Disease Detection in Cotton Plants Using Deep Learning

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December 14, 2023

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***Abstract*—This article suggests utilizing deep learning models to classify cotton leaves from images captured on the field as a means of identifying any potential lessons. The scourge of agricultural pests and diseases looms large, especially in tropical regions where cotton cultivation is widespread. The pernicious menace has the potential to severely impede crop yields and inflict major financial losses on farmers. Effective solutions are needed for these problems; however, initial symptoms can be challenging to differentiate between making it difficult for farmers to correctly identify lesions. To address this issue, researchers have proposed using deep learning methods that allow monitoring of crop health and better management decision-making through screening of cotton leaves. The use of automatic classifier CNN will assist with classification based on training samples gathered from two categories resulting in low error rates during training and improved accuracy when classifying new data examined by our simulation results thus far suggest success within implemented networks at minimum overall detriment or deviation among other variations tested so far respectively**

***Index Terms*—CNN, ResNet50,InceptionV3, VGG-16, Deep Learning**

I. Introduction

Over 50 % of the world's populace also uses cotton-related materials. Diseases that affect cotton have a severe negative effect on the quantity and quality of agricultural development. They are a very real danger to us as well. The importance of gathering data on the healthy growth and development of cotton in real time is stressed in industrial farming and hydroponics. Information collected from a variety of sources can be used to anticipate cotton infections before they manifest themselves during the cotton manufacturing process. The conventional approach to diagnosing cotton diseases heavily depends on visual observations made by experienced cotton professionals or producers in the field. This calls for ongoing supervision by knowledgeable farmers, which could be prohibitively costly on large farms. Undoubtedly, it may be necessary for farmers in some emerging economies to journey a great distance to visit agricultural growers, which is time-consuming, expensive, and difficult to plan for. It's fascinating to see how technology is transforming agriculture. With the rapid advancements in image processing and information processing, we can now diagnose plant diseases more efficiently than ever before. This fresh approach could have a significant impact on food production and sustainability,. on the latest developments in agriculture and it seems like image recognition and machine learning could really revolutionize the way we monitor and maintain crops. With these technologies, we could quickly identify any signs of disease or other issues and take action before it's too late. It's exciting to think about the potential impact this could have on food production and sustainability. A branch of machine learning called deep learning stacks algorithms together to build artificial neural networks that can learn and decide for themselves. The goal of Deep Transfer Learning, a branch of artificial intelligence that predates deep learning, is to modify a learned model so that it can successfully complete a different job. A specific classifier that separates image categories using different methods has been developed as a result of numerous previous works that concentrated on image recognition. Due to improvements in digital cameras and rising computing costs, fully automated image recognition technology has obviously demonstrated good performance in recent years. It has produced amazing results in a variety of areas, including manufacturing output, biometrics, and medical image analysis. The majority of plant diseases are initially found on the leaves and stems, which can be instantly identified by sophisticated image processing tools. One of the earliest nations still engaged in cultivation is India. Traditional agricultural practices are still in use, which results in low crop yields and few advantages for farmers. The state of Indian agriculture has been impacted by numerous variables. Choosing a crop to plant is one of the most difficult tasks that producers must complete when raising crops. The productivity of the agriculture industry is also impacted by the rise of numerous crop-related diseases. The destruction of the majority of the output due to illness is one of the frequent issues. The prevalence of diseases in the plants grown hinders the production process in a significant way. This causes an emphasis on efficient strategies for identifying plant diseases. For farmers, the existence of different plant diseases is a significant concern minimal. In recent years, improvements have been made in the recognition of plant illnesses. In a recent study, researchers examined the effectiveness of CNN models and image processing for identifying and categorizing plant diseases. The study incorporated applicable criteria to determine the accuracy of the technology. The study components, incorporating the applicable criteria that follow.

