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An Efficient CNN Model for Automated Cotton Leaf Disease Classification

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Abstract

Timely and accurate identification of cotton leaf diseases are essential for maintaining healthy crop production and minimizing agricultural losses. Early detection allows farmers to take preventive or corrective measures, reducing the risk of disease spread and improving overall yield. In the present study, we proposed a Convolutional Neural Network-based model for the automated classification of cotton leaf diseases using image-based detection techniques. The model was trained on a diverse dataset containing multiple categories of cotton leaf images, including both healthy and diseased samples. The Convolutional Neural Network architecture was designed to learn important features from the input images and classify them into predefined disease classes. Training was conducted over 100 epochs, allowing the model to achieve a strong balance between high accuracy and generalization. Performance was evaluated using several key metrics, including accuracy, precision, recall, and confusion matrix analysis. The results confirmed the effectiveness of the model in correctly identifying different types of cotton leaf diseases, with minimal misclassification observed across classes. The present study highlighted the potential of deep learning techniques, especially Convolutional Neural Networks, in the domain of precision agriculture. The proposed model enables early disease diagnosis, which is critical for timely intervention and effective disease management. In the future, improvements such as expanding the dataset, applying advanced data augmentation methods, and combining Convolutional Neural Network with other machine learning algorithms may further enhance model performance and adaptability. Additionally, deploying this model in a real-time environment, such as a mobile or web application can significantly increase its accessibility and usability for farmers and agricultural experts. Such tools can assist in on-field disease monitoring, leading to better-informed decision-making and more efficient crop management. Overall, this approach will support the development of smart agricultural solutions and contribute to sustainable farming practices.

Keywords: Agriculture, cotton leaf, machine learning, deep learning, convolutional neural network

INTRODUCTION

Indian agriculture plays a central role in national economy and contributes to global economic growth. One of the most important commercial crops in economics is cotton (*Gossypium* sp). India exports 23% of its cotton to other countries, making it one of the world's most important crops. Growth and disease are two factors that can affect the yield of a crop. Leaf diseases are categorized into bacterial, viral, and fungal types. Identifying diseases at an early stage will benefit in diagnosing and preventing unnecessary crop damage because farmers might be unable to identify the disease with naked eyes. Diseases can be detected by visible symptoms, and pesticides are recommended by plant pathologists. Traditionally, disease identification is done either by examining a leaf sample under a microscope or by consulting an expert. However, this approach might take a long

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time to implement. On the contrary, the automatic detection of disease is a faster approach that could assist farmers in preventing yield losses. To accomplish this, numerous image-processing methods are used to process the images and identify the disease. Machine learning (ML) and image processing, both are effective techniques for identifying the disease in the agriculture field. Damaged leaves can be detected more easily through this technological approach, and farmers can spend less time detecting diseased leaves. ML algorithms such as Support Vector Machine (SVM), Principal component analysis (PCA), K-means, K-Nearest Neighbor (KNN), Random Forest, Naïve Bayes, etc can be used. Additionally, recent advancements in Deep Learning (DL) technology extended into agriculture, provide the ability to solve complex problems quickly with the help of algorithms such as Convolutional Network, Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Generative Adversarial Networks (GANs), Long Short-Term Memory (LSTM) etc [1]. Image Processing algorithms are also used such as pigmentation, color, texture, shape, spectral reflection, quality, resolution, type, image segmentation, edge and shape, local binary pattern (LBP) and grab cut approaches, thermal imaging, Histogram equalization, contour tracing, Discrete Wave Transforms (DWT), decomposition, etc. The effectiveness of standard image processing algorithms largely depends on image quality, type, and resolution, along with the chosen feature descriptor and classifier [2]. For these models to run efficiently, quality corpus of that infection is required. All these methods use different approaches to detect disease. In the present paper, we developed a ML model that can distinguish between healthy and diseased leaves using convolutional neural network (CNN). Our major contributions in the present work were:

- Our goal was to classify Cotton leaf disease using CNN to determine which one performed better.
- The system predicted the type of disease when new images were provided as input.
- Agriculture is the backbone of the nation, and our work might help to improve yields in the field by early detection of diseased leaves.

