IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

COTTON PLANT AND LEAF DETECTION USING DEEP LEARNING

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Abstract:

Agriculture is a major industry in many nations, including India. Because farm output accounts for a large portion of the Indian financial system, careful examination of Critical challenges with food production exist. Crop infection nomenclature and identification now hold more scientific and financial weight in the agricultural industry. It may be highly expensive to keep track of plant ailments in an agricultural area with the assistance of professionals. A technique or system that can automatically diagnose is required. diseases because it has the potential to revolutionize monitoring. Massive crop fields and plant leaflets can be taken. Cotton leaf disease diagnosis is critical for preventing a catastrophic outbreak. Immediately following disease recognition, the purpose of this study is to provide guidance for the creation of an application that recognizes cotton plant leaf diseases. To use this, the user must first submit a photograph of a cotton leaf, and then use image processing to obtain a digitized color image of a damaged leaf, which may then be processed further by applying the mobilenet algorithm to anticipate the true root cause of the cotton leaf disease.

Keywords: Cotton plant, Cotton leaf, Disease, Detection, mobilenet, ResNet-50, Feature extraction,Image classification.

Introduction:

Agriculture, according to our nation's father, Mahatma Gandhi, is the backbone of the Indian economy. India is the world's second-largest agricultural producer. Farmers in India plant a limitless range of crops. It accounts for around 41.49 percent of Indian jobs and provides 18% of total GDP. Fast agricultural growth is critical not just for self-sufficiency but also for earning crucial foreign exchange.

Numerous factors, including climate circumstances, soil conditions, numerous diseases, and so on, impede crop yield. Detection of plant diseases will now be an important factor in a crop's overall production. Currently, the only way to identify plant diseases is via visual inspection, which requires more human labor, specially designed laboratories, and other resources. costly gadgets, and so on. Inadequate disease diagnosis may have resulted in erroneous pesticide use, which can contribute to the development of long-term pathogen resistance, limiting the crop's ability to back off. By looking at several parts of the affected plant, plant diseases can be found. Image processing utilizing Mobilenet is the approach used to detect plant diseases.

A. Objectives

Using pesticides and other treatments, crops can be shielded against pests. The major goal is to use image processing to identify plant diseases. By using the proper size reduction strategies, we may reduce the size of the photographs without significantly sacrificing quality. The above stated authors' work can be expanded upon such that the system also demonstrates the disease's cure. The algorithm suggests the name of the right insecticide to apply when the illness has been identified. The pathogens that cause the sickness are likewise named. This effort may also save time in addition to these related goals. In large-scale farming, the model budget would be cost-effective despite being relatively expensive for small-scale farming. Because it completes each operation in order, each result is produced.

Therefore, the key goals are: 1) To create a system to correctly identify crop disease and pest.

2) Establish a pesticide database for a specific pest or illness.

3) To provide a cure for the recognized condition.

B. Aims ‘

The creation of a system that can identify agricultural illnesses is the goal of this endeavor. In order to begin processing a picture, the user must first load a digital color image of the sick leaf into the computer. Plant disease can eventually be anticipated based on Mobilenet.

C. Identifying the issue

To stop a serious epidemic, it is absolutely essential to recognize cotton leaf disease. Insects, bacteria, and fungus are the main causes of cotton illnesses. To avoid the crops from suffering significant losses, a novel technique is suggested for thorough disease diagnosis and prompt treatment.

1. Related works:

Cotton Leaf Spot Diseases Detection Using SVM Classifier and Image Processing:

Cotton is one of among the most significant cash crops in India, where the majority of farmers grow it extensively. Over the past few decades, cotton diseases have caused a significant loss in production and output. It's crucial to diagnose cotton illnesses at an early stage. The aim of our proposed study is to develop a system for the automated identification of illnesses affecting cotton leaves utilizing a straightforward image processing technique. SVM classifier is used for classification based on choosing acceptable characteristics from pictures, such as color and texture. The photos were taken using a digital camera among cotton fields. Filtering, removing the background, and enhancing are just a few of the preprocessing methods used. To extract the sick segmented portion from the cotton leaf, color-based segmentation is used. Feature extraction is carried out on a segmented picture.