II. ARCHITECTURE

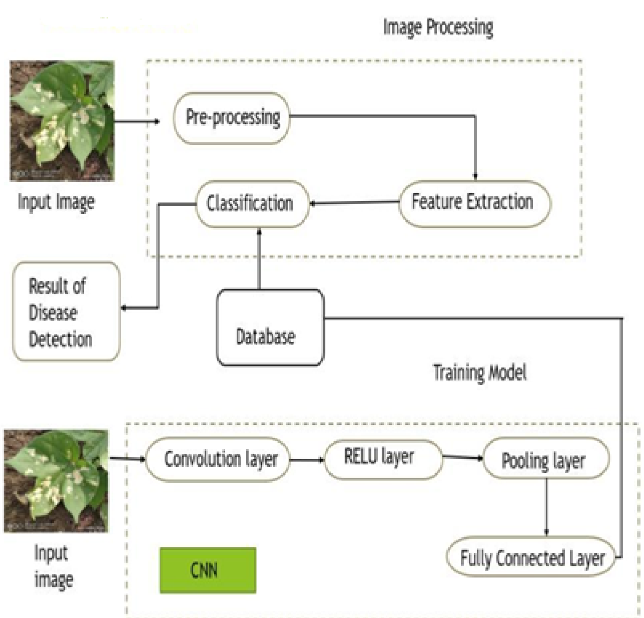

Fig. 1. Block Diagram

A. Maintaining the Integrity of the Specifications

Convolutional Neural Network (CNN) is a type of neural network that has found widespread application in deep learning for image and video recognition, natural language processing, and other domains. By automatically and adaptively learning spatial hierarchies of features from input data, such as images or videos, CNNs are designed to effectively exploit the spatial structure of the input data. This includes the ability to extract abstract and higher-level features by taking advantage of the spatial correlations between pixels in an image. In a typical CNN, the input data undergoes convolutional layers, where filters are applied to extract relevant features. These filters are then trained using backpropagation to learn to extract useful features for the task at hand. Following the convolutional layers, the output is passed through pooling layers, which down sample the feature maps while preserving the most important features. The integration of CNNs in agriculture is transforming the industry and has significant potential to impact food production and sustainability. With its ability to learn from input data, CNNs can be applied to various agricultural tasks, such as detecting plant diseases, predicting crop yields, and monitoring crop health. This technology has the potential to revolutionize the way we approach agriculture and ensure a more sustainable future for our planet. CNNs are an essential tool for deep learning, particularly for tasks that involve image and video recognition. They possess the ability to automatically learn hierarchical features from input data and achieve remarkable performance on a variety of tasks. After undergoing convolutional and pooling layers, the output is flattened and passed through fully connected layers for classification or regression. Overall, CNNs are an extensively used and powerful tool that can revolutionize industries such as agriculture.

III. METHODOLOGY

Accepts data in the form of three-dimensional images. Images are resized, annotated, and then run through the model during the data preprocessing step. Convolution Neural Network (CNN) is utilized for building up our blueprint. Similar to conventional supervised learning approaches, CNN gets input images, finds the features, and then rates them.

We have two distinct components to our system: Model for Training and Image Processing

A. Model for Training

The leaf image is fed into the training model and passes through four stages

- The first layer to extract features from the incoming images is the convolution layer.
- The picture passes through the RELU layer, which introduces non-linearity, after the convolution layer.
- When dealing with large images, it's important to reduce the number of parameters to improve performance. One way to do this is to send the image to the pooling layer after passing it through the RELU unit. This can help optimize the performance of CNNs, which are already a powerful and widely used tool for tasks like image and video recognition.
- Fully Connected Layer; capturing the characteristics of the pictures.

B. Image Processing

- Image pre-processing: Images that are higher clarity and resolution is needed. Every picture has been resized with a particular method and resolution. Image pre-processing uses data augmentation to eliminate noise from the images.
- Feature extraction: Some significant features of the defective leaf are discovered. It takes unstructured data and gets the structured data.
- Image Classification: Classification aids in measurement analysis to determine the groups to which

IV. IMPLEMENTATION

The following describes the phases of Google Colab's implementation.

- Data group gathering
- Inserting the file into the drive
- Opening Google Colab
- Mounting a disk
- Implementation, testing, and instruction for coding

A. Data group gathering

Images are captured through a web camera, they are stored in a database. These images are then transformed into both test and train images for future use.

B. Inserting the file into the drive

The test and train dataset, known as test cotton and train cotton, are uploaded using the submit folder option in Google Drive.