The present work included several existing works in this area, explanation of different types of CNN methods followed by a description of the methodology proposed in the current work. In the later sections, we have provided details about the experimental setup and the results obtained along with a detailed discussion of the results. The paper concluded by a discussion of possible future directions.

RELATED WORK

Several studies proposed digital image processing and ML algorithms for detecting and classifying cotton leaf diseases. Sarangdhar and Pawar introduced a comprehensive system for detecting and managing diseases affecting cotton leaves while also monitoring soil quality [3]. The proposed approach utilized a Support Vector Machine-based regression system to accurately identify and classify five common cotton leaf diseases, including Bacterial blight, Alternaria, Gray mildew, Cercospora, and Fusarium Wilt. Atole et al. [4] developed a CNN model for classification purposes. The dataset consisted of 600 samples, achieving an accuracy rate of 91.23%. The classification task involved distinguishing between healthy leaves, unhealthy leaves, and leaves infected by snails. Due to the unavailability of a specific disease dataset, the focus was on classifying the overall health status of the leaves. Prashar et al. introduced the feature descriptors including gray level co-occurrence matrix (GLCM), histogram of oriented gradients (HOG), and histogram (HIST) in the proposed model to detect and classify leaf diseases visually [5]. To minimize errors, double-layered modeling was used with KNN and SVM. Farahani et al. [6] introduced a clear definition of a ML methodology known as transfer learning, along with its categorization from various perspective. Furthermore, the paper introduced several real-world applications of transfer learning, spanning text classification, image classification, clustering, object detection, reinforcement learning, metric learning, and more. Sarwar et al. proposed training a deep learning Faster R-CNN model on a dataset specific to cotton crop leaves (CCL Dataset) for the purpose of detecting and classifying diseases, encompassing both healthy and diseased leaves [7]. The Plant Village dataset serves as a reference for selecting the optimal feature extractor from VGG-16, InceptionV1, and V2, with VGG-16 being the base model in Faster R-CNN. Transfer learning was employed on the CCL Dataset by fine-tuning the Faster R-CNN InceptionV2 model pre-trained on the COCO dataset, where the output layers of COCO were replaced with those specific to the CCL Dataset for disease detection and classification. Arvind and Negi presented the training of a deep learning Faster R-CNN model using a dataset of cotton crop leaves to detect and classify leaf diseases [8]. The benchmarking process involves utilizing the Plant Village dataset along with three different feature extractors—VGG-16, InceptionV1, and V2—to determine the most effective one. Rai and Pahuja introduced the challenge of detecting and classifying diseases in cotton plants by introducing an enhanced Deep Convolutional Neural Network (DCNN) model [9, 10]. The study explored three experimental setups to assess the effects of various factors such as data split ratios, pooling layer choices (max-pooling versus average-pooling), and epoch sizes. A novel deep learning approach—GANs—to augment the data to reduce class imbalances, while an ensemble-based approach combines feature vectors obtained from three deep learning architectures such as VGG16, Inception V3, and ResNet50. We proposed a method for automated detection of diseases in cotton crops that is more precise, efficient, and scalable [11].

METHODOLOGY USED FOR COTTON LEAF DISEASE DETECTION

The purpose of the present study was to detect and classify cotton leaf diseases using CNN. To develop an accurate and efficient disease detection system, a structured approach includes dataset acquisition, preprocessing, segmentation, feature extraction, classification, and monitoring. An annotated dataset containing images of healthy and diseased cotton leaves was required in the first phase. CNN models require properly labeled datasets for training and testing, since they enable the model to learn the distinctive patterns, textures, and colors associated with different diseases. Various sources of high-quality images were used to capture data, including publicly available datasets and real-time field captures as shown in Figure 1. These images show true labels from a dataset with distinct classes such as Green Cotton Ball, Target Spot, Cotton Ball Rot, Army Warm, and Powdry Mildew etc.

