An artificial intelligent system for cotton leaf disease detection

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Article Info

Article history:

Received Nov 27, 2024
Revised Jun 17, 2025
Accepted Jul 1, 2025

Keywords:

Convolution neural network
Cotton leaf disease
Keras
MATLAB
Tensorflow

ABSTRACT

This study aims to develop a deep learning-based system for the detection and classification of diseases in cotton leaves, with the goal of aiding in early diagnosis and disease management, thereby enhancing agricultural productivity in India. The study utilizes a dataset of cotton leaf images, classified into four categories: Fusarium wilt, Curl virus, Bacterial blight, and Healthy leaves. The dataset is used to train and evaluate various CNN models such as basic CNN, VGG19, Xception, InceptionV3, and ResNet50. These models were evaluated on their accuracy in identifying the presence of diseases and classifying cotton leaf images into the respective categories. The models were trained using standard deep learning frameworks and optimized for high performance. The results indicated that ResNet50 achieved the highest accuracy of 100%, followed by InceptionV3 with 98.75%, and VGG19 and Xception both with 97.50%. The basic CNN model showed an accuracy of 96.25%. These models demonstrated strong potential for accurate multi-class classification of cotton leaf diseases. This study emphasizes the potential of deep learning in agricultural diagnostics. Future research can focus on improving model robustness, incorporating larger datasets, and deploying the system for real-time field use to assist farmers in disease management and improving cotton production.

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1. INTRODUCTION

Agriculture is the backbone of India, but advanced technology has yet not been explored in the development of agronomy, and there are many problems in quality and production due to various diseases and pests [1], [2]. India produces over 445 kg of cotton per hectare. India has the distinction of having the largest area under cotton cultivation with around 37% of the rest of the world, making it the largest cotton manufacturer in the world. In particular, the system is aimed at farmers in the agricultural industry. Cotton is an important cash crop and fiber for India's industrial and agricultural economies. It gives the cotton textile industry its main raw material (cotton fiber). A total of six million Indian farmers makes their living from cotton, and 40–50 million people work in cotton processing and trade. The total amount of cotton produced in India in 2021–2022 was 34.1 million bales (bales of 170 kg each). With 8.516 million bales of the country's overall output, Gujarat generates the most cotton in India's Central Zone which includes the states of Maharashtra, Madhya Pradesh, and others. Saurashtra, with farmers in Amreli the biggest cotton district in Gujarat, accounts for around seventy percent of the crop in the state.

The Vidarbha districts of Yavatamal, Buldhana, Akola, Amravati, Nagpur, Washim, and Wardha are Maharashtra's biggest areas of cotton production. Comprising states including Tamil Nadu, Karnataka, and Andhra Pradesh, the Southern Zone ranks second among all the cotton growers worldwide. With the highest cotton in the Southern Zone, Telangana ranks third nationally among all states at 6.587 million bales. The cotton textile industry employs the second-highest number of people in the country, behind agriculture. It also has a substantial export market and provides a living for an estimated 6.5 million cotton growers.

Besides, all these cotton diseases are still a big threat to the yield of cotton. Pests, weeds, and diseases cause a loss of 15% to 25% of potential crop production in India. India's agriculture faces challenges from extreme weather events, including unpredictable monsoons, intense heat waves, weather anomalies, and environmental damage. The majority of diseases were found on the leaves of cotton, about 80–90%. Observing disease and pest outbreaks in cotton with bare eyes can be difficult.

In particular, this research is aimed at farmers in the agricultural industry. This research enables farmers to detect diseases on cotton leaves early and treat them accordingly. As a result of this, farmers can earn more profit by increasing efficiency and production. With the help of convolutional neural networks, this research develops a model for identifying cotton leaf diseases. The model also provides suggestions to farmers for treating the diseases. Drug dealers will also able to provide the appropriate pesticides and insecticides to farmers in time.

