Performance Analysis of Deep Transfer Learning Models for the Automated Detection of Cotton Plant Diseases

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ABSTRACT

Cotton is one of the most important agricultural products and is closely linked to the economic development of Pakistan. However, the cotton plant is susceptible to bacterial and viral diseases that can quickly spread and damage plants and ultimately affect the cotton yield. The automated and early detection of affected plants can significantly reduce the potential spread of the disease. This paper presents the implementation and performance analysis of bacterial blight and curl virus disease detection in cotton crops through deep learning techniques. The automated disease detection is performed through transfer learning of six pre-trained deep learning models, namely DenseNet121, DenseNet169, MobileNetV2, ResNet50V2, VGG16, and VGG19. A total of 1362 images of local agricultural fields and 1292 images from online resources were used to train and validate the models. Image augmentation techniques were performed to increase the dataset diversity and size. Transfer learning was implemented for different image resolutions ranging from 32×32 to 256×256 pixels. Performance metrics such as accuracy, precision, recall, F1 Score, and prediction time were evaluated for each implemented model. The results indicate higher accuracy, up to 96%, for DenseNet169 and ResNet50V2 models when trained on the 256×256 pixels image dataset. The lowest accuracy, 52%, was obtained by the MobileNetV2 model when trained on low-resolution, 32×32, images. The confusion matrix analysis indicates the true-positive prediction rates higher than 91% for fresh leaves, 87% for bacterial blight, and 76% for curl virus detection for all implemented models when trained and tested on an image dataset of 128×128 pixels or higher resolution.

Keywords-transfer learning; CNN; pretrained networks; disease detection; classification; cotton plants

I. INTRODUCTION

The agriculture sector plays a significant role in generating revenue and catering to the food demand [1]. It is the backbone of any country and works as a primary source of income for a large proportion of the people, particularly in developing countries. Cotton is a cash crop and produces natural fiber which is essential for the textile manufacturing industry. It is also an important source of vegetable oil and cottonseed cake. About 50% of the global population depends on cotton-related materials. The cotton plant's protection from diseases is very crucial as it significantly impacts the productivity of cotton yield. Detection of cotton plant diseases is a challenging task. It is difficult to distinguish between different diseases of cotton plants due to the harsh outdoor environment and complex structure of plant leaves with similarity in appearances. The cotton plant is susceptible to various diseases such as bacterial light, root knot nematode, fusarium wilt, root rot, and verticillium wilt. Traditional methods of disease detection such as visual inspection and laboratory analysis are time-consuming, labor-intensive, and often inaccurate. It is crucial to diagnose cotton diseases at an early stage to prevent the spread of diseases. Thus, efficient and effective methods for cotton crop disease detection are required. Computer vision-based system machine learning systems are developed for the accurate detection of diseases in cotton crops.

Deep learning-based Convolutional Neural Network (CNN) models are extensively employed in the agriculture field to recognize different plant diseases and pests, classify fruits, and identify weeds [3-7]. They are powerful tools for solving complex problems in various fields. Deep learning is an automatic learning method based on a multilayer network. The effectiveness of such learning techniques in the agricultural field has been proved [8].

In the current work, deep learning-based models are implemented for the automated detection of cotton crop diseases with high accuracy. Six different pre-trained CNN models awerere trained using the transfer learning approach: DenseNet121, DenseNet169, MobileNetV2, ResNet50V2, VGG16, and VGG19. The plant image dataset indicating bacterial blight, curl virus, and healthy leaves were collected from local cotton crop fields to train and validate the transfer learning-based CNN model. The performance metrics of all trained models are evaluated and compared. The current work can be used in the field to recognize the different diseases at an early stage and thus to increase cotton productivity.