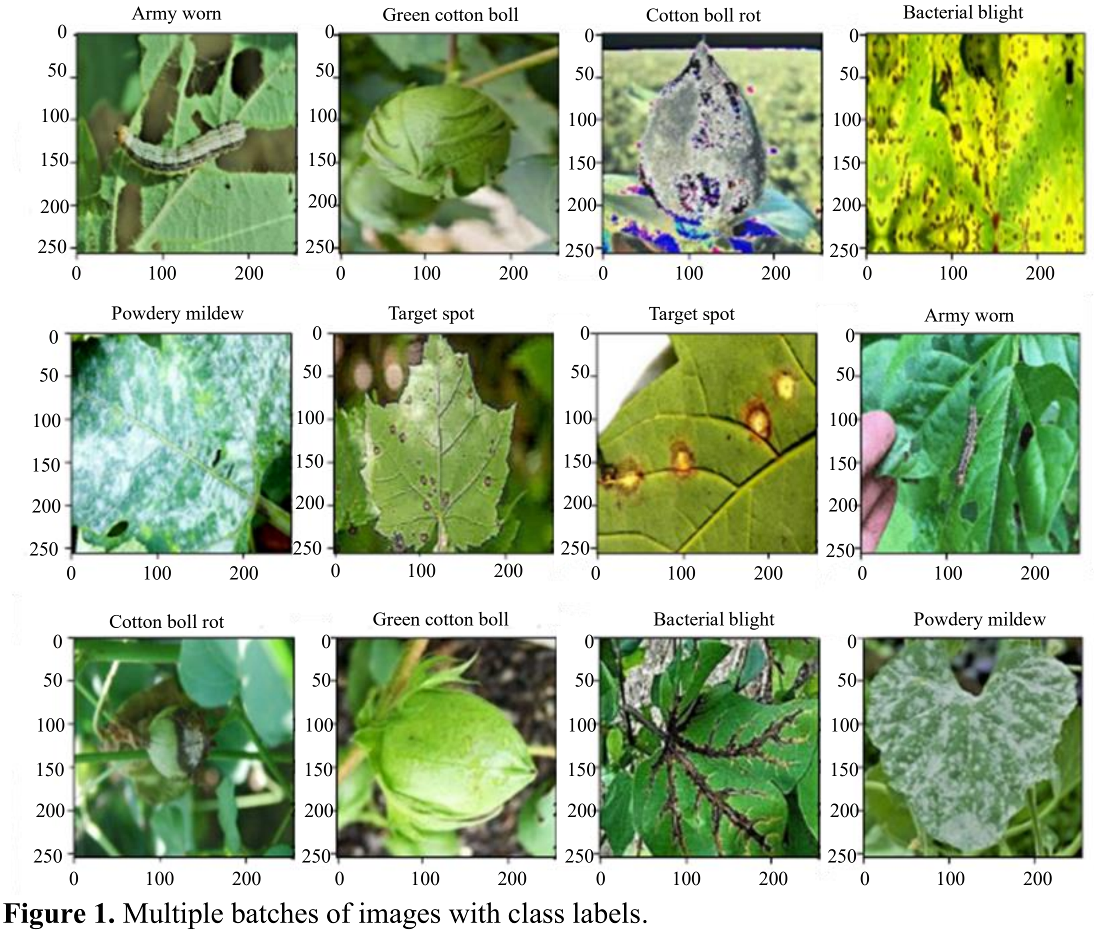
Army worn
Green cotton boll
Cotton boll rot
Bacterial blight
Powdery mildew
Target spot
Target spot
Army worn
Cotton boll rot
Green cotton boll
Bacterial blight
Powdery mildew

Figure 1. Multiple batches of images with class labels.

The CNN was trained by applying preprocessing techniques such as image resizing, normalization (scaling pixel values between 0 and 1), and data augmentation (rotation, flipping, contrast adjustments, and noise addition). Taking the leaf image and extracting the interested region from the natural background is termed as segmentation after it has been reduced in size. In the CNN model, key features are extracted from segmented leaf images using convolutional layers for pattern detection, pooling layers for dimensionality reduction, and fully connected layers for classification. In the classification phase, all those candidate regions will be input to a CNN trained on those categories [12, 13].

