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DEEP INSIGHTS INTO PLANT DISEASE IDENTIFICATION: A COMPARATIVE EVALUATION OF NEURAL NETWORKS

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Abstract. Cotton, a vital crop in India constituting 23% of exports, grapples with challenges like diminished yield due to leaf diseases such as Cercospora, Bacterial blight, Ascochyta blight, and Target spot. Traditional manual observation by farmers is not only time-consuming and expensive but also prone to inaccuracies. This research addresses the pressing need for an effective model to enhance the detection of cotton leaf diseases. The study leverages various deep learning methods, including Convolutional Neural Network (CNN), Inception V3, VGG 16, VGG 19, and RESNET 152. A comprehensive dataset, sourced from Kaggle, encompasses images of both diseased and fresh cotton leaves and plants, totaling 2400 specimens for robust training. Implemented using Python 3.7.3 and equipped with Keras, TensorFlow, and Jupyter in the developmental environment, the models were meticulously evaluated by adjusting parameters such as batch size, dropout, and epochs. Remarkably, the models achieved disease-classification accuracy rates of 94.87%, 73.55%, 73.65%, 73.81%, and 97.33% for InceptionV3, VGG 16, VGG 19, CNN, and RESNET152V2, respectively, after 10 epochs. These accuracy rates outshined traditional handcrafted-feature-based approaches. Notably, the RESNET152V2 model not only exhibited superior accuracy but also demanded less training time. The results underscore a significant leap towards accurate and efficient detection of cotton leaf diseases, providing valuable insights for the agricultural sector. This research holds promise for revolutionizing disease management in cotton cultivation, contributing to increased yield and sustainable farming practices.

Keywords: Convolutional Neural Network (CNN), Inception V3, RESNET 152.

Introduction

Plant diseases pose a significant threat to agricultural security by substantially reducing crop yields and compromising their quality. Pests and diseases lead to the destruction of crops or plant parts, resulting in decreased food production and contributing to food insecurity. The accurate and precise diagnosis of these diseases has been a considerable challenge, traditionally relying on human annotation through visual inspection. Identifying plant diseases early is crucial as they affect the growth of their respective species.

Cotton plants, in particular, are susceptible to various attacks, including biotic and abiotic constraints like temperature fluctuations, diseases, and pests. Globally, nearly 576 kg per hectare of cotton crops are produced, with a 10% production loss attributed to different cotton leaf diseases. The increased use of technology has enhanced the efficacy and accuracy of disease detection in plants.

Research in the field of machine learning for plant disease detection has employed traditional approaches such as random forest, artificial neural networks, support vector machines (SVM), fuzzy logic, and the K-means method. These methods can be further improved by incorporating deep learning architectures like convolutional neural networks (CNNs), recurrent neural networks, and recursive neural networks, enhancing disease recognition rates and result accuracy.

This study aims to compare deep learning methods, including the conventional neural network (CNN), Inception V3, VGG 16, VGG 19, and RESNET 152, for identifying and diagnosing diseases in cotton leaves. Deep Neural Networks form the foundation of computer vision technologies, functioning similarly to neural networks with learnable weights and biases. A deep neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. Neural networks consist of neurons, synapses, weights, biases, and functions. Deep learning, a subset of machine learning, employs multiple layers to progressively extract higher-level features from raw input. Inspired by the human brain, deep learning algorithms learn from vast amounts of data, refining their tasks through repeated iterations in multiple layers to enhance outcomes.