II. LITERATURE REVIEW

There are numerous studies that classify and identify cotton crop leaf diseases [9]. Authors in [10] collected cotton leave images from the field and prepared a dataset of healthy and unhealthy leaves. They employed four different ML techniques, i.e. CNN, VGG16, novel meta deep learning, and ResNet50 on the augmented data. They developed a generalized meta learning-based model to detect different diseases such as bacterial blight, leaf spot, powdery mildew, and leaf curl with an accuracy of 98.53%. Authors in [11] used ResNet50 and VGG16-based transfer learning models to detect crop diseases. Authors in [12] developed a CNN-based model to detect cotton diseases and pests, such as leaf miner, spider mite, and bacterial blight. The K-fold cross-validation approach was used to split and augment the dataset. The model had an overall accuracy of 96.4%. Authors in [13] used a Deep Convolutional Neural Network (D-CNN)-based DCPLD-CNN model to classify and detect cotton plant and leaf diseases. They found that existing techniques have some limitations to detect Malvacearum and leaf roll dwarf viruses. They used pre-trained architectures and added extra dense layers to fine-tune the developed DCNN model, obtaining an identification accuracy of 98.60% to. Authors in [14] used a deep-learning approach to identify cotton plant diseases. They integrated a CNN-based model with the softmax layer and a pre-trained ResNet model for image classification. The focal loss function was used to improve the model's ability to learn smaller features. They recommended implementing the model on mobile devices to facilitate the farmers so that they can detect cotton crop diseases in real-time. Authors in [15] studied smart farming techniques and the parameters essential for increasing productivity in modern agriculture. They used a decision tree classifier based on the data of different parameters such as temperature and soil moisture to predict the diseases of cotton crops. Authors in [16] proposed a robust hybrid Automated Cotton crop Disease Recognition (ACDR) system. The results showed that the model has auratic and visual features and it has outperformed the existing models. The model has 89.08% sensitivity and 41% specificity which is higher than the SIFT (Scale-Invariant Feature Transform) and SASI-based ACDRs.

Authors in [17] presented an automated image processing-based system for the diagnosis of cotton leaf diseases. They used a dataset of 130 images to train an SVM classifier. The dataset consists of 50 bacterial blight images, 50 magnesium deficiency images, and 30 images of healthy plants. The classification of the images was based on features such as color and texture of images, achieving an accuracy of 98.46%. Authors in [18-19] employed pre-trained GoogleNet in their models to classify diseases of various crops, achieving accuracy of 94% and 99.53%. Authors in [20] used a quadruped robot to capture images of the cotton field. They developed a ConvNeXt-based cotton crop detection system with a Multiscale Spatial Pyramid Attention (MSPA) module. The ConvNeXt with MSPA achieved accuracy in the range of 97.2% to 100% on different datasets of cotton. Authors in [21] developed a web-based system for cotton crop disease detection using CNNs. They trained the model with 141 images of each disease and achieved an accuracy of 80%. Authors in [22] employed numerous deep-learning approaches to recognize different plant leaf diseases. They developed a camera-based real-time automated system for collecting images of cotton crops. The VGG16 network showed the best performance among different Machine Learning (ML) models and achieved 99.908% accuracy. Authors in [23, 24] developed a hardware-based prototype for plan disease recognition and classification. They used Raspberry Pi 4 and Arduino microcontrollers in the hardware prototypes. Authors in [25, 26] developed a robotic system for the detection of plant diseases. They used different ML algorithms such as the principal component analysis algorithm, Densenet121, ResNet34, ResNet50, and VGG-16. The system achieved an accuracy of 98.3%. Authors in [27] built an efficient and automated robot to remove diseases-infected plants from the stem. The robot identifies the leaf diseases in cotton plants and removes them. In summary, deep learning-based techniques may deliver many opportunities in the agriculture sector by monitoring the health of plants in real-time using deep learning helps to identify the diseases at early stages.

III. METHODOLOGY

A. Pre-trained CNN Models

CNNs can automatically learn and extract meaningful features from huge data sets by reducing the need for manual feature extraction. They facilitate prior learning by training the model on the large-scale generalized dataset. Pre-trained models can be trained for the new task by using the available dataset which modifies the final layers of the pre-trained network. In this study, six pre-trained models are used. They are trained on new data sets for the detection of bacterial blight, curl virus, and fresh leaves in cotton plants. The main features and properties of the pre-trained models are discussed below.

1) DenseNet121

It is a CNN architecture with 121 weight layers and dense connections among layers [28]. The model has 8 million parameters and efficiently captures complex input-output relationships. It is pre-trained on ImageNet and suitable for different computer vision tasks such as object detection, semantic segmentation, and image classification.

2) DenseNet169

It comprises 169 weight layers and dense connections between each layer [29]. The model consists of approximately 14 million parameters and efficiently captures complex relationships. It is trained with ImageNet similar to the DenseNet121 model with 1 million images and 100 classes. The shallow architecture and dense connections in the model provide improved and computationally efficient performance on complex data.