CNN for Model Training

CNN with multiple layers is an effective method for extracting features from cotton leaf diseases. This model starts with an input layer that processes images with the dimensions 256×256×3. Multiple filters are applied during the convolutional layers to extract important features such as edges and textures. A max-pooling layer follows them, which reduces the spatial dimension of feature maps while preserving critical features, thereby minimizing computational complexity. There are six convolutional layers, each with an increasing filter size (from 32 to 64), and max-pooling layers that reduce the size of the feature map from 254×254×32 to 2×2×64. Neural Networks are used to detect cotton leaf diseases as shown in Figure 2. The components of neural network are [1]:

- *Input Layer (Left Side):* Input images of cotton plant is shown in the leftmost part of the figure. As input data for the neural network, these images may contain healthy or diseased leaves.
- *Hidden Layers (Middle Section):* Each neuron in the central block is connected to several neurons in the next layer of the fully connected neural network (FCNN). The hidden layers learn patterns associated with healthy and diseased leaves from the input images. Neurons relate to black arrows, which indicate how data flows between them.
- *Output Layer (Right Side):* Predictions are generated by the final output layer, putting the input image into one of two categories, that is healthy leaf or diseased leaf.

As a result, the model can distinguish between healthy and infected cotton leaves based on features in the image. Convolutional and pooling operations are followed by a flattening layer (Flatten) that converts 2D feature maps into a 1D vector of size 256. It prepares the extracted features for classification. After this vector has been processed, the dense layers (Dense) contain 16 neurons for further feature refinement, and an output layer contains eight neurons that classify the input into different categories as shown in Table 1. The figure presents the summary of a CNN model designed for image classification or feature extraction. It processes input images of size 256×256×3 and consists of multiple convolutional layers, each followed by max pooling layers to gradually reduce spatial dimensions while increasing the number of feature maps [2, 3].

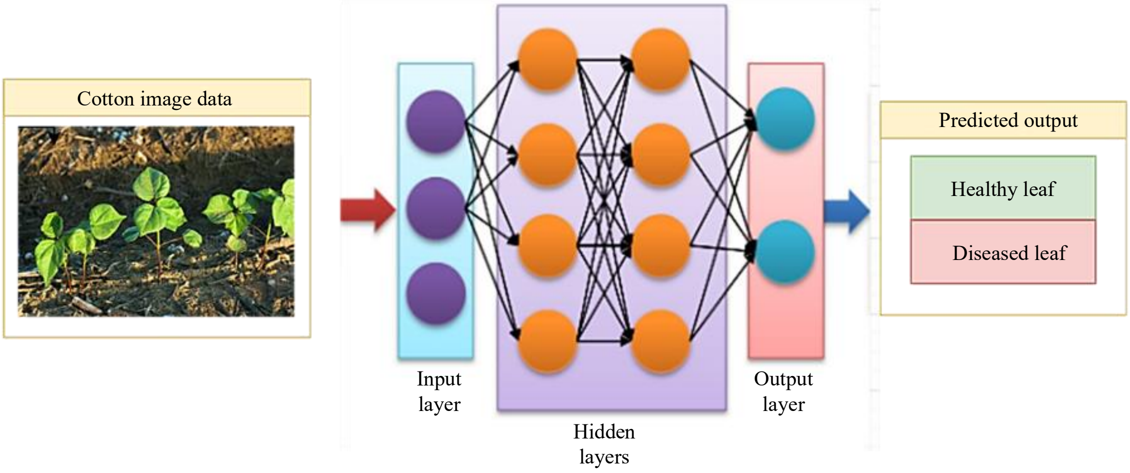

Figure 2. Neural network-based cotton leaf disease detection system.

Table 1. CNN architecture for leaf disease classification.