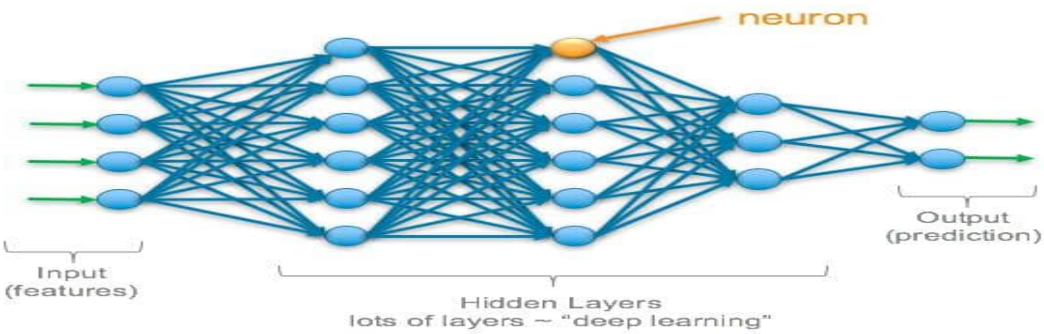

Fig 1. Deep Learning

Deep learning methods have proven to be highly effective tools in various computer vision tasks, including object recognition, biometric detection, and classification. These methods have the capability to match filters directly derived from the data. The paper is structured as follows: Section 1 introduces the application of deep neural networks in identifying cotton diseases. Section 2 reviews related works on the recognition of plant diseases. Section 3 outlines our methodology. Information regarding the results and discussions can be found in Section 4. Finally, Section 5 offers conclusions and suggestions for further research.

Literature Review

Zhong L. et al. (2019) introduced a deep learning-based classification framework for remotely sensed time series, conducted in Yolo County, California. The study compared the performance of different classifiers, including Long Short-Term Memory (LSTM), one-dimensional convolutional (Conv1D) layers, XGBoost, Random Forest, and Support Vector Machine. The Conv1D-based model exhibited the highest accuracy (85.54%) and F1 score (0.73), outperforming other classifiers.

In their 2017 review, Ray M et al. discussed the detection of fungal diseases in plants, emphasizing the potential of biosensors as an alternative solution, albeit requiring further modifications, improvements, and validation for on-field applications.

A survey by A Kamilaris et al. (2018) explored 40 research efforts utilizing deep learning techniques in various agricultural and food production challenges. Their findings indicated that deep learning consistently provided high accuracy, surpassing commonly used image processing techniques.

Yu Sun et al. (2018) proposed a deep learning approach for automatically discovering discriminative features in plant disease severity classification. Fine-tuning on pretrained deep models, particularly the VGG16 model, demonstrated superior performance, achieving an accuracy of 90.4% on the test set.

Parul Sharma et al. (2020) investigated the feasibility of training a convolutional neural network (CNN) using segmented and annotated images. Utilizing segmented images (S-CNN) significantly improved model performance, increasing from 42.3% to 98.6% on independent data.

M. Nagaraju et al. (2020) conducted a review focusing on neural network techniques for processing image data, with an emphasis on detecting crop diseases. The study covered data acquisition sources, deep learning models/architectures, evaluation results, and highlighted future prospects for hyperspectral data analysis.

Anupam Bapat et al. (2020) performed a study on plant leaf disease detection using deep learning, exploring various representations from the Plantsvillages dataset and achieving improved results through block-scaled optimization. Siddhartha Arjaria et al. (2020) applied a Convolution Neural Network (CNN)-based approach for plant disease detection, achieving high accuracy and demonstrating superiority over pre-trained models such as VGG16, InceptionV3, and MobileNet.

Yalcin, H et al. (2016) proposed a CNN architecture for classifying plant types using image sequences from smart agro-stations. The study emphasized the significance of preprocessing steps and validated the effectiveness of the CNN model on the TARBIL dataset.

Rahnemoonfar M. et al. (2017) presented a simulated deep convolutional neural network for yield estimation, addressing the challenges of manual counting and offering a time-efficient alternative. Bargoti S. et al. (2016) utilized the Faster R-CNN object detection framework for fruit detection in orchards, conducting ablation studies to understand the practical deployment of the detection network.