Using machine learning for cotton disease detection has several advantages, including higher accuracy rates, faster detection, and cost-effectiveness. For instance, a study developed a TensorFlow machine learning model to detect boll rot and fungal leaf spot diseases in cotton, achieving an accuracy of 90% [3]. Another study analyzed various machine-learning algorithms of segmentation, detection, and classification techniques to identify cotton diseases and found that machine learning algorithms outperformed traditional methods in terms of accuracy and efficiency [4].

However, there are also some disadvantages to using machine-learning for cotton disease detection, such as the need for large amounts of data to train the models, the potential for overfitting, and the requirement for technical expertise to develop and maintain the models. Additionally, some studies have noted the lack of suitable datasets of cotton diseases and pests with complex backgrounds, which can limit the effectiveness of machine-learning models [5], [6]. Therefore, while machine-learning has shown potential in improving cotton disease detection, it is important to consider both the advantages and disadvantages before implementing these models in practice. This study aims to develop a discriminative model for cotton leaf diseases using different deep learningmodels like basic CNN, VGG19, Xception, IndeptionV3, and ResNet50. Diseases detected are–Fusarium wilt, Bacterial Blight, and Curl virus.

The remaining work is arranged as follows. Section 2 offers an overview of some recently conducted research aimed at the identification of cotton diseases in literature. Section 3 presents with approach applied in this study. Section 4 offers the findings together with an analysis grounded on them. The paper ends finally in the section on conclusions.

2. LITERATURE REVIEW

Zhang *et al.* [7] presented a deep learning technique (CNN) to analyze and detect cotton leaf disease and estimate cotton quality. He used CNN model in his research. In this, the user uploads a digital image of leaf to start image processing and in turn detecting disease using CNN. The proposed method was 99.67% effective.

Singh *et al.* [8] presented an approach for cotton diseases prediction using deep learning. This study used a balanced dataset with 22 leaf disease types. The proposed model was evaluated on the dataset using several models where CNN achieves an accuracy of 99.39% and less computational time outperforming all other models.

Kotian *et al.* [9] presented and approach which combines Transfer learning (ResNet50) and KNN machine learning algorithms for cotton leaf diseases detection. This method uses RESNET50 to separates healthy and unhealthy leaves with an accuracy of 95% out perming KNN which achieved 86% accuracy. In this work, two diseases are identified: Bacterial blight and curl disease.

Sitharam *et al.* [10] presented a method for cotton leaf disease detection that works on hybrid dataset which compromises of images from the Kaggle dataset and real-time images. Deep learning models VGG16 and VGG19 are applied on this hybrid dataset for disease detection of cotton leaves. A systematic comparison of the VGG16 and VGG19 models reveals their functional differences in disease detection. VGG16 and VGG19 has achieved accuracy of 94% and 95%.

Bishshash *et al.* [11] presented an inclusive analysis of cotton disease detection using deep learning methods. They trained and evaluated several CNN models on a dataset which is derived by themselves. Their results demonstrated that the Inception V3 model performs well achieving an accuracy of 96.03%.

Chopda *et al.* [12] used decision tree classifiers to find diseases. Try addressing smart farming using machine learning. They have taken into account variables like soil moisture and temperature. Points including image processing, machine learning, and neural networks were highlighted in the paper's section on the existing systems. Diagrams of the suggested system and hardware architecture are also included. The writers noted that they will be concentrating on creating an Android application in the future in the conclusion section.

Jenifa *et al.* [13] implemented deep neural networks. By using image processing to find patterns, the disease is recognized. Those are Bacterial blight and Target spot as the most common diseases. Then Cercospora and Ascochyta blight as other diseases with Healthy as the non-affected category. 96% accuracy is the average. Images are downsized to 512*512 pixels while processing. There are three types of learning processes: supervised, unsupervised, and semi-supervised. Execution is in MATLAB. Because they resemble one another but have different diseases until leaves are categorized incorrectly. Future improvement authors concentrate on growing data images and addressing more diseases.

