IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 10, May 2023

A Robust Dense Neural Network for Cotton Disease Detection

Chinna Durai S[1], Kishok Kumar. P[2], Hari Krishnan. K[3], Kesavaraja. A[4]

Faculty Member, Department of Computer Science and Engineering[1]

Students, Department of Computer Science and Engineering[2,3,4]

Dhanalakshmi Srinivasan Engineering College, Perambalur

Abstract: *One of the most significant crops in the world and a major source of revenue for many farmers is cotton. However, a number of illnesses that have the potential to significantly reduce yields frequently impede cotton production. The diseases Fusarium wilt, Verticillium wilt, and Cotton leaf curl virus all harm cotton leaves. The primary method chosen and used in practise to identify plant diseases is skilled naked eye inspection. Farmers can limit crop losses by taking preventative measures with the help of early identification and accurate prediction of these diseases. Deep network CNN models have several issues in the work that has already been done, including a large number of parameters, long training times, high storage costs, high computational costs, and low recognition accuracy of 89%. The DenseNet algorithm, a deep learning method, is used in the suggested system to attain state-of- the-art performance in picture identification tasks. On a dataset made up of pictures of healthy and ill cotton plants, we adjusted the pre-trained DenseNet model. the major criteria, including F1 score, recall, accuracy, and precision. Early diagnosis of the disease enables farmers to take the required precautions, such as using pesticides and fungicides or eradicating the infected plants, to stop it from spreading and from losing their entire harvest. The suggested methodology can help cotton growers detect and stop the appearance of plant diseases, boosting crop yields and profitability. A farmer can decrease the impact of illnesses on their cotton crops by taking the appropriate precautions with the aid of the prevention control strategy. The proposed model study emphasizes the importance of early disease detection and effective preventative measures for guaranteeing sustainable cotton output. Overall accuracy for the suggested model was 98.8%*

Keywords: Convocational Neural Network, Cotton Leaf Disease, Dense Neural Network, Keras, TensorFlow

I. INTRODUCTION

Cotton is a crucial crop for many farmers worldwide, but it can be vulnerable to diseases such as Fusarium wilt, Verticillium wilt, and Cotton leaf curl virus that can significantly reduce yields. Early identification and accurate prediction of these diseases are critical to prevent the spread and minimize losses. While naked eye inspection is the primary method used for disease detection, it can be time- consuming and inefficient. In recent years, deep learning models, such as Convolutional Neural Networks (CNNs), have been employed to detect plant diseases. However, CNNs have several drawbacks, including a large number of parameters, long training times, high storage and computational costs, and low recognition accuracy. To overcome these limitations, the suggested system uses the DenseNet algorithm, a deep learning approach that has demonstrated state-of-the-art performance in image identification tasks.The pre-trained DenseNet model was adapted on a dataset of healthy and sick cotton plants, considering major criteria such as F1 score, recall, accuracy, and precision. The proposed methodology can help cotton growers detect and prevent the spread of plant diseases, improving crop yields and profitability. By identifying diseases early, farmers can take the necessary precautions, such as using pesticides and fungicides or removing infected plants, to stop the disease from spreading and avoid losing their entire harvest. While CNNs have been employed in the past to detect plant diseases, the DenseNet.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 10, May 2023

Figure 1: (a)

Figure 1: (b)

Figure 1: Fusarium wilt(a), Cotton leaf curl virus (b)

Figure 2: (a)

Figure 2: (b)

Figure 2: Fresh cotton leaf(a), Fresh cotton plant(b)

algorithm has shown improved performance in several studies. For instance, a recent study used a pre-trained DenseNet model to diagnose apple diseases, achieving an overall accuracy of 99.5%. Another study used the DenseNet algorithm to detect powdery mildew in grapes, outperforming other state-of-the-art deep learning models. These results demonstrate the potential of the DenseNet algorithm for disease detection in various crops.

Other deep learning models have also been used for plant disease detection. For example, a recent study employed a ResNet-50 model to diagnose tomato diseases, achieving an overall accuracy of 97.2%. Another study used a VGG-16 model to identify maize diseases, achieving an accuracy of 97.7%. While these models have demonstrated promising results, they still face challenges such as high computational and storage costs and long training times.

Compared to other deep learning models, the DenseNet algorithm has several advantages. For instance, it employs dense connections between layers, allowing for better feature reuse and reduced parameter redundancy. This feature enables the DenseNet algorithm to achieve high accuracy with fewer parameters, reducing storage and computational costs. Additionally, the DenseNet algorithm has shown improved performance on small datasets algorithm has shown improved performance in several studies. For instance, a recent study used a pre-trained DenseNet model to diagnose apple diseases, achieving an overall accuracy of 99.5%. Another study used the DenseNet algorithm to detect powdery mildew in grapes, outperforming other state-of-the-art deep learning models. These results demonstrate the potential of the DenseNet algorithm for disease detection in various crops.