Using IoT, a machine learning regression approach for detecting and managing cotton leaf disease

Indian farmers rely heavily on cotton as one of their main income crops. Because of the disease's attacks, cotton productivity is decreasing yearly. Insect pests and pathogens typically cause plant diseases, which if not promptly managed, significantly reduce yield. In addition to describing a system for monitoring soil quality, this work also describes a method for detecting and treating illnesses that affect cotton leaves. The research suggests a Support Vector Machine (SVM) based regression approach for identifying and categorizing five cotton leaf diseases, including Microbial Blight, Alternaria, to Gray Mildew, Cereospra, and Fusarium wilt. An Android app will be used to inform farmers of a disease's name and treatment options when it has been detected. Along with the water level in a tank, the Android App is also utilized to display data for soil characteristics including temperature, wetness, and humidity. Farmers may control the motor and sprinkler system by turning the relay ON or OFF using an Android app. The Raspberry Pi is used to connect the sensors for monitoring soil quality as well as the systems for detecting leaf disease, making it a self-sufficient and reasonably priced system.

From unrestricted photos, diseases may be detected and their severity can be estimated in cotton plants.

The main goal of this study is to use photographs to identify illness in a cotton plant and determine its stage. The cotton leaf reflects the majority of illness symptoms. The originality of the idea, in contrast to past methods, is in analyzing photographs taken in the field by an inexperienced individual using a regular camera or a cell phone under uncontrolled circumstances. Leaf segmentation is quite difficult in such field photos because of the dense background. The two cascaded classifiers used in the proposed study. Leaf is separated from the background using a first classifier using local statistical characteristics. Another classifier is then trained to identify diseases and determine their stages using hue and brightness from the HSV color space. The created algorithm is versatile and may be used to treat any illness. The widespread fungal illness Grey Mildew, which is found in North Gujarat, India, serves as a showcase, though.

automated extraction of three different cotton leaf diseases' characteristics from digital images:

The technology revolution is advancing the world. In practically every aspect of life, computers are seen to be the key component. Applications of biotechnology are vitally important in this case since they can help address difficult issues. Agriculture includes the cotton plant as a significant industry. Infection of that specific plant might result in losses for the agricultural industry as well. The goal of this essay is to discuss cotton disease and how severe it is depending on the time of year. The Pakistani economy greatly benefits from the growth of the cotton plant, one of the essential plants that are grown there in large quantities. Each year, certain extremely dangerous diseases damage cotton plants, reducing the yield and quality. Due to the fact that in this research we provide a way to determine the severity degree of a frequent and complicated illness called Cotton leaf curl illness (CLCuD) by applying methods of image processing and machine learning approaches. When extracting data from an input image, color and texture characteristics are utilized, and deep learning is applied for decision-making. A 1600 picture dataset is put up for the experimenting procedure. The classification is performed using a Deep Convolutional Neural Network (CNN). In terms of correct identification and classification, the suggested model has a cumulative accuracy of 89.4%. The results of this study will be helpful to harvesters both domestically and abroad, and they may be utilized to develop time-based preventive strategies to lower loss percentages.

A study on the identification and grading of illnesses affecting cotton leaves:

Indian farmers' primary source of income is cotton. Out of all the cash crops grown in the nation, it is sometimes referred to as "White Gold" or "The King of Fibers." The diseases Alternaria leaf spot, Cercosporin leaf spot, Bacterial blight, and Red spot account for about 80–90% of illnesses that affect cotton leaves. Detection and categorization of illnesses affecting cotton leaves are covered in this article. The precise form of leaf disease that affects a plant's leaf might be challenging for human sight to recognize. Thus, using image processing and machine learning approaches can be useful for reliably identifying the illnesses of cotton leaves. Digital cameras were utilized to capture the photographs from the cotton field that were used in this project. The backdrop of the image is removed using a background removal technique during the pre-processing stage. The background-removed pictures are then subjected to further processing utilizing the Otsu thresholding approach for image segmentation. To extract elements like color, shape, and texture from the photos, several segmented images will be employed. Finally, the classifier will employ these extracted characteristics as inputs.

2. Methodology:

Proposed system:

In the suggested system, we suggest a Deep Learning method that uses Mobilenet and ResNet-50 with transfer learning models to automatically identify the photographs. This technology might be extremely helpful in solving such issues. These methods make it simple to find and recognize illnesses. Therefore, accurate categorization is crucial for the correct therapy, which will be made feasible by applying the technique we have suggested. Below is a block schematic of the suggested technique.