Hassan *et al.* [14] used the Python and Keras packages to create a deep learning-based model, while Jupyter was used as the development environment. This research study has conducted numerous tests to obtain an effective model by adjusting various factors, including dataset color, epoch number, augmentation, and regularization techniques. With augmentation, the RGB-color image dataset gave the model a 15% improvement in performance. Because of Epoch counts the model improved by 10% as well as by regularization 5.2%. Accuracy for training is 80%, but accuracy is 89% for testing.

Kumbhar *et al.* [15] developed a web-based application based on a convolutional neural network was created. The authors' rationale for selecting CNN over KNN, SVM, Random Forest, and ANN was discussed in the introductory section. There are three sections in the methodology section. The project description is the focus of the first section, which also includes sections on image acquisition, convolutional layers, and disease prediction. Information on hyperparameters, such as the number of filters, stride, and padding, is provided in the algorithm part. In the section titled Implementation Details, comprehensive details about the IDE, database servers, activation function, max pooling, filter size, and stride size are provided. For training, accuracy is 80%, but for testing, accuracy is 89%.

Caldeira *et al.* [16] presented a fruitful method that demonstrates that deep learning can help in the crop diseases detection using different CNNs. They show that when deep learning models are applied, the major outcome is an increase in overall accuracy. Additionally, the software they developed in such a way that it can be used in real field visits to catch images and filled to the proposed algorithm, making it real time detection model.

Kukadiya and Meva [17] examine the application of neural network models for identifying plant diseases. According to the research, traits including color, texture, and morphology are ideal for identifying and categorizing plant diseases. Future research may include assessing how well the algorithm rule can identify the lesion's underlying etiology (what pest or disease). Additionally, a program that can be used during actual field trips will be used to enforce the proposed algorithms and make it easier to create maps showing the degree of pest and disease infestation.

Azath *et al.* [18] implemented CNN and Transfer learning approach. Four different implementation models used are InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0. The Accuracy rates achieved are 98.42%, 99.11%, 97.02%, and 99.56% respectively.

Noon *et al.* [19] utilized a transfer learning strategy and CNN. Various parameters, such as batch size, dropout, and various numbers of epochs, are used. InceptionV3, ResNetV2, MobileNetV2, and EfficientNetB0 are four alternative implementation models that are employed. They achieved accuracy rates are 98.42%, 99.11%, 97.02%, and 99.56%.

Singh *et al.* [20] employed machine learning and image processing methods to identify cotton leaf diseases. In this research, Images are processed through several phases, including acquisition, pre-processing, feature extraction, feature categorization, disease detection, and fertilizer suggestion. They achieved the highest accuracy with RseNet V2 model.

Karthika *et al.* [21] discovered thew diseses leaf spot, black arm spot, and bacterium blight using dep and machine learning. They used multi-SVM classification and K-means clustering in their research. Image processing, segmentation, feature extraction, training, and classification are some of the steps taken in the methodology. They achieved very reasonable performance with their proposed research.

Many cotton leaf disease classification studies have used simple CNNs to accurately identify damaged and healthy leaves. Deep learning may help diagnose and classify cotton leaf diseases through image analysis, but there are still gaps in the research. Lack of large, diverse datasets may cause a decrease in accuracy and overfitting. Earlier research didn't use validation to check and overcome from model overfitting to training data. Simple CNNs are used for classification in most of the earlier research work. However advanced models like VGG19, InceptionV3, ResNet50, and Xception may also be effective in classifying cotton leaf diseases. This study uses advanced CNN algorithms to classify cotton leaf diseases using image analysis to fill a gap in the literature.