Xiaoyue Xie et al. (2020) proposed a real-time detector for grape leaf diseases based on an improved deep convolutional neural network, achieving promising results in terms of precision and detection speed. Nilay Ganatra et al. (2020) conducted a comprehensive review of research on deep learning applications in precision agriculture, highlighting the high potential of these techniques.

Zhang X. et al. (2018) introduced a deep learning-based model for leaf disease recognition in maize, achieving high accuracy with reduced model parameters compared to VGG and AlexNet structures. Dyrmann M. et al. (2016) designed and trained a deep convolutional neural network for efficient filter capacity and coverage in product image classification. Tamoor K et al. (2020) presented a novel approach to fruit production prediction using deep neural networks, achieving accuracy through different optimization methods. Zhang Y et al. (2017) designed a 13-layer convolutional neural network (CNN) with various data augmentation methods and observed superior performance compared to state-of-the-art approaches. The study validated the effectiveness of the 13-layer structure and highlighted significant GPU acceleration benefits.

Materials and Methods

The main aim of the articles is to automatically detect the cotton disease using images which helps to assess during the farming activities. For this research we have downloaded cotton leaf dataset from Kaggle. Kaggle is a data source where 50,000 public datasets and 400,000 public notebooks available. Every day a new dataset is uploaded on Kaggle. We have 4 categories of images diseases cotton leaf, diseased cotton plant, fresh cotton leaf, fresh cotton plant. The images are kept inside folders train, test, and validation folders. The images are further grouped into subfolders each containing separate class of images. For this research, nearly 2400 specimens (600 images in each class) were accessed for training purposes. This developed model is implemented using python version 3.7.3 and the model is equipped on the deep learning package called Keras.

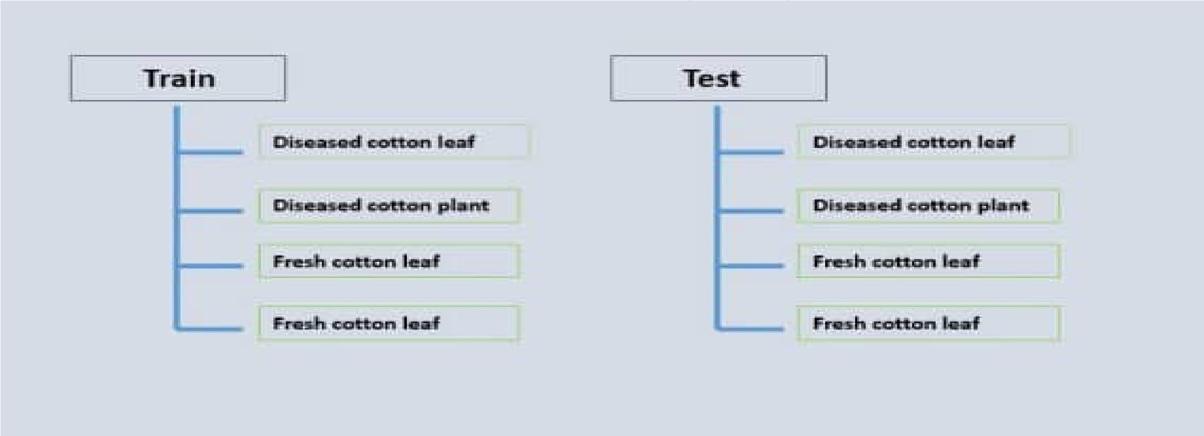

Figure 2. Types of Datasets

System Architecture

The framework for the plant disease identification system leverages deep learning methods to train models for detecting diseases in plant leaves, utilizing images sourced from primary and secondary agricultural data. The initial step in our disease identification system involves acquiring images from an online data source. Subsequently, image pre-processing techniques are applied to prepare the acquired images for further analysis. The pre-processed images are then fed into the Convolutional Neural Network (CNN) algorithm for feature extraction through neural networks. The most suitable features representing the image are extracted using an image analysis technique. Based on these extracted features, training and testing data are generated for disease identification. Finally, a trained knowledge base classifies a new image into its corresponding syndrome class. This process is repeated, and other deep learning algorithms such as Inception V3, VGG 16, VGG 19, and RESNET152V2 are applied to identify the best model for cotton leaf identification.