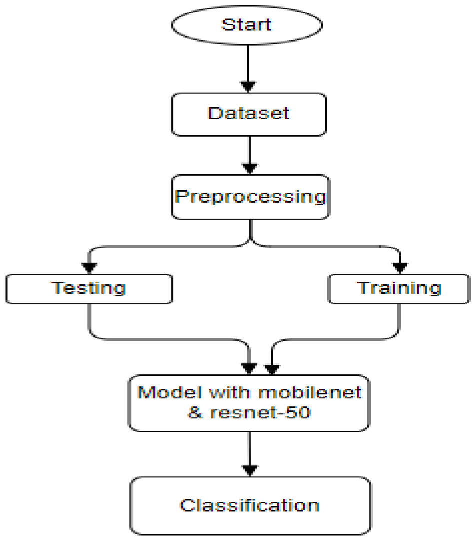


Figure 1: Block diagram of proposed method

3. Implementation:

The project has been put into practice using the algorithm mentioned below.

Mobilenet:

A deep learning system called mobilenet was created by researchers at Google in 2017. The technique was created to support embedded and mobile devices with little memory and processing capacity for on-device machine learning applications.

In order to separate the ordinary convolution operation into the two smaller operations of depth wise convolution and pointwise convolution, a technique called depth wise separable convolution, which is the foundation of mobilenet, is used. Traditional convolutional neural networks use a basic convolution operation that applies a filter to the whole input tensor, resulting in a lot of parameters and calculations. To combine the result of depth wise convolution, pointwise convolution applies a 1x1 filter to each input channel, in contrast to depth wise convolution, which applies a single filter to each input channel. Convolutional layers' computational expense is decreased while accuracy is maintained.

Additionally, mobilenet employs a method known as linear obstructions, which further minimizes the quantity of filters utilized in the layers of convolution. Before the convolution in depth wise and after the pointwise convolution, a linear bottleneck layer decreases the total number of input channels and increases the number of output channels. This method makes the calculation process more efficient while preserving accuracy by reducing the amount of parameters and calculations needed.

There are many variants of Mobilenet that range in size and accuracy. 28 elements and 4.2 million characteristics make up the original Mobilenet, whereas 53 layers and a total of 3.4 million parameters make up MobileNetV2. Accuracy and speed have both increased with MobileNetV3.

In order to classify images and identify objects on mobile devices, mobilenet has been extensively employed. It is used, as an illustration, in Google's TensorFlow Lite programming structure, which offers a collection of tools for creating machine learning applications for mobile and embedded devices. For the purpose of object identification and picture classification, TensorFlow Lite comes with a have been trained version of Mobilenet.

Other real-time applications, such mobile robots and self-driving cars, where low latency is essential, employ Mobilenet as well. Machine learning activities must be able to be completed on-device in these applications in order to decrease latency and boost responsiveness.

Compared to conventional convolutional neural networks, Mobilenet offers a number of benefits. First of all, it is far more effective in terms of memory utilization and computational cost, making it appropriate for use on embedded and mobile devices. In addition, it uses less parameters and calculations to achieve excellent accuracy compared to conventional convolutional neural networks. Last but not least, developers who are already familiar with deep learning frameworks like TensorFlow and PyTorch may use it because it is simple to integrate into them.

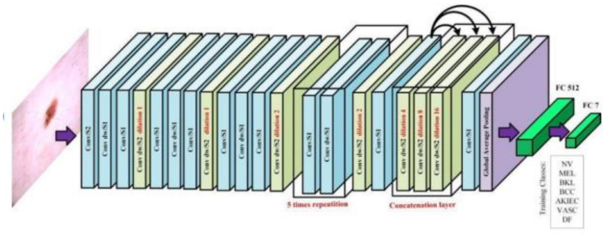


Fig. Architecture diagram of Mobilenet

However, Mobilenet also has some limitations. Due to its simplified architecture, it may not be as effective as traditional convolutional neural networks for certain tasks that require more complex processing. Additionally, its accuracy may be lower than traditional convolutional neural networks for certain image classification tasks that require high precision.

In summary, Mobilenet is a deep learning algorithm designed for mobile and embedded devices with limited computing power and memory. It is based on the idea of depth wise separable convolution and linear bottlenecks, which reduce the computational cost and memory usage of convolutional layers while maintaining accuracy. Mobilenet is widely used for image classification and object detection tasks on mobile devices, and has several advantages over traditional convolutional neural networks, including efficiency and accuracy. However, it may not be as effective for certain tasks that require more complex processing, and its accuracy may be lower for certain image classification tasks.

ResNet-50:

Kaiming He et al. Proposed the deep convolutional neural network (CNN) architecture known as ResNet-50. in 2015. It is primarily utilized for images recognition tasks and is a ResNet architecture variant.

