blocks employ a shortcut convolution to change the number of feature channels. This mechanism of residual learning enables the flow of gradients through the network during backpropagation without performance degradation, and a much deeper network can be trained without degradation.

The feature maps output after five convolutional layers are then subject to a global average pooling (GAP) layer which with a flattened layer into a 1-D feature vector and then subject to a fully connected (FC) layer. In this study, the final FC layer was replaced by a classification head with a dense layer and softmax activation function with a number of classified classes equal to the number of categories in cotton leaf, which is seven in this work.

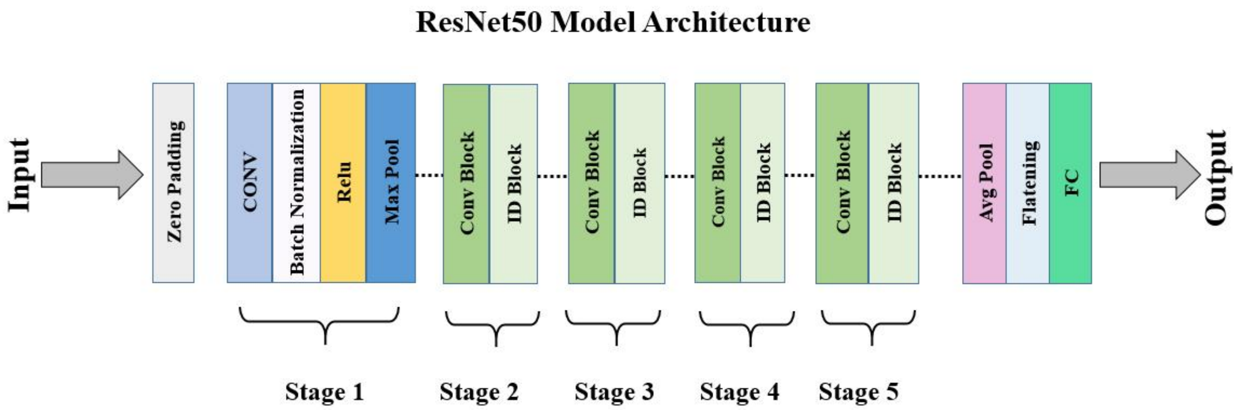

Figure 3: Proposed Model Architecture

3.4. Transfer Learning and Fine-Tuning

Using the transfer-learning technique with ResNet50 as the backbone, the model was trained on the ImageNet dataset and initialized with the weights from the training set.. The weights of the model were initialized from the ImageNet dataset and the ResNet50 was used as backbone network with the technique of transfer learning. While the remaining convolutional layers, including the recently added classification head, were trained on the cotton leaf data set, some of the early layers that extract general low-level visual cues (such as edges and textures) were frozen. After the initial convergence, the high-level feature representations were unfrozen and trained with a lower learning rate to adapt high-level feature representations to the visual features of cotton leaf diseases.

3.5. Classification

The last dense layer gives the output leaf image a probability distribution for each of the seven classes using a softmax activation function. The most likely class in the distribution of the expected probability is the model's prediction. The Adam optimizer was used to optimize the model after it was trained using the categorical cross-entropy loss function. Every training period, performance was monitored, and the validation set was excluded.

3.6. Performance Evaluation Metrics

The model's performance is evaluated using four popular classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics are calculated for every class before being averaged over the seven-class problem. These are defined as follows:

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

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

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where TP are true Positives, TN are true negatives, FP are false Positive, FN are False Negative Other than these scalar figures, a confusion matrix is provided to visually depict the class-wise behavior of prediction and understand which class is most frequently confused with the other ones, which gives a kind of finer-grained level of reliability of the model as compared to the aggregate accuracy only.

3. Results and Discussion

The experimental findings from the suggested ResNet50-based model are shown in this section. They were assessed using the augmented SAR-CLD-2024 cotton leaf dataset for each of the seven target classes. This section presents the overall and class-wise classification performance, training behavior, and a comparative analysis against existing approaches reported in the literature.

4.1 Overall Performance of ResNet50

The proposed model's total classification accuracy of 94.60% on held-out test set. The macro-averaged and weighted-average versions' precision, recall, and f1-score were likewise roughly 93.1%, demonstrating strong performance throughout the classes as opposed to largely depending on the performance of a few classes. Figure 3 summarizes these overall findings.