Step 1: Dataset selection.
Step 2: Feature selection using information gain and ranking.
Step 3: Application of the CNN classification algorithm.
Step 4: Calculation of each feature value in the input layer.
Step 5: Determination of the bias class for each feature.
Step 6: Generation of the feature map, proceeding to the forward pass in the input layer.
Step 7: Calculation of convolution cores in a feature pattern.
Step 8: Production of a sub-sample layer and feature values.
Step 9: Backpropagation of the input deviation of the kth neuron in the output layer.
Step 10: Presentation of the selected features and classification results.

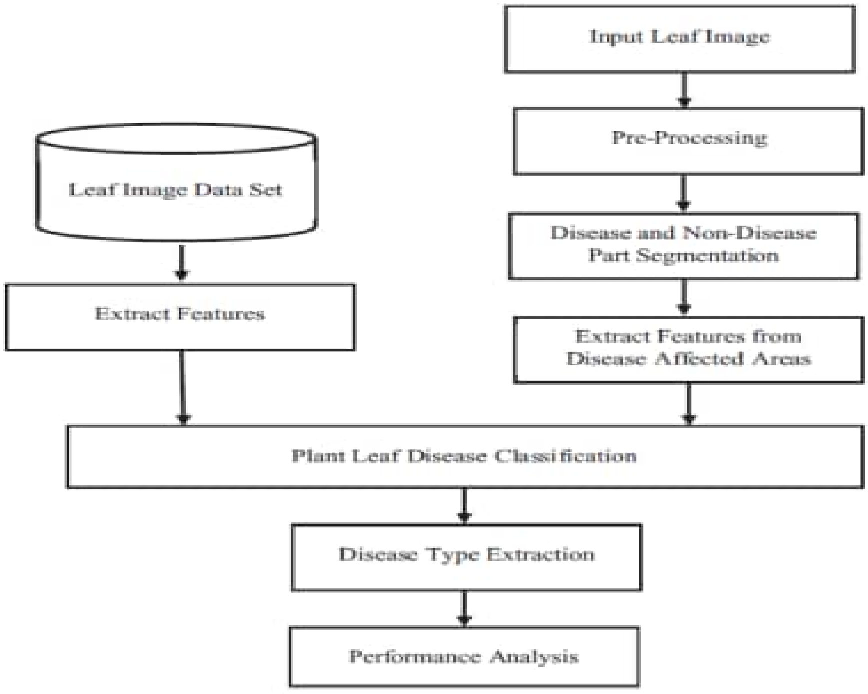

Fig 3. Block diagram of automatic disease identification system

Result and analysis

To assess the performance of the models, various parameters such as batch size, dropout, and different numbers of epochs were incorporated. The implemented models achieved disease-classification accuracy rates of 94.87%, 73.55%, 73.65%, 73.81%, and 97.33% using InceptionV3, VGG 16, VGG 19, CNN, and RESNET152V2, respectively, with respect to 10 epochs. These rates surpassed those of traditional handcrafted-feature-based approaches. In comparison with other deep-learning models, the implemented RESNET152V2 model demonstrated superior performance in terms of accuracy and required less training time. Through the utilization of deep learning models, leaf diseases are identified based on the pigments in the leaf, distinguishing between healthy and diseased leaves. The binary cross-entropy function is employed to calculate the loss. Increasing the number of epochs may enhance accuracy, but it also poses the risk of overfitting and increased waiting time. The trained model provides results and the probability of disease occurrence. This paper successfully achieves the goal of detecting diseases in leaves through the implementation of Convolution Neural Network.