Other deep learning models have also been used for plant disease detection. For example, a recent study employed a ResNet-50 model to diagnose tomato diseases, achieving an overall accuracy of 97.2%. Another study used a VGG-16 model to identify maize diseases, achieving an accuracy of 97.7%. While these models have demonstrated promising results, they still face challenges such as high computational and storage costs and long training times.

Compared to other deep learning models, the DenseNet algorithm has several advantages. For instance, it employs dense connections between layers, allowing for better feature reuse and reduced parameter redundancy. This feature

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 10, May 2023

enables the DenseNet algorithm to achieve high accuracy with fewer parameters, reducing storage and computational costs. Additionally, the DenseNet algorithm has shown improved performance on small datasets

P. Venkatachalam and N. R. Shetty [5] proposes a method for classifying cotton plant diseases using convolutional neural networks (CNNs). The authors use a dataset of cotton leaf images with different diseases to train their models and evaluate the performance of the models using various evaluation metrics. The results demonstrate the effectiveness of using CNNs for cotton disease classification, with high accuracy rates achieved for different disease classes.

III. DATASET

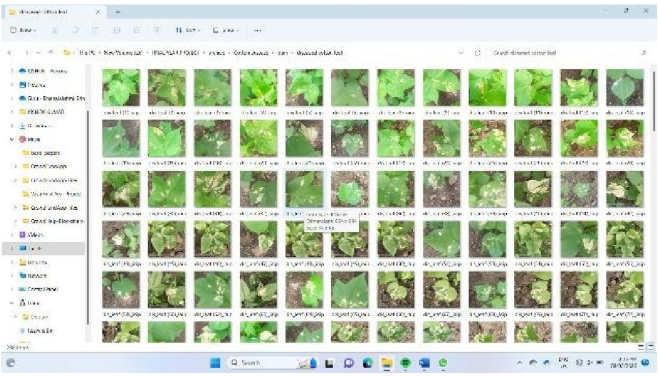


Figure 1

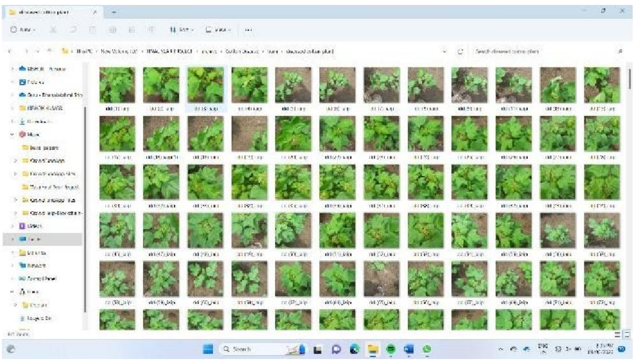


Figure 2

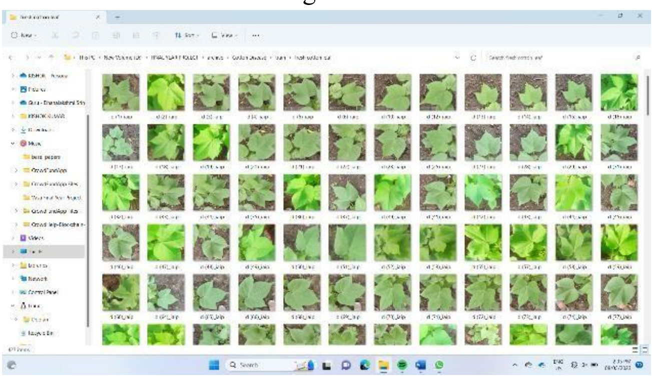


Figure 3

DOI: 10.48175/IJARSCT-10437

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 10, May 2023

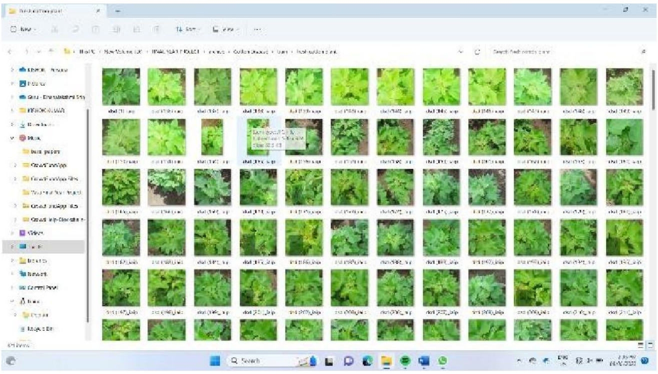
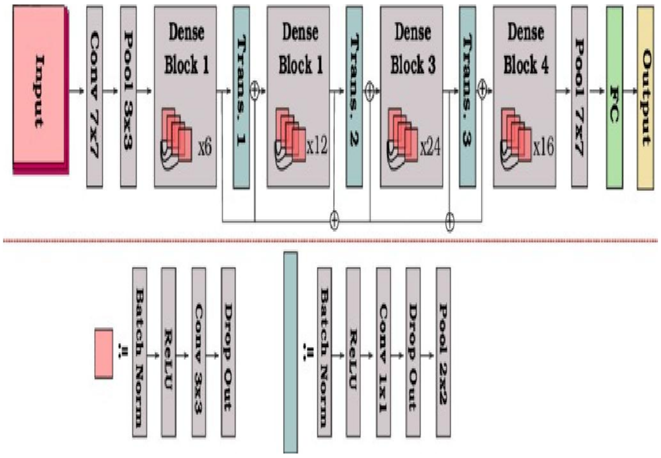