3. METHOD

The proposed methodology comprises five primary stages: data collection, data preprocessing, model training, and assessment. Initial phase entails acquisition of diseased leaf images. Due to restricted data accessibility, augmentation techniques employed for producing supplementary images. Five prevalent models—ResNet50, VGG19, Xception, InceptionV3, and ResNet50—were chosen and evaluated to enhance the accuracy of the model for cotton leaf disease detection. The suggested method employs DL models for assessing diseased cotton leaf images, facilitating precise classification and diagnosis based on visual attributes. The algorithm can categorize the illness very accurately, rendering it a valued instrument for diagnisong cotton diseases rapidly and precisely in agricultural contexts. The phases and processes encompassed in the proposed methodology are depicted in Figure 1.

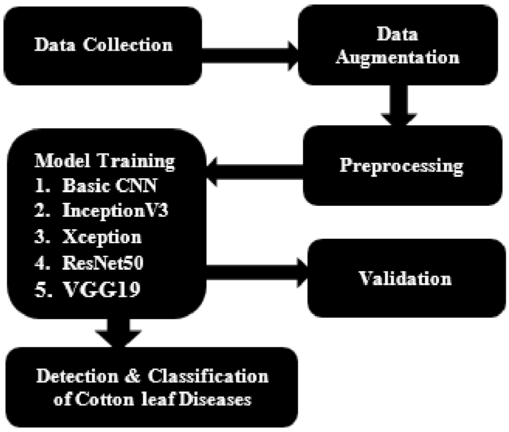

Figure 1. Proposed methodology

3.1. Data collection

The dataset we have used contains over 1,700 images of healthy and unhealthy leaves of cotton. They are divided into 4 directories where the name of the directory represents the class of the image, the classes are shown in Figures 2 and 3 [21].

3.2. Preprocessing

In image analysis, the preprocessing phase is crucial since it enhances the data's consistency and quality. Data augmentation, image normalization, and image scaling were among the preprocessing procedures used in this study. To make sure that all of the images in the current study had the same dimensions and to facilitate the model's processing of the data, entire images were reduced to 224×224 pixels. To minimize the impact of changes in lighting and contrast, the photos were normalized. To do this, the values of pixels are converted in a range of zero to one. Data augmentation techniques, including rotation, flipping, and zipping, were employed to enhance the dataset size and mitigate overfitting. This increased the data range and improved the model's performance. Standard data augmentation techniques can be employed to increase the dataset's size. These techniques encompass height shift range, rotation range, zoom range, vertical flip, width shift range, and shear range. This helps in generation of new images with minor modifications in the original images, so producing a more extensive and a new mixed dataset for DL model’s training.

Figure 2. Dataset dictionary

Figure 3. Sample images

3.3. Model selection and training

Five pretrained deep learning models such as basic CNN, VGG19, Xception, InceptionV3, and ResNet50 are carefully chosen for classification evaluation in this researchy. We chose these models because of their exceptional capacity to precisely categorize images when aligned with our dataset. These selected models are trained using the images achieved after preprocessing, and evaluated using the accuracy, precision, recall, and F1-score metrics.

3.3.1. VGG

In 2014 Oxford University's visual geometry group (VGG) developed a CNN known as VGG-16 [18]. It calls for 13 convolutional layers, five max pooling layers, and three thick layers. Its 16 layers with learnable weight values [22] have led it to be called VGG-16 Comprising 16 convolutional layers, 5 max-pooling layers, and 3 dense layers, the VGG-19 model is a variation on VGG-16.

3.3.2. ResNet50

The vanishing gradient problem makes training an exceptionally deep neural network difficult; minor gradients transported back to previous layers reduces over a given depth. By using skip connections, which let some layers in the network to be bypassed, the researchers aimed to reduce the vanishing gradient problem. Resual blocks—that is, the basis of the ResNet design—are the levels in the network that make use of skip connections [23]. We use ResNet-50, with one average pooling layer, one max pooling layer, and 48 convolutional layers.

3.3.3. Inception-V3

A group of Google researchers working on the Inception network implements the idea of growing the network instead of deepening it [24]. To extract image characteristics at several scales prior to forwarding them to the next layer, the Inception network architecture uses four simultaneous convolutional layers with different kernel sizes at a given network level. We use a 48-layer Inception-v3 network comprising among other convolutional, pooling, batch normalizing, layers.