TRAINING AND TESTING OUTCOME FOR CONVOLUTIONAL NEURAL NETWORK

CNN Model:

A Convolutional Neural Network (CNN) is a type of neural network model that enables the extraction of higher-level representations for image content. In contrast to classical image recognition, where features are manually defined, CNN takes raw pixel data from images, trains the model, and automatically extracts features for improved classification. Our models are built on convolutional neural networks, known for their effectiveness in image recognition and categorization.

The foundational model serves as a base, and we enhance its accuracy by adjusting hyperparameters and modifying the CNN model structure. The convolutional neural network comprises two layers using a 3 x 3 filter, with Rectified Linear Unit (relu) as the activation function. Relu is a commonly used activation function in deep learning models, returning 0 for any negative input and the input value for positive values (f(x) = max(0, x)). The output layer employs the sigmoid function.

Figure 4. Training CNN Model

In this study, we constructed a CNN model consisting of 32 filters in the convolutional layer, a kernel size of 3, and pooling size of (2,2). The architecture includes four convolutional layers with the rectified linear unit (relu) activation function. To reduce the dimensions of feature maps, four pooling layers were applied. Additionally, three dropout layers with rates of 50%, 10%, and 25% were incorporated. The Dropout layer randomly sets input units to 0 during training, preventing overfitting. The model was compiled using CNN with the Adam optimizer, a stochastic gradient descent method based on adaptive estimation of first-order and second-order moments.

The training process was conducted for ten epochs, where an epoch refers to one cycle through the full training dataset in artificial neural networks. Training a neural network for multiple epochs enhances its ability to generalize to new, unseen input data during testing. The model concludes with two fully connected layers followed by a dense layer with four units and a SoftMax for output. This extensive network comprises approximately 14,965,578 parameters, with 250,890 trainable and 14,714,688 non-trainable parameters.