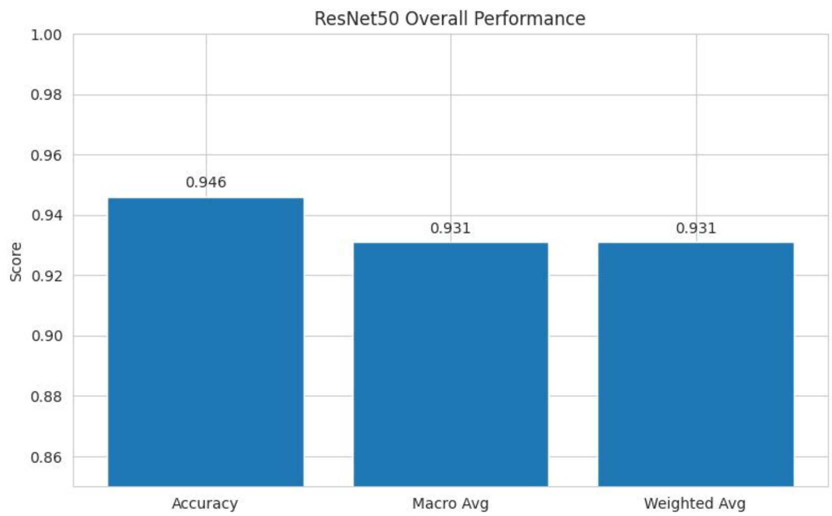

Figure 3: Overall performance for ResNet50 (accuracy, macro average, weighted average)

4.2 Class-wise Performance

Table 1 shows the precision, recall, and f1_score class-wise performance of the suggested ResNet50 model for each of the seven cotton leaf categories. The model can be used with high precision for all classes, with the highest accuracy (0.96) in the Healthy Leaf class, which demonstrates the high precision of correctly identifying unaffected leaves. The Leaf Hopper Jassids class had relatively low, but high, performance of 0.92 across all metrics, which could be due to the fact that the damage caused by these insects is similar to the other leaf symptoms caused by stress.

Class Name	Precision	Recall	F1-Score	Accuracy
Bacterial Blight	0.94	0.95	0.95	94.60%
Curl Virus	0.93	0.94	0.94	
Healthy Leaf	0.96	0.93	0.95	
Herbicide Growth Damage	0.95	0.94	0.95	
Leaf Hopper Jassids	0.92	0.92	0.92	