3.3.4. Xception

Designed by Google in 2017, this enhanced form of the Inception network is Xception uses mostly the idea of improving the convolution operation performance inside Inception blocks. This was achieved in two stages: point-wise convolution then depth-wise convolution using altered depth-wise separable convolution. While depth-wise convolution marks the channel-wise spatial convolution, point-wise convolution changes the dimensions [25].

4. RESULTS AND DISCUSSION

The classification performance of the applied DL models evaluated using metrics; f1 score, recall, accuracy, and precision [26]. The authors have used adam optimizer and categorical cross entropy as loss function. This research selected the categorical_crossentropy loss function. The classification performance results are shown in Table 1. The findings indicate that the ResNet50 architecture outperformed the other models, attaining accuracy of 100% by epoch 35. Additionally, it yielded accuracy scores of 96.25%, 97.50%, 97.50%, and 98.75 at epochs 14, 18, 24, and 28 for basic CNN, VGG19, Xception, and InceptionV3 respectively. Figures 4 to 8 presents plots for the training and validation losses and accuracies of all models used. The plot illustrates the variations in training accuracy and validation accuracy between epochs 1 to 40. We have used the concept the stagnation to stop the unnecessary execution of the models. Total epochs considered are 40. Our models stop their execution as soon as it produces same results for five consecutive epochs. Then it considers the epoch as a best epoch from where the stagnation starts. The optimal epoch was selected to mitigate both overfitting and underfitting. Figures 9 to 13 presents the confusion matrices for the models employed in this study. The confusion matrix illustrates the count of images classified by the model as a specific class (actual), despite belonging to a different class (prediction).

Table 1. Performance of the classifier models

Classifier model	Accuracy	Precision	Recall	F1-Score
Basic CNN	0.9625	0.9630	0.9625	0.9625
VGG19	0.9700	0.9462	0.9600	0.9505
Xception	0.9750	0.9773	0.9750	0.9749
InceptionV3	0.9875	0.9881	0.9875	0.9875
ResNet50	1.000	1.000	1.000	1.000