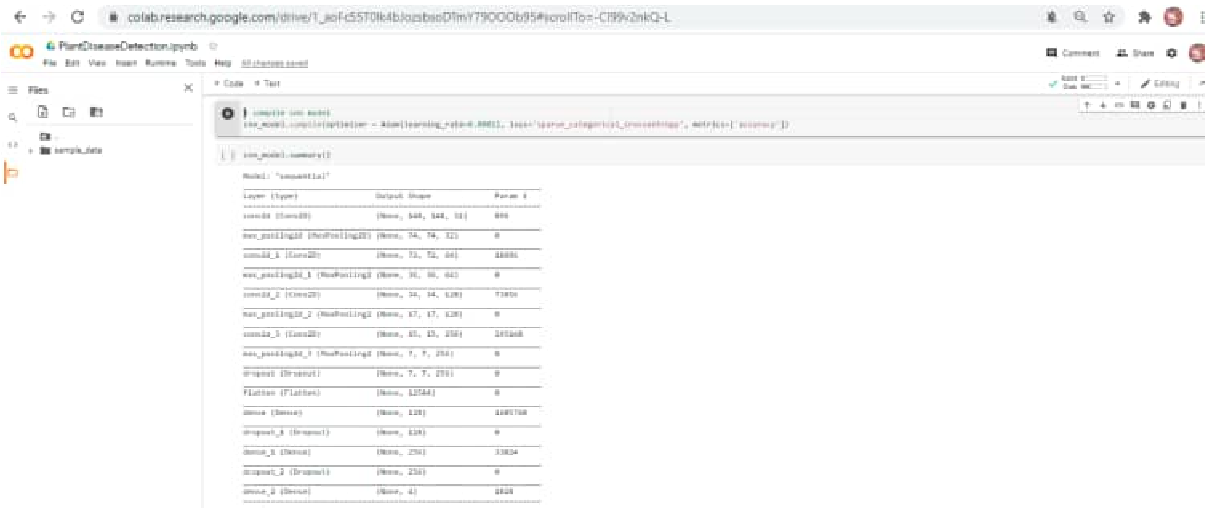

Figure 5: CNN Model Summary

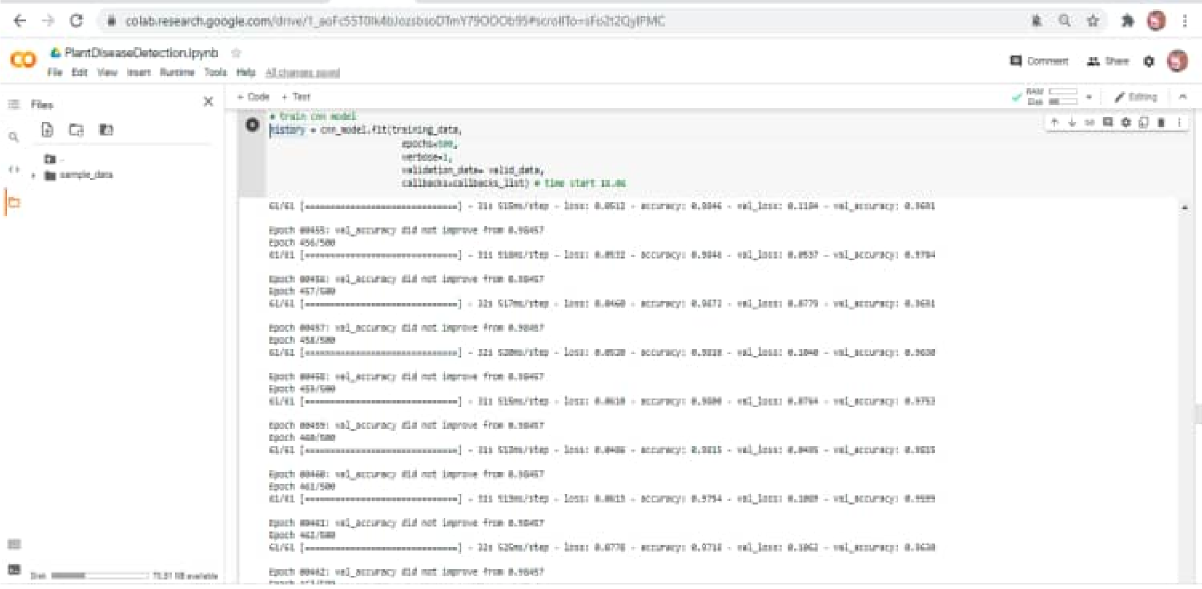

Figure 6: Accuracy of CNN Model

Accuracy and Loss are the two most well-known metrics in Deep learning. Accuracy is a method for measuring a classification model's performance. It is typically expressed as a percentage. Accuracy is the count of predictions where the predicted value is equal to the true value. It is binary (true/false) for a particular sample. Accuracy is often graphed and monitored during the training phase though the value is often associated with the overall or final model accuracy. In our CNN model initially accuracy was very low but with increase in epoch we received a high accuracy. Initially training and testing loss was very high and with increase in epoch loss started decreasing. After 10 epoch we received accuracy of 97.62%.