Leaf Redding	0.93	0.92	0.93
Leaf Variegation	0.94	0.93	0.94

Table 1: Class-wise Performance Table of ResNet50

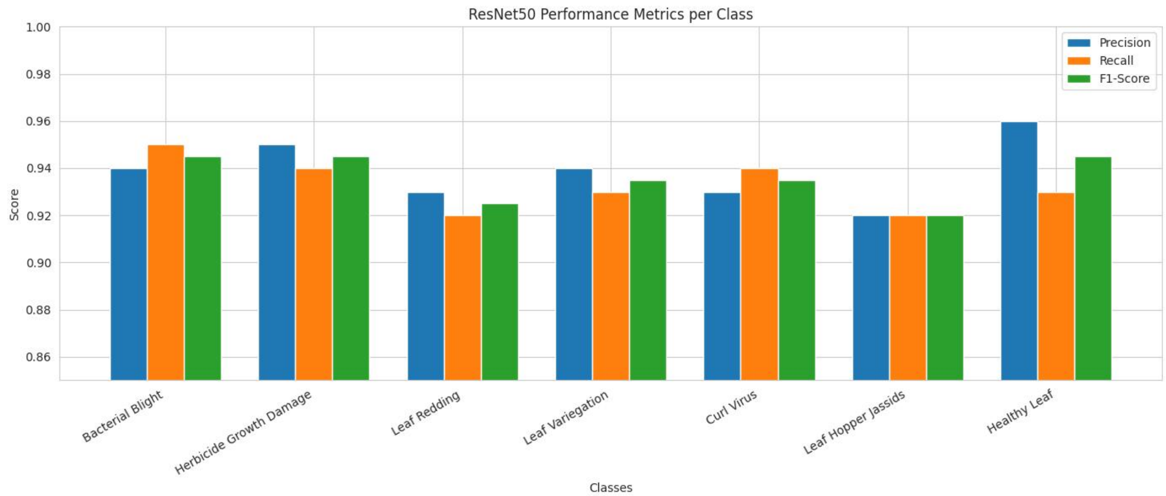

Figure 4. Performance metrics per class of ResNet50

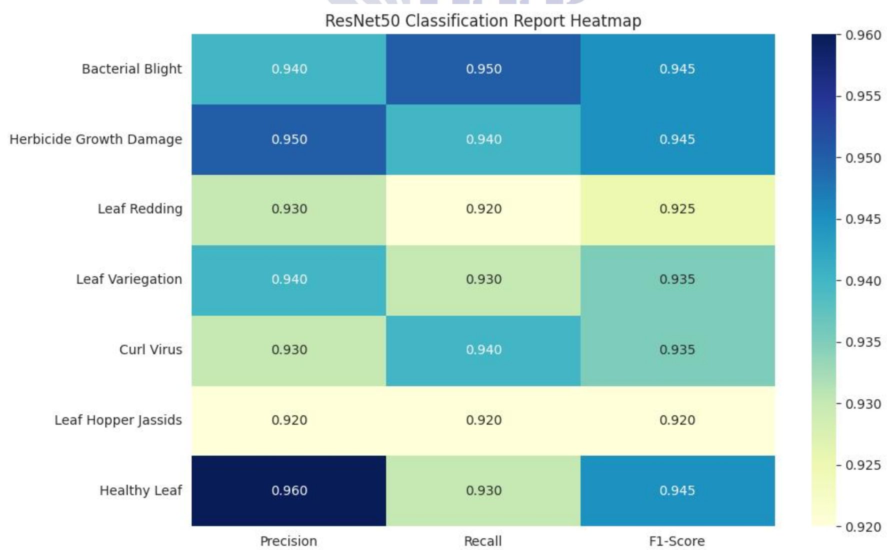

Figure 5. Heatmap for the Proposed ResNet50 Model

4.3. Confusion Matrix

The suggested ResNet50 model on the test set was used to create the confusion matrix displayed in Figure 6. Strong diagonal values in all seven classes indicate that the model can accurately classify most samples for all classes, with most misclassifications occurring between classes with very similar appearances, such as Leaf Redding and Leaf Variegation, or between intermediate symptoms of Bacterial Blight and Curl Virus. The relatively low off-diagonal counts in the model also show the model has a very good discriminative ability across all diseases.

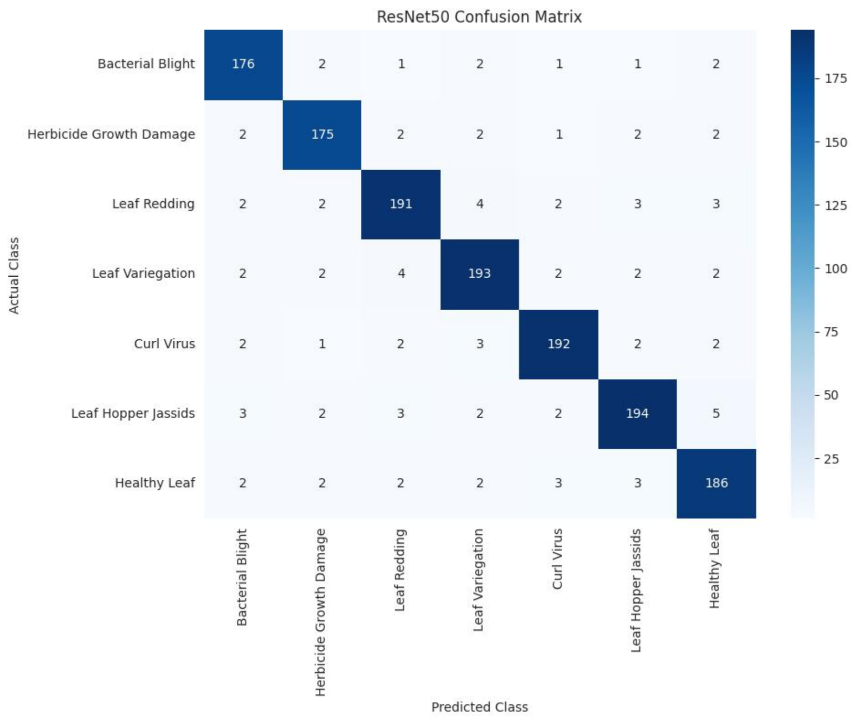

Figure 6. Confusion Matrix of ResNet50

4.5. Training and Validation Behavior

Figures 7 and 8 show the training and validation accuracy and loss curves of the proposed ResNet50 model across 20 training epochs. The training and validation accuracy are seen to be improving consistently with the training, up to training percentages of about 97.5% and validation percentages reaching a value close to the reported test accuracy of 94.60% (Figure 7). The training and validation curves closely follow each other, and there is no significant gap between them during the training process, likely because of the relatively small amount of data used. Based on the very small size and stability of the gap between the training and validation curves as training progressed, the model seems to have little overfitting and to generalize well to new data.