Model: "sequential_3"		
Layer (type)	***Output Shape***	***Param #***
sequential (Sequential)	(None, 256, 256, 3)	0
sequential_1 (Sequential)	(None, 256, 256, 3)	0
conv2d_6 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_6 (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_7 (Conv2D)	(None, 125, 125, 64)	18, 496
max_pooling2d_7 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_8 (Conv2D)	(None, 60, 60, 64)	36, 928
max_pooling2d_8 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_9 (Conv2D)	(None, 28, 28, 64)	36, 928
max_pooling2d_9 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_10 (Conv2D)	(None, 12, 12, 64)	36, 928
max_pooling2d_10 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_11 (Conv2D)	(None, 4, 4, 64)	36, 928
max_pooling2d_11 (MaxPooling2D)	(None, 2, 2, 64)	0
flatten_1 (Flatten)	(None, 256)	0
dense_2 (Dense)	(None, 16)	4, 112
dense_3 (Dense)	(None, 8)	136
Total params: 171,352 (669.34 KB) **Trainable params:** 171,352 (669.34 KB) **Non-trainable params:** 0 (0.00 B)		

The convolutional layers begin with 32 filters and progressively increase to 64, allowing the model to extract hierarchical features. Max pooling layers downsample the feature maps, reducing computational complexity while retaining important information. After the final convolutional layer, which outputs a 2×2×64 feature map, a flattening operation converts it into a one-dimensional vector of size 256. This is followed by two fully connected layers with 16 and 8 neurons, leading to the final output. The model contains a total of 171,352 trainable parameters, with all layers contributing to the training process. This structured architecture, combining convolutional and fully connected layers, suggests that the model is optimized for classification tasks, likely distinguishing between eight different categories based on the final layer's output. Using this structured CNN pipeline, cotton leaf disease is robustly detected for a variety of reasons, including the ability to learn hierarchical features and gradually refine the classification process from there [4].

RESULT AND ANALYSIS

The Cotton disease dataset is structured to support the classification of cotton leaf diseases, comprising both training and validation sets. The training set initially contains 6,628 images, divided across eight categories—healthy leaves (800), target spot (788), army worm (800), powdery mildew (800), green cotton boll (880), aphids (800), cotton boll rot (960), and bacterial blight (800). However, this dataset was further split into a train set (80%) and a test set (20%), ensuring a balanced evaluation of the model's performance. Additionally, the validation set consisted of 357 images, with target spot (41), aphids (39), healthy leaves (39), bacterial blight (40), army worm (40), green cotton boll (59), powdery mildew (38), and cotton boll rot (61). This structured division ensured that the model underwent rigorous training and testing before validation, leading to a well-generalized cotton leaf disease classification system for precision agriculture. Across both training and validation datasets, the model achieved high accuracy greater than 98%. The trained model with CNN classified the images. In the training time, a model can learn to distinguish between various classes when meaningful labels are assigned to images based on their content. In the present study, each image is labeled with its corresponding category, such as "Healthy," "Target Spot," "Bacterial Blight," or "Army Worm" [5, 6].

The training results of the CNN are presented in Table 2. The table shows key performance metrics such as accuracy, precision, recall, F1 score, and mean average precision (mAP) at different training epochs. Initially, at 20 epochs, the model achieved an accuracy of 96.51%, with precision, recall, and F1 score maintaining similar values, indicating a well-balanced classification. As training progressed, accuracy improved, reaching 97.77% at 60 epochs, demonstrating effective learning. However, while mean average precision fluctuated slightly, it remained consistently high. The model achieved its peak performance at 100 epochs, where it recorded the highest accuracy of 98.22% along with optimal precision, recall, and F1 score. At this stage, the mAP was also at its highest, indicating strong ranking ability in predictions.

However, at 120 epochs, accuracy slightly decreased to 97.92%, and mAP dropped to 0.9621, suggesting possible overfitting or diminishing returns. Based on these results, training beyond 100 epochs does not significantly enhance performance and may lead to slight degradation, making 100 epochs the most optimal stopping point [7].