Figure 4. Losses and accuracies graph of basic CNN

Figure 5. Losses and accuracies graph of inceptionv3

Figure 6. Losses and accuracies graph of Xception

Figure 7. Losses and accuracies graph of VGG19

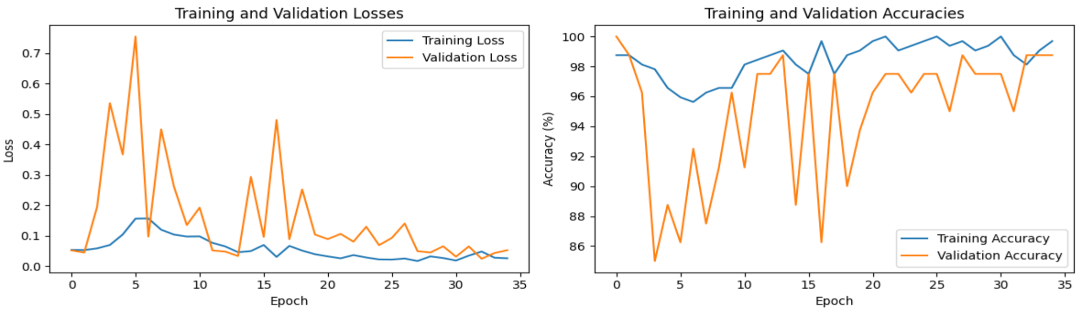

Figure 8. Losses and accuracies graph of ResNet50

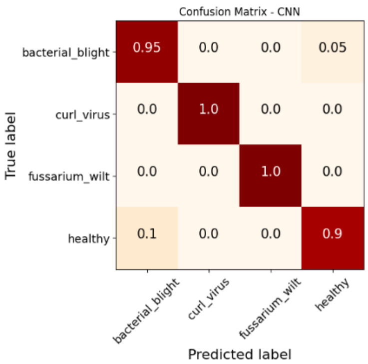

Figure 9. Confusion matrix for Bacic CNN model

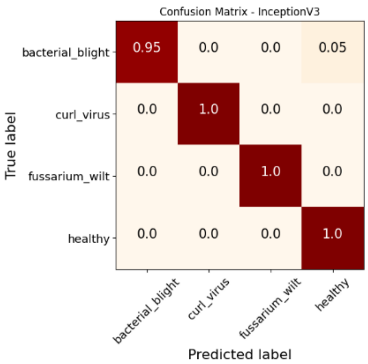

Figure 10. Confusion matrix for inceptionv3 model

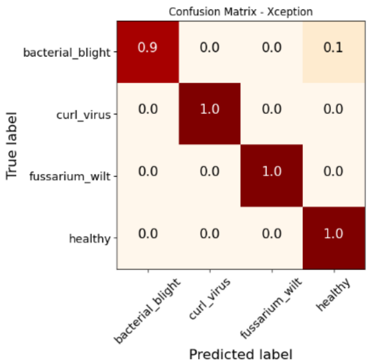

Figure 11. Confusion matrix for Xception model

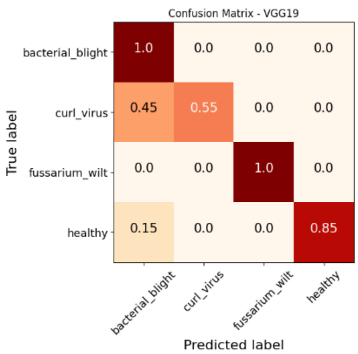

Figure 12. Confusion matrix for VGG19 model

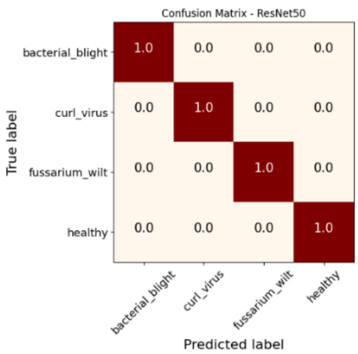

Figure 13. Confusion matrix for ResNet model

The models were assessed with our dataset, demonstrating favorable outcomes regarding accuracy, precision, recall, and F1-score relative to the majority of existing research in the field. We specifically contrasted our results with the models available in literature, such as Basic CNN, VGG16, InceptionV3, and VGG19. The performance evaluation states that our research surpasses rest of the models regarding accuracy, precision, recall, and F1-score. The ResNet50 model demonstrated marginally superior performance regarding the evaluation metrics. The results indicate that the suggested work is viable and shows a strong fitness for the datset used in comparison to deep learning models used in comparison.

Research on the application of deep learning for cotton leaf disease detection remains sparse. Our models were trained utilizing both complete augmented data and augmented training data. This method enhances performance in scenarios with limited instances. Augmentation was applied to the entire dataset; however, this resulted in an imbalance in the validation and testing data, with a predominance of healthy cases. Conversely, when augmentation was solely applied to the training data, the validation and testing datasets also exhibited imbalance, predominantly characterized by diseased cases. The models demonstrated strong performance, with only a single instance of misclassification, despite the data imbalance. The model presented in Table 1 achieved the highest performance level.

5. CONCLUSION

This work aimed to improve deep learning-based methods for cotton leaf disease diagnosis such that their accuracy would be higher than those of present systems. Using the Basic CNN, VGG19, VGG16, InceptionV3, and ResNet50 models, a novel technique was presented and shown the maximum performance with an accuracy score of 100% (ResNet50). The suggested approach proved better than the ones described in past studies. This method could be used in the future for real-time cotton leaf disease detection forecasts on cellphones. Further studies could need looking at larger image sizes in order to support the viability of the approach. We think that quick diagnosis, classification, and treatment of cotton leaf disease detection will be made easier by this study and related ones. Our results are hopeful since they suggest that our model might be a modern deep learning method for early cotton leaf disease diagnosis. Our method is a possibly useful tool for quick and accurate diagnosis in clinical settings since it reached a notable degree of accuracy in classifying cotton leaf disease detection inside both the training and test sets.