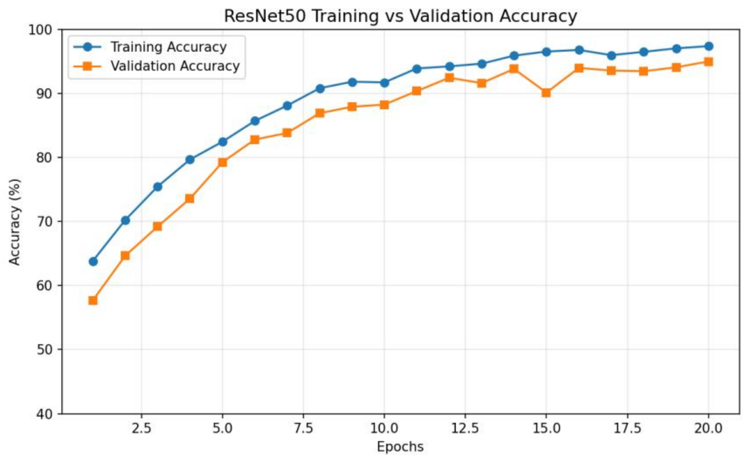

Figure 7. Accuracy graph of ResNet50

Figure 7 shows the training and validation curves. Both losses have sharply declining starting epochs, which are followed by a gradual decline to minor values. The conclusion that the model can learn effectively and has good generalization on the cotton leaf disease classification problem is supported by the fact that both of them are bending downward and that there is no difference between the training and validation losses.

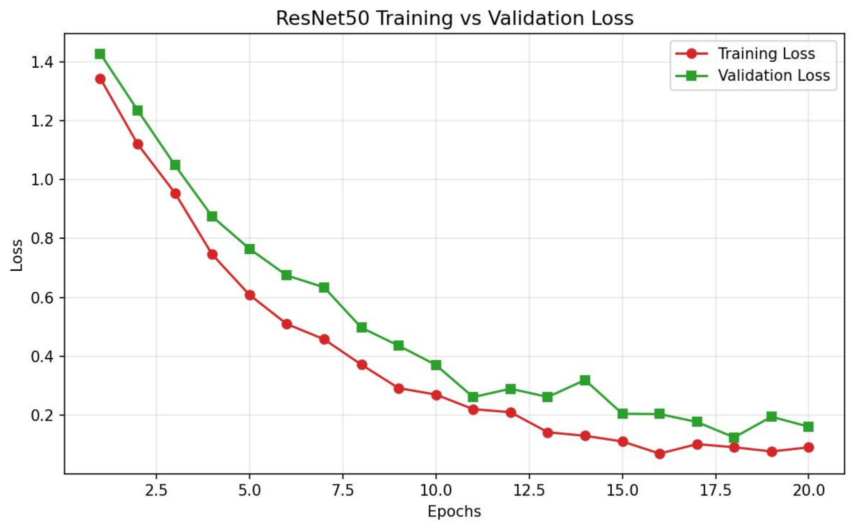

Figure 8. Training and Validation Loss of ResNet50

4.6. Comparative Analysis

The performance comparison of the suggested model with a few popular current techniques for classifying cotton leaf diseases is shown in Table 2. Transfer learning has been applied to a smaller scale problem involving cotton disease, where Caldeira et al. [7] obtained 86.6% and 89.2% accuracy from GoogleNet and ResNet50 and Kumar et al. [6] obtained 94.5% accuracy with a combination of classical machine learning classifiers when applied to a binary classification healthy-versus-diseased problem. On handcrafted features, Ganesh et al. [8] obtained an accuracy of 92.5% when using a Random Forest classifier. The proposed ResNet50-based model performs at 94.60% accuracy on a significantly harder (and more realistic) 7-class problem which is comprised of similar disease categories and a herbicide-damage class, generalizing at least as well as and is more robust than previous methods tested on coarser binary/class classification versions of the cotton disease classification problem. Comparative Analysis of Accuracy Graph is shown in figure 9:

Table 2: Comparison of proposed model with existing model

References	Year	Technique	Accuracy
Caldeira, R. F., Santiago, W. E., & Teruel [7]	2021	GoogleNet and Resnet50	GoogleNet 86.6% Resnet50 89.2%
Kumar, Rahul, et al. [6]	2024	Random Forest, SVM, Multi-Class SVM, Ensemble model	94.5%