C. Opening Google Colab

Sign in to your Google accounts first. Go to the Google Colab welcome screen after that. To start a new session, select the new Python 3 notebook option. To pick GPU, use the runtime menu or notebook option. Set up the notebook instance to obtain the required files.

D. Mounting a disk

Select Mount Drive from the menu, Google Drive generates an authorization code to get the image folder path.

V. RESULT

Our research endeavors were aimed at the development of a bespoke Convolutional Neural Network (CNN) architecture, with the purpose of predicting cotton diseases. Our approach involved the implementation of a model comprising of four convolutional layers, each with filters of 32, 64, 128, and 256, consecutively followed by four max pooling layers. Subsequently, we applied a dropout of 50% to the output of the last max pooling layer, and subsequently flattened the output before feeding it into two fully connected dense layers. This systematic process facilitated the achievement of accurate and efficient prediction of cotton diseases.

Our team successfully implemented a bespoke Convolutional Neural Network (CNN) architecture for the accurate prediction of cotton diseases. To produce a probability distribution over the four possible classes, we incorporated two fully connected dense layers and a final layer with four neurons utilizing a softmax activation function. The initial dense layer was comprised of 128 neurons with a ReLU activation function and a 10% dropout, while the secondary dense layer consisted of 256 neurons with a ReLU activation function and a 25% dropout. Our systematic approach yielded efficient and precise results, allowing for optimal prediction of cotton diseases.

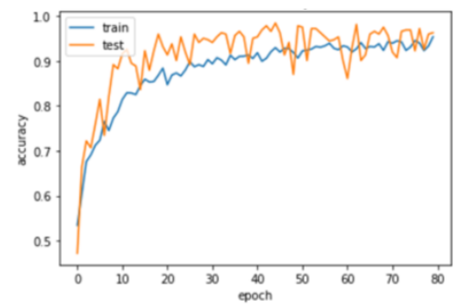

Fig. 2. Performance Evaluation for CNN model accuracy

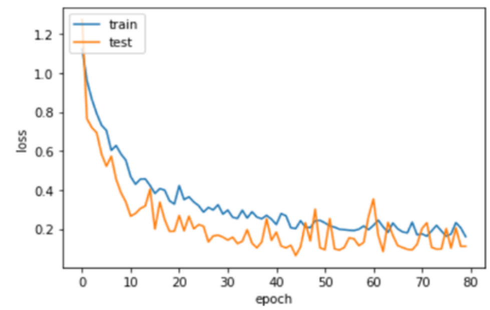

Fig. 3. Performance Evaluation for CNN model loss

The model was compiled using the Adam optimizer with a learning rate of 0.0001 and the sparse categorical cross-entropy loss function was utilized to calculate the loss during training. The model was trained for 80 epochs and the best-performing model was saved based on validation accuracy. This approach yielded highly accurate predictions of cotton diseases through a bespoke Convolutional Neural Network (CNN) architecture.

The trained CNN model achieved an accuracy of 0.9539.These results indicate that the model is highly accurate in predicting cotton diseases. The graph showed that the loss decreased as the epochs increased, indicating that it can effectively distinguish between healthy cotton plants and plants infected with different diseases. [h] [h]

VI. CONCLUSION & FUTURE SCOPE

Our study examined the effectiveness of a custom Convolutional Neural Network (CNN) architecture in predicting cotton diseases. The validation accuracy achieved by the architecture was 0.96, indicating high accuracy in prediction. The results demonstrate that this custom CNN architecture has the potential to be a valuable tool for the early detection and control of cotton diseases, leading to increased crop yield and reduced economic losses for farmers. In summary, our study highlights the efficacy of the custom CNN architecture in predicting cotton diseases, with a validation accuracy of 0.96. This technology has the potential to become an important asset in the cotton industry for detecting and controlling diseases, ultimately contributing to the improvement of crop yield and economic sustainability for farmers.

Our future plans include the creation of a more comprehensive dataset that encompasses a wide range of attributes, as well as the application of yield predictions, preventative and corrective measures, the use of pesticides, and the likely cost of suggested pesticides. If adequate data is available for another crop, we can expand the system to accommodate it. Moreover, we can incorporate other illnesses for identification and use IoT devices to capture images in fields. Finally, we may include a forum on the web interface where users can discuss the patterns in various diseases they are currently experiencing.

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