3) MobileNetV2

MobileNetV2 is a compact CNN architecture offered by Google AI for devices having limited computational resources [30]. It provides high accuracy and efficient computational power and minimum power consumption. The model has 3.5 million parameters, which makes it lightweight and easy to deploy on mobile and embedded devices. The use of depth-wise separable convolutions and inverted residual blocks in the model captures complex relationships. It is suitable for deployment on devices with limited computational resources.

4) ResNet50V2

ResNet50V2 is a variation of the ResNet50 deep CNN architecture with improved learning ability [31]. It uses identity shortcuts and batch normalization to capture complex input data representations. The model has 50 weight layers and is trained on the ImageNet dataset. Compared to other popular models, the ResNet50V2 has a deeper architecture but is shallower than ResNet50.

5) VGG16

It is a well-known CNN architecture introduced in 2014 [32]. The architecture is characterized by its uniform design, where all layers have the same number of filters and filter size, which reduces overfitting and enhances the model's ability to generalize to new data. The VGG16 architecture consists of 16 weight layers and comprises 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers.

6) VGG19

It is primarily designed for image classification tasks [33]. In contrast to VGG16, it comprises 19 layers including 6 convolutional layers and 3 fully connected layers resulting in a significant number of parameters (approximately 143 million as compared to the 138 million for VGG16). VGG19 remains a popular choice for transfer learning due to its strong performance across a wide range of image classification tasks and its ability to extract useful features from images. The large number of parameters in VGG19 allows for the learning of complex image representations, making it an ideal starting point for fine-tuning new image classification tasks.

B. Data Collection and Augmentation

The dataset used in this study consists of images collected from the local agriculture fields and online sources. The cotton crop images were collected from two distinct locations in Pakistan, namely Tando Allahyar and Kotri. The local dataset collection allowed the training of model on real-world data which increases the models' reliability for local implementation. The dataset includes 562 images of fresh cotton leaves, 300 images of cotton leaves with curl virus, and 500 images of bacterial blight. Figure 1(a) shows the class-wise distribution of images acquired from both locations. Moreover, 1,292 images representing the same classes were sourced from Kaggle [34]. Thus, a combined dataset of 2,654 unique images was utilized for training and testing of the models.

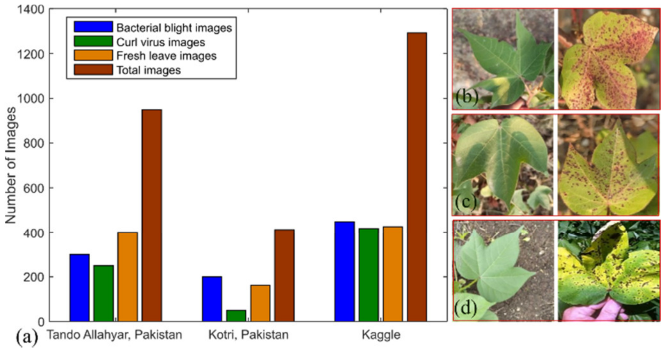

Fig. 1. (a) The quantified distribution images collected from local sites and sourced from Kaggle, (b) sample images collected from Tando Allahyar, Pakistan, (c) sample images collected from Kotri, Pakistan, and (d) the sample images collected from Kaggle.

To optimize the training of a deep CNN model, a large quantity of training images is necessary. We employed the image data augmentation technique to increase the number of images and to introduce dataset variations. The data augmentation increased the diversity of the input, expanded its generalization capacity, and reduced the risk of overfitting. The data augmentation process included flipping, rotation, shifting, scaling, shearing, and scaling of all available images proving a total of 13,270 images which were then utilized for the model training and validation. Figure 2 shows the distribution of training and validation dataset images for each class after the augmentation.

C. Model Implementation and Transfer Learning

The training and validation implementation of pre-trained models involved 5 main steps as represented in the block diagram in Figure 3. The first step included the acquisition and organization of the dataset in a local repository. In the second step, the image augmentation techniques were applied as discussed in the previous section. The dataset annotation for three classes, bacterial blight, curl virus, and fresh leaves, was performed in the third step which also includes the splitting of images into training and validation image sets. 70% of the total images were used for training the models while the remaining 30% were used during validation. In the next step, the training validation sets were fed to the pre-trained CNN model for transfer learning, where the weights of the models were fine-tuned based on the supplied dataset. Transfer learning leverages the knowledge acquired from a prior task to improve generalization performance for the new task. The pre-trained network is modified by replacing the final few layers with new layers, including a fully connected layer and a softmax classification layer, where the number of classes is three in the current study representing fresh leaves, curl virus, and bacterial blight.