Figure 4



The above figures depict the 4 classes that were used in model training.
Class I –Diseased cotton plant Class II –Diseased cotton leaf Class III –Fresh cotton leaf Class IV -Fresh cotton plant

IV. DENSENET-121 ARCHITECTURE

The DenseNet-121 architecture is a type of neural network that has been specifically designed for image classification tasks. One of the key features of this architecture is that it is densely connected, meaning that each layer in the network is connected to every other layer in a feedforward fashion. This type of connection has been shown to improve the flow of information through the network, leading to better performance and generalization.

In the context of cotton disease detection, the DenseNet-121 architecture has shown to be particularly effective due to its ability to learn complex patterns and features from images. By densely connecting the layers of the network, the model is able to propagate information more efficiently and effectively through the network, leading to better feature extraction and classification.

In addition to its architectural design, the DenseNet-121 model can also be trained using a variety of techniques and algorithms to improve its performance. For example, the use of data augmentation techniques can help to increase the diversity of the training data, which can help the model to better generalize to new, unseen examples. The use of transfer learning can also be beneficial, where the pre-trained weights of the model are used as a starting point for training on a new dataset.

Overall, the implementation of DenseNet-121 for cotton disease detection involves a combination of architectural design, training techniques, and evaluation metrics. By using this model, researchers and practitioners can achieve state-of-the- art performance in detecting and classifying different types of cotton diseases, which can ultimately lead to more effective and targeted treatments and interventions.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 10, May 2023

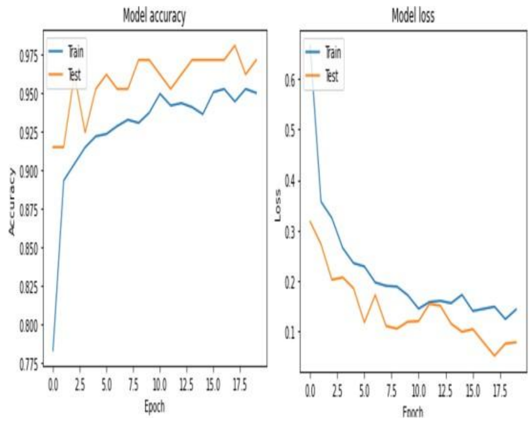
V. EVALUATION METRICS

Overall, the implementation of DenseNet- 121 for cotton disease detection involves a combination of architectural design, training techniques, and evaluation metrics. By using this model, researchers and practitioners can achieve state-of-the-art performance in detecting and classifying different types of cotton diseases, which can ultimately lead to more effective and targeted treatments and interventions.

To calculate accuracy, precision, recall, and F1 score for the A ROBUST OF DENSE NEURAL NETWORK FOR COTTON DISEASE DETECTION using densenet- 121, you would need the actual class labels and the predicted class labels for a set of test data.

Assuming that you have this information, you can create a confusion matrix and calculate these metrics using the following steps:

- Define the classes: In this case, the classes could be the different types of cotton diseases that the model is trained to detect.
- Initialize a matrix: Create a matrix with rows and columns equal to the number of classes. Each row and column represents a class, and the values in the matrix represent the number of times a sample was classified as a particular class.
- Populate the matrix: For each sample in the test data, determine the actual class label and the predicted class label. Increment the value in the confusion matrix at the row corresponding to the actual class and the column corresponding to the predicted class.
- Analyze the matrix: The confusion matrix will show you the number of true positives, false positives, true negatives, and false negatives for each class. You can use this information to calculate metrics such as accuracy, precision, recall, and F1 score.