ACKNOWLEDGMENTS

We consider it an immense pleasure to convey our deep sense of gratitude to KPGU, Vadodara, and RIT, Rajaramnagar for making available guidance to study comparative analysis. Online resources are used for acquiring information in the realm of image processing and machine learning.

FUNDING INFORMATION

No funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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Nitesh Sureja	✓	✓		✓			✓	✓		✓		✓	✓	
Nandini Chaudhari	✓		✓	✓			✓			✓			✓	
Heli Sureja	✓		✓					✓	✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author Nitesh Sureja on request.

REFERENCES

[1] A. Krishna and G. Naik, “Addressing crisis in Indian agriculture through agricultural information delivery,” *IIMB Management Review*, vol. 32, no. 2, pp. 217–229, Jun. 2020, doi: 10.1016/j.iimb.2020.09.004.

[2] S. Shukla, D. Upadhyay, A. Mishra, T. Jindal, and K. Shukla, “Challenges faced by farmers in crops production due to fungal pathogens and their effect on indian economy,” in *Fungal diversity, ecology and control management*, Springer Nature Singapore, 2022, pp. 495–505.

[3] U. Dewangan, R. H. Talwekar, and S. Bera, “A systematic review on cotton plant disease detection and classification using machine and deep learning approach,” in *2023 1st DMIHER International Conference on Artificial Intelligence in Education and Industry 4.0, IDICAIEI 2023*, Nov. 2023, pp. 1–6, doi: 10.1109/IDICAIEI58380.2023.10406941.

[4] S. Kumar *et al.*, “A comparative analysis of machine learning algorithms for detection of organic and nonorganic cotton diseases,” *Mathematical Problems in Engineering*, vol. 2021, pp. 1–18, Jun. 2021, doi: 10.1155/2021/1790171.

[5] S. Kumar, R. Ratan, and J. V. Desai, “Cotton disease detection using TensorFlow machine learning technique,” *Advances in Multimedia*, vol. 2022, pp. 1–10, Aug. 2022, doi: 10.1155/2022/1812025.

[6] A. Herok and S. Ahmed, “Cotton leaf disease identification using transfer learning,” in *2023 International Conference on Information and Communication Technology for Sustainable Development, ICICT4SD 2023 - Proceedings*, Sep. 2023, pp. 158–162, doi: 10.1109/ICICT4SD59951.2023.10303323.

[7] Y. Zhang, B. Ma, Y. Hu, C. Li, and Y. Li, “Accurate cotton diseases and pests detection in complex background based on an improved YOLOX model,” *Computers and Electronics in Agriculture*, vol. 203, p. 107484, 2022, doi: 10.1016/j.compag.2022.107484.

[8] P. Singh, P. Singh, U. Farooq, S. S. Khurana, J. K. Verma, and M. Kumar, “Retraction note: CottonLeafNet: cotton plant leaf disease detection using deep neural networks (Multimedia Tools and Applications, (2023), 82, 24, (37151-37176), 10.1007/s11042-023-14954-5),” *Multimedia Tools and Applications*, vol. 83, no. 30, p. 75439, Jul. 2024, doi: 10.1007/s11042-024-19855-9.

[9] S. Kotian, P. Ettam, S. Kharche, K. Saravanan, and K. Ashokkumar, “Cotton leaf disease detection using machine learning,” *SSRN Electronic Journal*, vol. 2022.

[10] M. Sitharam, V. Anusha, P. N. Sri, and G. H. Sri, “A novel methodology for cotton leaf disease detection using CNN,” in *Proceedings of the 3rd International Conference on Applied Artificial Intelligence and Computing, ICAAIC 2024*, Jun. 2024, pp. 202–207, doi: 10.1109/ICAAIC60222.2024.10575876.