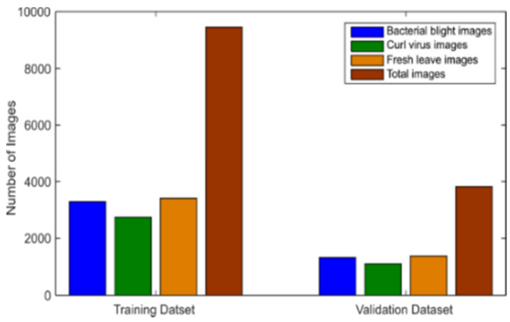

Fig. 2. Distribution of the augmented image dataset representing each class and segmented to training and validation sets.

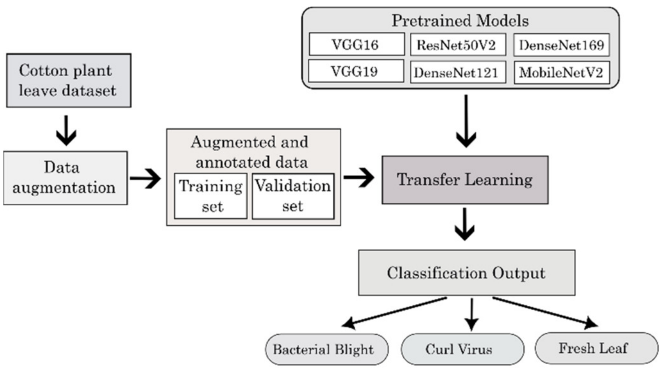

Fig. 3. Implementation block diagram for the transfer learning of pre-trained models with augmented and annotated datasets.

Each model underwent layer unfreezing, accompanied by the addition of an activation layer, a batch-normalization layer, and a dropout layer. The models were tested using consistent values for dropout, learning rate, and batch size, with varying input image sizes of 32×32, 64×64, 128×128, and 256×256 pixels. The training was performed with a learning rate of 0.0001, a batch size of 32, and 200 epochs, which were chosen after the established best practices in the field. Once the transfer learning process was complete, the weights of the trained models were evaluated for each image size in terms of accuracy, precision, recall, F1 score, and confusion matrix. The confusion matrix is a graphical representation that summarizes the performance of the model by showing the number of correct and incorrect predictions for each class. It consists of four metrics: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). TP represents the number of correctly predicted positive instances, while FP represents the number of negative instances incorrectly predicted as positive. FN represents the number of positive instances incorrectly predicted as negative, while TN represents the number of correctly predicted negative instances. The models were trained using Google Colab on a Tesla T4 GPU running 525.85.12 driver version and 12.0 CUDA version. Subsequently, the trained models were tested on a laptop computer equipped with 8 GB of RAM, a 2.40GHz Intel Core-i5 CPU, and an Intel HD Graphics 520. All implementations were performed on Jupyter Notebook IDE on a Windows 10 operating system.

IV. RESULTS AND DISCUSSION

The confusion matrix of each implemented model was analyzed for the different resolutions of the image dataset and a thorough comparison was performed between the different models. The primary objective of this analysis was to provide insight into the performance of each model and facilitate the selection of the most effective one for the proposed task. The performance of the implemented models for the detection of cotton plant diseases was evaluated by employing commonly used performance metrics used for the classification task. The classification report provides a succinct summary of essential classification metrics such as training accuracy, validation accuracy, precision, recall, and F1 score. These metrics are derived by comparing the model's predictions to the true values present in the data. Training accuracy is a measure of the model performance on the training set, while validation accuracy indicates the model performance on the validation set. Precision quantifies the proportion of TPs among all the samples that were predicted as positive, whereas recall measures the proportion of TPS among all the genuinely positive samples. The F1 score represents the harmonic mean of precision and recall, providing a single performance metric that can be used to compare the overall effectiveness of the model.