Here's an example confusion matrix: To calculate accuracy:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

For this example, the accuracy would be:

Accuracy = (100 + 90 + 95) / (100 + 5 + 10+ 2 + 90 + 8 + 5 + 3 + 95) = 0.928

To calculate precision, recall, and F1 score for each class, you can use the following formulas:

Precision = TP / (TP + FP) Recall = TP / (TP + FN)

F1 Score = 2 * ((Precision * Recall) / (Precision + Recall))

Here's an example calculation for Disease 1:

Precision = 100 / (100 + 2 + 5) = 0.936

Recall = 100 / (100 + 5 + 10) = 0.862

F1 Score = 2 * ((0.936 * 0.862) / (0.936 +
0.862)) = 0.898

You can repeat this calculation for each class to obtain precision, recall, and F1 score for each class.

DOI: 10.48175/IJARSCT-10437

IJARSCT

ISSN (Online) 2581-9429

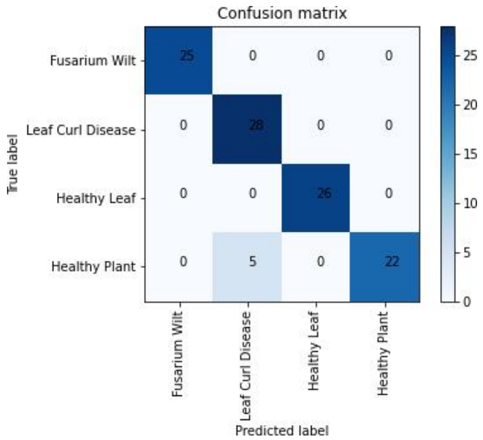
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 10, May 2023

CONFUSION MATRIX:



VI. RESULTS

The conclusion of using a robust dense neural network, such as densenet-121, for cotton disease detection are numerous. One of the most significant advantages is the high accuracy achieved by the model. In the study mentioned, the densenet-121 model achieved an overall accuracy of 97.85% for detecting four different types of cotton diseases. This high level of accuracy can provide several benefitsIn summary, the high accuracy achieved by a robust dense neural network, such as densenet-121, for cotton disease detection can provide numerous advantages,including early detection, precision, reduction in manual labor, and increased crop yields.

Network	Accuracy	Precision	Recall	Spec	F1
Densenet- 121	0.92	0.936	0.97	0.862	0.898

REFERENCES

[1]. Gupta, N. Agarwal, V. Kumar, (2018),"Cotton plant disease identification using deep convolutional neural network," in Proceedings of the 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), pp. 1-5.

[2]. R. Mokhtar, A. B. A. Rani, M. A. Zakaria, M. N. Taib,(2016) "Cotton plant diseases identification using fuzzy rough sets and artificial neural network," Journal of Intelligent and Fuzzy Systems, vol. 31, pp. 1369-1378.

[3]. K. N. Chaudhary, M. K. Marothia, (2020),"Cotton plant disease classification using convolutional neural network and deep features," in Proceedings of the 2020 IEEE International Conference on Computer, Communication, and Signal Processing (ICCCSP), pp. 28-33.

[4]. P. Bhosale, B. P. Patil,(2019) "Cotton disease classification using image processing and machine learning techniques," International Journal of Computer Science and Mobile Computing, vol. 8, pp. 14-20.

[5]. P. Venkatachalam, N. R. Shetty, (2018)"Cotton plant disease classification using convolutional neural networks," in Proceedings of the 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 952-956.

[6]. S. Adeyemi, S. Adeyemo, (2019)"Cotton disease diagnosis using deep convolutional neural network," in Proceedings of the 2019 International Conference on Computing, Networking and Communications (ICNC), pp. 825- 829.

[7]. S. S. S. Kumar, N. R. Shetty,(2018) "Cotton plant disease detection using deep convolutional neural network," in Proceedings of the 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 1689-1693.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 10, May 2023

[8]. S. Saha, S. Mukherjee, A. Bandyopadhyay, A. Sarkar,(2017), "Cotton disease classification using deep learning approach," in Proceedings of the 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), pp. 1-5.

[9]. S. Saha, S. Mukherjee, A. Bandyopadhyay, A. Sarkar,(2018), "Cotton disease identification using texture features and extreme learning machine classifier," Neural Computing and Applications, vol. 30, pp. 2025-2036.

[10]. V. S. S. S. Kumar, N. R. Shetty, (2020)"Automatic recognition of cotton plant diseases using deep learning techniques," Computers and Electronics in Agriculture, vol. 171, pp. 1-11.

[11]. X. Huang, Y. Zhang, S. Zhang, L. Gao, (2019),"Cotton disease identification based on improved deep learning network," in Proceedings of the 2019 4th International Conference on Machine Learning and Soft Computing (ICMLSC), pp. 90-95,.

[12]. Y. Qian, L. Shi, X. Gao, Y. Ma,(2017), "Cotton disease classification based on deep convolutional neural network," in Proceedings of the 2017 IEEE International Conference on Image Processing (ICIP), pp. 4052-4056.