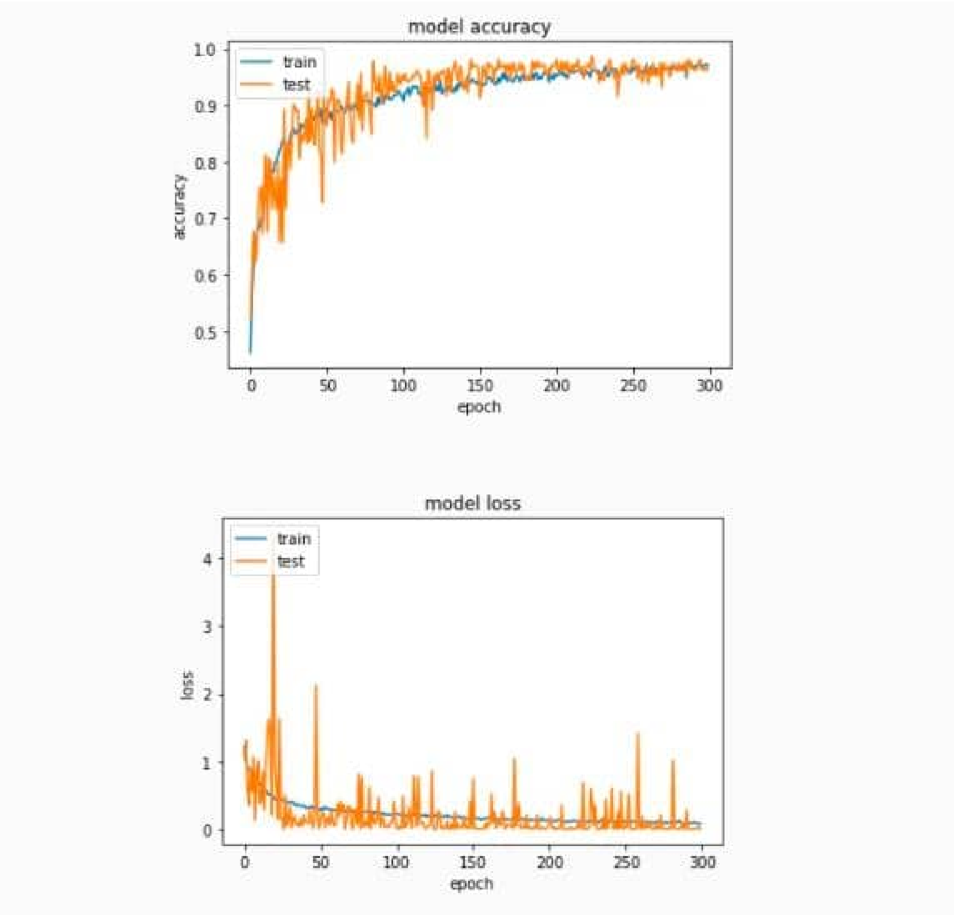

Figure 7. Accuracy and Loss of CNN Model

Table 1. TRAINING AND TESTING OUTCOME FOR CNN

Epochs	Training Data Lost	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	1.2668	0.4239	1.1550	0.8176
2	1.0705	0.5295	0.9566	0.9195
3	0.9644	0.5920	1.1414	0.9707
4	0.8841	0.6284	0.8928	0.9208
5	0.8573	0.6509	0.9468	0.9208
6	0.8248	0.6740	0.9649	0.9762
7	0.8101	0.6807	0.8196	1.0000
8	0.7123	0.6921	0.8876	0.9345
9	0.7111	0.7129	0.8926	0.9873
10	0.6912	0.7381	0.8997	0.9762

TRAINING AND TESTING OUTCOME FOR INCEPTION V3

Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifer to propagate label information lower down the network (along with the use of batch normalization for layers in the sidehead). Inception v3 is a convolutional neural network **for assisting in image analysis and object detection**, and got its start as a module for Googlenet. It is the third edition of Google's Inception Convolutional Neural Network, originally introduced during the ImageNet Recognition Challenge. We have tested same data set through Inspection V3 model and we receive 100% accuracy after 10 epoch.

Table 2. TRAINING AND TESTING OUTCOME FOR INCEPTION V3

Epochs	Training Data Lost	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	2.0140	0.7401	1.0249	0.7222
2	0.7547	0.8785	0.2171	0.9444
3	0.4645	0.9149	0.1363	0.9444
4	0.6390	0.9021	0.1251	0.9444
5	0.6016	0.9190	0.0513	0.9444
6	0.4437	0.9329	0.0368	1.0000
7	0.8518	0.9021	0.6182	0.9444
8	0.4498	0.9416	0.1105	0.9444
9	0.5562	0.9426	0.0010	1.0000
10	0.5157	0.9487	0.0010	1.0000

TRAINING AND TESTING OUTCOME FOR VGG 16 AND VGG 19

VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR(Imagenet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights. We have tested same data set through VGG16 model and we receive 77.78% accuracy after 10 epoch.