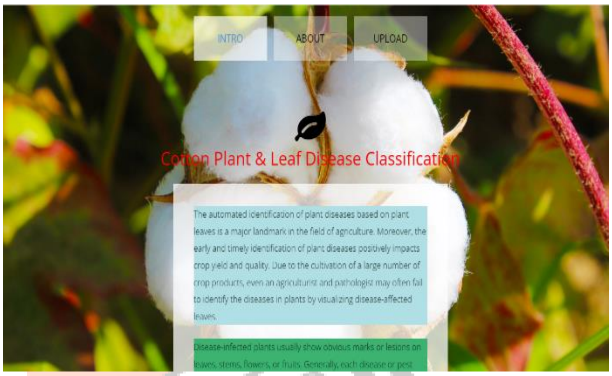
The 50-layer ResNet-50 architecture makes use of skip connections, also known as residual connections.The network can learn residual functions that can be added to the input through these connections, bypassing one or more layers. In deep netural networks, the vanishing gradient problem can arise when the gradient signal becomes too weak to effectively update the weights of earlier layers. This help to mitigate this issue. The ResNet-50 design comprises of various lingering blocks, with each block comprising of numerous convolutional layers and a skip association.The initial feature extraction is carried out by a 7×7 convolutional layer with stride 2. A max pooling layer with stride 2 that reduces the feature maps' spatial dimensions comes text .

The residual blocks that make up the remainder of the network are made up of multiple 3×3 convolutional layer, a skip connection , and a batch normalisation layer.Starting at 64, the number of filters in each block gradually grows, and it doubles after each max pooling layer. The last result of organisations is created by a worldwide normal pooling layer that midpoints the component maps over the spatial aspect and a complelely association layer with softmax enactment.ImageNet, COCO and PASCAL VOC are just a few of benchmark image recognition dataset that ResNet-50 has outperformed.The use of batch normalisation, which helps to reduce the effects of covariate shift and improves the network's stability during training, and use of residual connections which enable the network to effectively learn representation of the input data, are to blame for its success.In conclusion, ResNet-50 is a deep convolutional neural network architecture that enables the training of very deep network my marking use of residual connections.It as been extensively utilized in numerous computer vision applications and has demonstrated cutting-edge performance on a number of benchmark image recognition tasks .

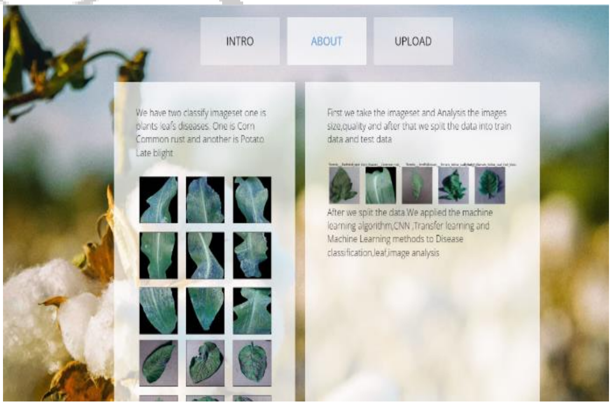
4. Results and Discussion:

The procedure of our project will be clearly represented in the photographs below.

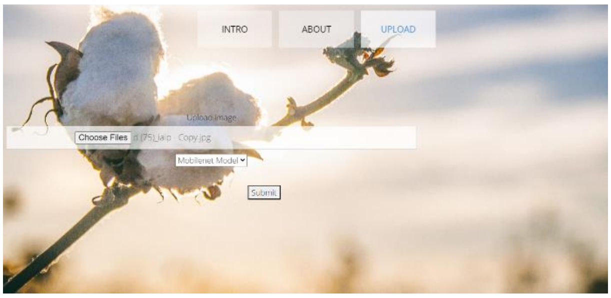
Home page: The Cotton Leaf Decision Prediction homepage may be found here. Here we can see the modules of the project.



About page: It's all about a page where we can get to know the process (working) of project.



Upload page: Here we should upload the image which needs to classify and predict.



Prediction: This page displays predicted image with disease.

5. Conclusion:

In this project we have successfully classified the images of defected images of cotton plant and leaf, is either affected or normal using the deep learning techniques. Here, we have considered the dataset of cotton plant and leaf images which will be of 2 different types (affected and normal) and trained using Mobilenet along with transfer learning methods. After the training we have tested by uploading the image and classified it.

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