Figure 4 shows the training accuracy vs the number of epochs for all the implemented models. The result indicates lower model accuracy, as observed in Figure 4(a) when the training is performed at an image dataset resolution of 32×32 pixels. Similarly, it is also noticed that the accuracy does not improve after the 50 epochs and mainly remains within the limited range of 45-75% for all the implemented models. It is also noticed that the training accuracy of MobileNetV2 is lower while the best accuracy is observed for DenseNet169. Moreover, the analysis of Figure 4 indicates a significant improvement in training accuracy as the pixel resolution of the image dataset is increased. The DenseNet169 and ResNet50V2 show the highest accuracy, up to 96%, when trained on 256×256 pixel images. The lowest accuracy, 52%, is observed for MobileNetV2 implementation when trained on 32×32 pixels images. DenseNet169 achieved 96% efficiency due to its dense connections in its model architecture, which promote information flow and feature reuse, providing an advantage for cotton crop disease identification on the gathered dataset over other models. ResNet50V2's model design overcomes vanishing gradients and stabilizes training using identity shortcuts and batch normalization. The residual connections in its design provide smooth gradient flow, while batch normalization minimizes variance, resulting in increased performance when compared to competing models.

The confusion matrix was obtained to evaluate the prediction capability for each implemented model. Figure 5 shows the consolidated representation of the confusion matrix for all the implemented models at different resolutions of the image dataset. The results indicate a significant number of FPs and TNs for most of the classes when the 32×32 image dataset is chosen. The higher number of incorrect predictions is associated with the low resolution of training and validation images. Figure 5 further indicates improved TP predictions when the image size increased to 256×256 pixels, which can be observed by looking at the diagonal values at the bottom half of the figure. The overall results indicate the average TP prediction rate greater than 89% for all models when they are trained and validated on high resolution (256×256) images.

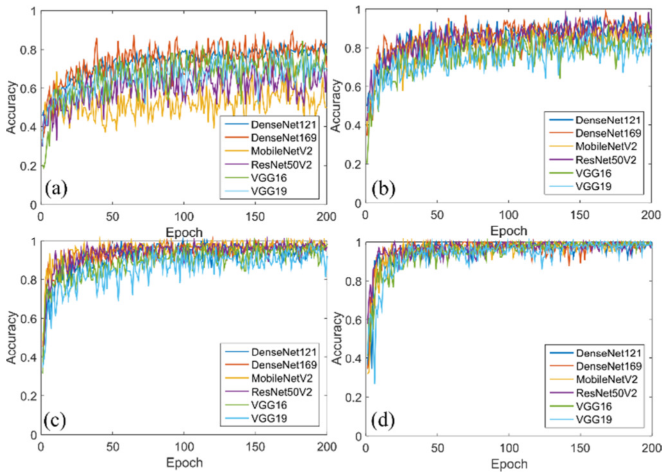

Fig. 4. Training accuracy of the implemented models vs the number of the epochs for image sizes of (a) 32×32, (b) 64×64, (c) 128×128, and (d) 256×256 pixels.

TABLE I. DETAILED PERFORMANCE METRICS OF ALL IMPLEMENTED MODELS

	Classification	Performance metrics															
		Precision				Recall				F1-Score				Accuracy			
		32×32	64×64	128×128	256×256	32×32	64×64	128×128	256×256	32×32	64×64	128×128	256×256	32×32	64×64	128×128	256×256
DenseNet 121	Bacterial Blight	0.64	0.75	0.8	0.91	0.53	0.83	0.84	0.92	0.58	0.79	0.82	0.92	0.73	0.84	0.92	0.95
	Curl Virus	0.64	0.79	0.79	0.89	0.48	0.73	0.82	0.83	0.55	0.76	0.81	0.86				
	Healthy Leave	0.63	0.79	0.88	0.88	0.86	0.76	0.82	0.92	0.73	0.77	0.85	0.9				
DenseNet 169	Bacterial Blight	0.68	0.74	0.83	0.95	0.6	0.79	0.89	0.88	0.64	0.76	0.86	0.92	0.74	0.85	0.93	0.96
	Curl Virus	0.48	0.74	0.95	0.88	0.39	0.66	0.65	0.89	0.43	0.7	0.77	0.89				
	Healthy Leave	0.77	0.95	0.83	0.91	0.98	0.97	0.98	0.96	0.86	0.96	0.9	0.93				
MobileNetV2	Bacterial Blight	0.52	0.7	0.86	0.9	0.46	0.77	0.92	0.93	0.49	0.73	0.89	0.91	0.52	0.81	0.95	0.95
	Curl Virus	0.46	0.69	0.89	0.97	0.44	0.6	0.78	0.77	0.45	0.64	0.83	0.86				
	Healthy Leave	0.59	0.87	0.89	0.87	0.68	0.89	0.92	0.98	0.63	0.88	0.91	0.92				
ResNet50V2	Bacterial Blight	0.57	0.94	0.88	0.95	0.58	0.67	0.9	0.96	0.57	0.79	0.89	0.95	0.6	0.84	0.93	0.96
	Curl Virus	0.59	0.87	0.91	0.94	0.41	0.77	0.87	0.9	0.49	0.81	0.89	0.92				
	Healthy Leave	0.63	0.7	0.91	0.94	0.77	0.96	0.92	0.95	0.69	0.81	0.91	0.95				
VGG16	Bacterial Blight	0.62	0.73	0.73	0.89	0.73	0.82	0.97	0.95	0.67	0.77	0.83	0.92	0.66	0.76	0.89	0.94
	Curl Virus	0.5	0.73	0.89	0.89	0.35	0.6	0.71	0.85	0.41	0.66	0.79	0.87				
	Healthy Leave	0.65	0.82	0.92	0.93	0.69	0.85	0.78	0.91	0.67	0.83	0.84	0.92				
VGG19	Bacterial Blight	0.68	0.71	0.68	0.87	0.76	0.86	0.88	0.87	0.72	0.78	0.77	0.87	0.65	0.75	0.85	0.93
	Curl Virus	0.57	0.71	0.78	0.95	0.56	0.43	0.79	0.82	0.57	0.54	0.78	0.88				
	Healthy Leave	0.72	0.74	0.83	0.85	0.69	0.83	0.59	0.94	0.69	0.78	0.69	0.9				