Figure 3 presents four plots that illustrate the training and validation performance of a CNN over 120 epochs. Top two graphs show training accuracy (left) and validation accuracy (right), while the bottom two depict training loss (left) and validation loss (right). In the training accuracy plot, the accuracy fluctuated between 0.975 and nearly 1.0, indicating stable but slightly varying performance throughout training. Similarly, the validation accuracy plot showed an overall high accuracy but with fluctuations, suggesting possible overfitting or variations in model generalization. The training loss plot indicated that the loss values remain low, though they exhibit occasional spikes, which may be due to variations in learning dynamics. The validation loss plot showed a similar pattern, but with slightly higher and more frequent fluctuations, which could indicate instability in generalization.

Optimal Model Selection at 100 Epochs

Based on the training and validation performance metrics, we select the model trained for 100 epochs for the final results. The accuracy and loss plots indicate that the model achieves its highest and most stable performance around this point, with training accuracy nearing 98.22% and validation accuracy remaining consistently high. While the model continues training up to 120 epochs, slight fluctuations in accuracy and an increase in validation loss suggest potential overfitting. Therefore, selecting the 100-epoch model ensures an optimal balance between performance and generalization, making it the best choice for final evaluation and deployment [12, 13].

Figure 4 displays a set of classification results for a plant disease detection model. It consists of ten different images of cotton leaves, each labeled with a predicted class ("Pred:") and the actual ground truth ("True:"). The results are presented in two rows, with most of the predictions correctly matching the true labels, except for one misclassification. In the first row, all five images are correctly classified. The model successfully identified leaves as “Healthy”, “Cotton Boll Rot”, “Powdery Mildew”, and “Target Spot”, with the predictions matching the true labels. In the second row, the first four images were also correctly classified as “Aphids”, “Army Worm”, “Healthy”, and “Target Spot”. However, the last image in the second row was misclassified. The true label was “Bacterial Blight”, but the model incorrectly predicted it as “Army Worm”. This misclassification is highlighted in red, differentiating it from the correct classifications shown in green.

Table 2. Training performance metrics of the CNN model at different epochs.

Epochs	Accuracy	Precision	Recall	F1 Score	mAP
20	0.9651	0.9654	0.9651	0.9611	0.9620
40	0.9733	0.9737	0.9733	0.9733	0.9511
60	0.9777	0.9787	0.9777	0.9778	0.9595
80	0.9733	0.9744	0.9733	0.9732	0.9515
100	0.9822	0.9823	0.9822	0.9822	0.9668
120	0.9792	0.9798	0.9792	0.9792	0.9621