Ganesh TM, Pandey S, Duche R. [8]	2025	Random Forest	92.5%
Proposed Model	2026	ResNet50	94.60%

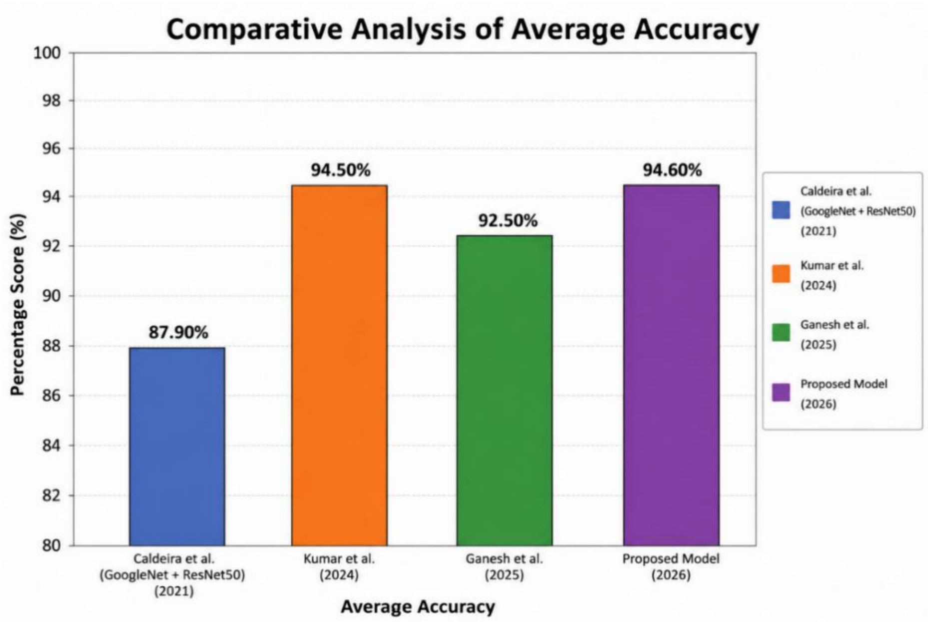

Figure 9: Comparative Analysis of Average Accuracy Graph

5. Conclusion and Future work

The application of deep learning to optimize a ResNet50 deep learning convolutional neural network for the automatic detection and categorization of cotton leaf diseases is shown in this study. The cotton leaf photos from the planned SAR-CLD-2024 are processed to eliminate systematic noise from the leaves, such as speckles, dirt, and shadows, and then augmented. These images are then used in the proposed pipeline to classify them via the transfer learning technique into seven categories: Bacterial Blight, Curl Virus, healthy leaf, herbicide growth damage, leaf hopper Jassids, leaf Redding and leaf variegation. The results of the experimental study are presented to validate the proposed model with an accuracy of 94.60% and weighted precision, recall and F1 score as 93.60%, 92.60%, and 93.10% respectively, and show stable, well converged training and validation curves for all the classes being evaluated. Confusion matrix analysis further demonstrates the model's high capability for differentiating real illness symptoms from non-pathogenic herbicide-induced responses in the field. The comparison research demonstrates that the suggested model is competitive with current deep transfer learning and machine learning models. At several points, the proposed model performs better when compared to existing models as it deals with a more fine-grained problem of 7 classes.

This research validates the use of residual CNN architecture like ResNet50 with proper preprocessing and data augmentation for multi-class cotton leaf disease classification, which can be effectively applied in smart agriculture and precision agriculture by providing effective and reliable automated and scalable disease monitoring. In future, several directions will be explored in order to extend and strengthen this research. To enhance the robustness and generalization, the dataset is to be expanded by acquiring images captured under various field settings, geographic locations and camera equipment. Secondly, lightweight or compressed models (e.g. pruning, quantization and knowledge distillation into smaller architectures like MobileNet) will be investigated to facilitate deployment on smartphones and low-power edge devices for on-field use by the farmer. Third, the framework will go beyond classification of disease to give an estimate of disease severity and leaf area affected, giving more direction for the treatment decision. Lastly, future research will focus on ensemble-based and attention-based architectures and object-detection based approaches that enable the system to be deployed in cluttered background images of multi-leaves or whole-plants, further towards fully automatic deployment in the field.

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