Table 3. TRAINING AND TESTING OUTCOME FOR VGG 16 AND VGG 19

Epochs	Training Data Lost	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	1.2868	0.4936	1.1249	0.5556
2	0.9862	0.6053	1.1933	0.6111
3	0.9024	0.6412	0.7966	0.7778
4	0.8691	0.6627	0.8158	0.6667
5	0.9322	0.6361	1.0051	0.6667
6	0.8368	0.6730	0.6658	0.7778
7	0.7391	0.7176	0.6687	0.7778
8	0.7539	0.6914	0.5906	0.7778
9	0.6641	0.7381	1.0657	0.7222
10	0.9751	0.6674	0.8098	0.7778

TRAINING AND TESTING OUTCOME FOR RESNET152V2

Residual Network having 152 layers variant. In this post, we will cover the concept of ResNet50 which can be generalized to any other variant of ResNet. Prior to the explanation of the deep residual network, I would like to talk about simple deep networks (networks having more number of convolution, pooling and activation layers stacked one over the other). Since 2013, the Deep Learning community started to build deeper networks because they were able to achieve high accuracy values. Furthermore, deeper networks can represent more complex features, therefore the model robustness and performance can be increased. We have tested same data set through Resnet 152 V2 model and we receive 88.89% accuracy after 10 epoch.

Table 4. TRAINING AND TESTING OUTCOME FOR **RESNET152V2**

Epochs	Training Data Lost	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	1.4618	0.8093	0.0069	1.0000
2	0.4206	0.9288	0.0103	1.0000
3	0.3835	0.9416	0.3192	0.8889
4	0.3231	0.9498	0.9201	0.8889
5	0.1914	0.9662	0.3125	0.9444
6	0.2973	0.9616	0.7044	0.9444
7	0.2958	0.9657	0.0167	1.0000
8	0.3025	0.9692	1.0431	0.9444
9	0.3309	0.9682	0.5506	0.9444
10	0.2806	0.9733	0.4829	0.8889

The trained InceptionV3, VGG 16, VGG 19, CNN and RESNET152V2 model is tested with different cotton disease; cotton stage and cotton weed image dataset. Parameters like accuracy value, loss value, ETA (Estimated time of arrival value) are computed. Diseases like cercospora leaf spot, fusarium wilt, verticillium wilt, and cotton boll rot, bacteria blight are recognized. Cotton stages like flower stage, cotton boll, matured cotton and barnyard grass, lambs quarters weed are also recognized. One Epoch is defined as the total of all images processed one time forward and backward individually in the convolution neural network. Epoch are used once to update the weights one

$$epoch = \frac{numberofiteration * batchsize}{totalnumberofimagesintrainin}$$

Conclusion

In this research, our objective is to compare the effectiveness of various deep learning methods, including conventional neural network (CNN), Inception V3, VGG 16, VGG 19, and RESNET 152, for identifying and diagnosing diseases in cotton leaves. The implementation of deep learning models was carried out using Python and the Keras package, with Jupyter serving as the development environment. Multiple experiments were conducted to optimize the model by adjusting parameters such as dataset color, the number of epochs, augmentation techniques, and regularization methods.

The performance of the models was evaluated by considering different parameters, including batch size, dropout rates, and varying numbers of epochs. The implemented models demonstrated disease-classification accuracy rates of 94.87%, 73.55%, 73.65%, 73.81%, and 97.33% using InceptionV3, VGG 16, VGG 19, CNN, and RESNET152V2, respectively, over ten epochs. These accuracy rates surpassed those achieved by traditional handcrafted-feature-based approaches. It was observed that increasing the number of epochs led to improved accuracy; however, it also raised the risk of overfitting. Notably, the RESNET152V2 model outperformed other deep-learning models in terms of accuracy while requiring less training time.

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