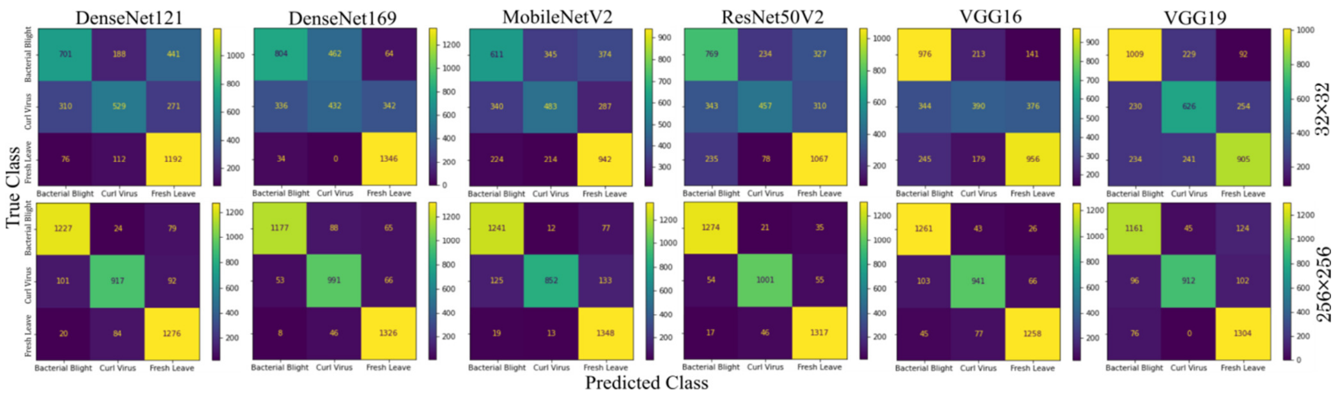

Fig. 5. Confusion matrices for lowest and highest image resolutions for all implemented models.

V. CONCLUSION

This work presented the implementation and performance analysis of automated disease detection in cotton plants based on the transfer learning of six state-of-the-art pre-trained deep learning networks that included DenseNet121, DenseNet169, MobileNetV2, ResNet50V2, VGG16, and VGG19. The two most common diseases of cotton plants, i.e. bacterial blight, and curl virus were considered. A significant part of the image dataset covering the target diseases was collected from local fields in Pakistan. Standard image augmentation techniques were applied to increase the size and versatility of the dataset. The transfer learning was implemented for four different image resolutions representing the multiple levels of image features. The performance comparison of the implemented models indicated lower accuracy when trained on low-resolution images. The inter-model comparison suggested the DenseNet169 model as most accurate providing training accuracy up to 96%.

The present work provides practical insight for implementing transfer learning models to real-time cotton disease detection systems. However, it still has some limitations which require further investigation. The current study includes a limited local dataset collected from two locations only. The reliability and accuracy of the models can be further improved by collecting datasets across the country with diverse geographical and climate features. Additionally, the current implementation is performed on CPU which limits its practical use. The future implementation of models on mobile platforms such as smartphones and embedded controllers will escalate its impact and enable its reach to end users.

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