[11] P. Bishshash, A. S. Nirob, H. Shikder, A. H. Sarower, T. Bhuiyan, and S. R. H. Noori, “A comprehensive cotton leaf disease dataset for enhanced detection and classification,” *Data in Brief*, vol. 57, p. 110913, Dec. 2024, doi: 10.1016/j.dib.2024.110913.

[12] J. Chopda, H. Raveshiya, S. Nakum, and V. Nakrani, “Cotton crop disease detection using decision tree classifier,” in *2018 International Conference on Smart City and Emerging Technology, ICSCET 2018*, Jan. 2018, pp. 1–5, doi: 10.1109/ICSCET.2018.8537336.

[13] A. Jenifa, R. Ramalakshmi, and V. Ramachandran, “Cotton leaf disease classification using deep convolution neural network for sustainable cotton production,” in *2019 International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development, INCCES 2019*, Dec. 2019, pp. 1–3, doi: 10.1109/INCCES47820.2019.9167715.

[14] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, “Identification of plant-leaf diseases using cnn and transfer-learning approach,” *Electronics (Switzerland)*, vol. 10, no. 12, p. 1388, Jun. 2021, doi: 10.3390/electronics10121388.

[15] S. Kumbhar, S. Patil, A. Nilawar, B. Mahalakshmi, and M. Nipane, “Farmer buddy-web based cotton leaf disease detection using CNN,” *International Journal of Applied Engineering Research*, vol. 14, no. 11, pp. 2662–2666, 2020.

[16] R. F. Caldeira, W. E. Santiago, and B. Teruel, “Identification of cotton leaf lesions using deep learning techniques,” *Sensors*, vol. 21, no. 9, p. 3169, May 2021, doi: 10.3390/s21093169.

[17] H. Kukadiya and D. Meva, “Automatic cotton leaf disease classification and detection by convolutional neural network,” in *Communications in Computer and Information Science*, vol. 1759 CCIS, Springer Nature Switzerland, 2022, pp. 247–266.

[18] M. Azath, M. Zekiwos, and A. Bruck, “Deep learning-based image processing for cotton leaf disease and pest diagnosis,” *Journal of Electrical and Computer Engineering*, vol. 2021, pp. 1–10, Jun. 2021, doi: 10.1155/2021/9981437.

[19] S. K. Noon, M. Amjad, M. Ali Qureshi, and A. Mannan, “Computationally light deep learning framework to recognize cotton leaf diseases,” *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 6, pp. 12383–12398, Jun. 2021, doi: 10.3233/JIFS-210516.

[20] M. K. Singh, M. Gupta, M. Amaan, N. Naeem, M. S. Saifi, and M. Askari, “Leaf disease detection using deep learning,” *AIP Conference Proceedings*, vol. 3224, no. 1, pp. 3995–3999, Jun. 2025, doi: 10.1063/5.0246989.

[21] J. Karthika, K. M. Kumar, M. Santhose, T. Sharan, and S. S. Hariharan, “Disease detection in cotton leaf spot using image processing,” *Journal of Physics: Conference Series*, vol. 1916, no. 1, p. 012224, 2021.

[22] “Cotton leaf disease dataset,” 2024. https://www.kaggle.com/datasets/seroshkarim/cotton-leaf-disease-dataset.

[23] L. Fei-Fei, J. Deng, and K. Li, “ImageNet: Constructing a large-scale image database,” *Journal of Vision*, vol. 9, no. 8, pp. 1037–1037, Mar. 2010, doi: 10.1167/9.8.1037.

[24] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2016, vol. 2016-December, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[25] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2016, vol. 2016-Decem, pp. 2818–2826, doi: 10.1109/CVPR.2016.308.

[26] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, Jul. 2017, vol. 2017-January, pp. 1800–1807, doi: 10.1109/CVPR.2017.195.

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