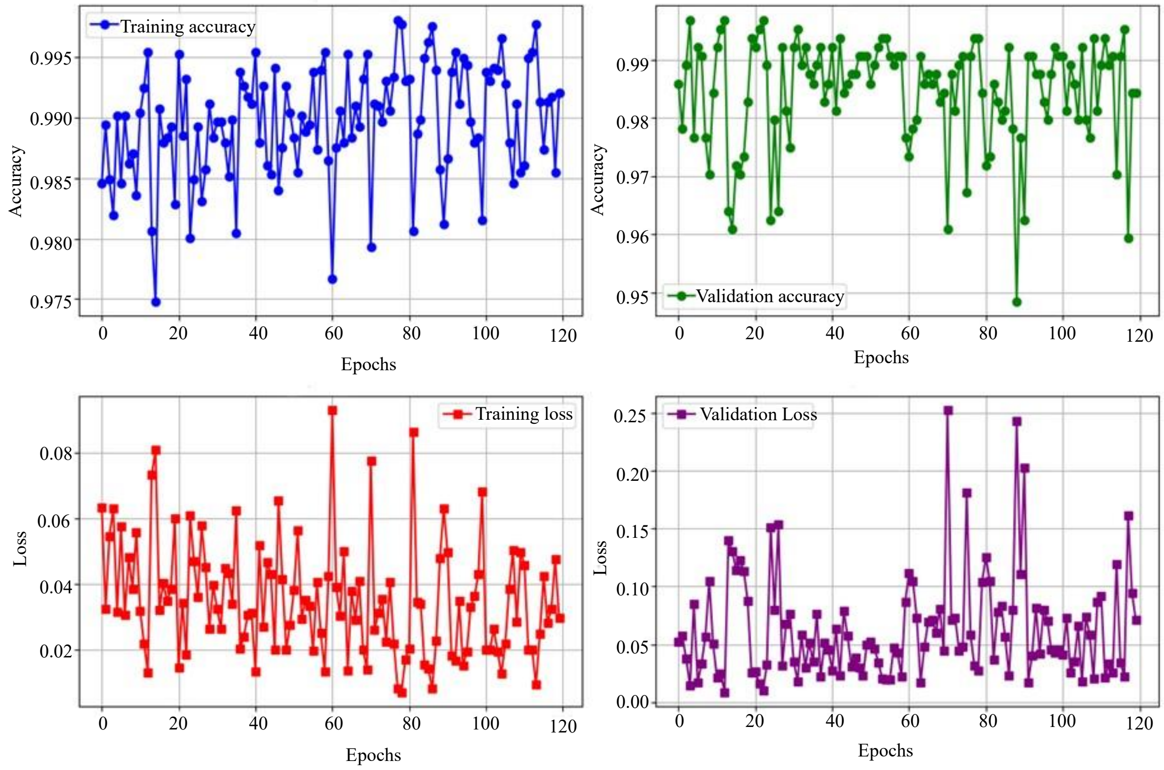

Figure 3. Training and validation performance of the model.

Figure 4. Cotton leaf disease classification results.

Overall, the model appears to perform well, accurately identifying most of the plant diseases and conditions, with only one incorrect classification. This suggests that while the model is effective, further improvements are required to enhance its accuracy, particularly in differentiating between visually similar conditions [14].

Confusion Matrix Analysis

Confusion matrixes provide a visual representation of the classification performance of a model in predicting different types of cotton leaf diseases and healthy leaves. Actual labels are shown in the rows, and predicted labels are shown in the columns. Off-diagonal values show instances that have been misclassified, while diagonal values indicate instances that have been correctly classified. The CNN model performed well across most categories, with high accuracy as shown in Figure 5.

Among “Cotton Bolt Rot” and “Army Worm” cases, 90 and 84 were correctly classified, respectively. Some misclassifications, however, have been observed. "Powdery Mildew" was misclassified once and taken as "Army Worm" three times. There were 88 correct predictions for "Bacterial Blight" but one incorrect prediction for "Army Worm". "Healthy" leaves were classified correctly in 69 out of 80 cases, indicating some errors. Further, 83 instances of "Target Spot" were classified correctly, with four instances incorrectly classified as "Bacterial Blight."

This misclassification suggests that certain categories may need to be differentiated better in the model. An expanded training dataset, improved feature extraction methods, or improved model architecture could improve this misclassification. It may also be beneficial to carry out further analysis to determine if certain diseases exhibit similar visual characteristics that contribute to misclassification.

The overall performance of the CNN model demonstrated high classification accuracy across different plant diseases and health categories. The training and validation accuracy remained consistently high, with the best model selected at 100 epochs to balance performance and generalization. The confusion matrix further confirmed the model’s effectiveness, showing strong classification results with minimal misclassifications. Most classes exhibited high precision and recall, with only a few instances of incorrect predictions. While minor fluctuations in validation loss and accuracy suggested potential overfitting in later epochs, the model maintained strong predictive capabilities. These results indicated that the CNN model is well-suited for accurate plant disease detection and classification.

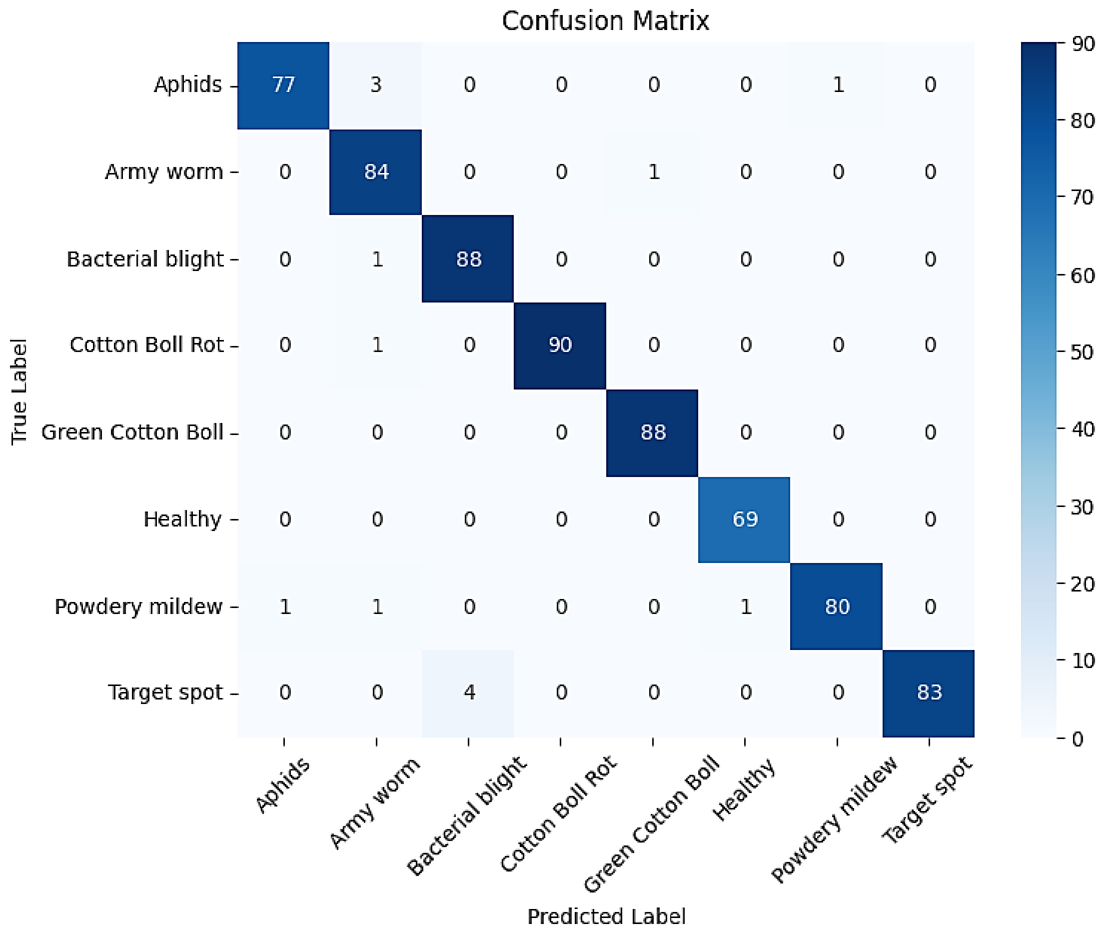

Figure 5. Confusion matrix of the CNN model's performance.

CONCLUSION AND FUTURE SCOPE

The present study demonstrated the effectiveness of a CNN-based model in accurately classifying plant diseases, achieving high precision, recall, and overall performance. The selected model at 100 epochs striked an optimal balance between accuracy and generalization, minimizing overfitting while maintaining reliability. The confusion matrix confirmed the model's robustness, with most predictions aligning closely with actual labels and only a few misclassifications. These results highlighted the potential of deep learning in revolutionizing plant disease detection, offering a powerful tool for early diagnosis and agricultural decision-making. Looking ahead, several enhancements can further refine the model's performance and applicability. Expanding the dataset with more diverse and real-world samples will improve adaptability to varying conditions. Implementing advanced data augmentation techniques and transfer learning could enhance accuracy and robustness. Additionally, deploying the model as a real-time mobile or web-based application would make it more accessible to farmers.

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