INDIAN AGRICULTURE USING DEEP LEARNING TECHNIQUES

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Abstract: Crop diseases are a significant threat to food security, however, due to the lack of the requisite resources, their rapid detection remains difficult in many areas of the world. Plants play a key role in climate change, agriculture and the economy of the world. It is really important to take care of the plants. Like humans, plants are infected by a variety of diseases caused by bacteria, fungi and viruses. The timely diagnosis and healing of these diseases is necessary to avoid the degradation of the whole plant. Crop diseases are a significant threat to food supplies. As a part of the rise of mobile technology around the board. It has now become theoretically possible for the world to utilize Image analysis methods for plant form of identification Illness from a clear picture. This paper proposes a deep learning model called a plant disease detector. The model is capable of detecting a variety of diseases from plants using images of their leaves. Identifying diseases will lead to faster measures that can be applied to reduce the impact of crop diseases on food supplies. So here are using the concept of Convolutional Neural Network to detect Plant Disease Detection.

I. INTRODUCTION

Indian Agriculture is one of the vast fields where the latest technologies of deep learning can be utilized. We can use deep learning to detect plant, also we can use deep learning to detect the plant disease detection. In this project we will be doing detection of plant disease detection, which is on rog the important application of deep learning in the field of Indian agriculture. Convolutional Neural Network is the Neural Network that we are using to detect images. Here we are identifying the disease by training model using the images of plant diseases.

Despite having seen numerous changes in mass production and access to food, food security remains compromised by a number of factors, such as the loss of pollinators and plant diseases. In the developed world, more than 80% of agricultural production is produced by smallholder farmers and records a loss of yield of more than 50% due to pests and diseases are common.

In particular, smartphones provide very innovative approaches to help detect diseases due to their processing power, high-resolution screens and robust built-in accessories, such as sophisticated HD cameras. It is currently projected that about 6 billion phones will be available in 2050. The input to the algorithm in this paper would be 2D photographs of diseased and stable plant leaves. I would use a deep convolutionary network, a generative adversarial network, and a semi-supervised learning approach that uses a network of ladders. These various methods would be used to create a projected type of disease or a type of stable plant organisms.

Some of the typical symptoms of disease in plants are Leaf rust, Stem rust, Sclerotinia, Powdery mildew, Birds-eye spot on berries, Damping of seedlings, Leaf spot, Chlorosis. These diseases can be defined by the physical state of the leaves of plants. Experts can identify whether the plant is defective or not by looking at the leaves or the fruit. This strategy requires a lot of human capital for this particular work. In this age of technology and automation, it is not a very effective solution, it would be much safer if we had an integrated device that automatically identifies disease in plants.

In this era of technology and automation, it is not a very efficient approach, it would be much better if we had an automated system that automatically detects disease in plants. A lot of research has already been conducted to achieve this aim, most of which use conventional machine learning methods. The aim of this study is to create such an automated system for the detection of plant diseases by means of a deep learning technique. Deep learning is a sub-set of machine learning. The advantage of deep learning over machine learning is that one does not need to worry about domain expertise because, unlike traditional machine learning approaches, there is no need for feature engineering. Like other previous research, our method uses photographs of plant leaves to diagnose disease in plants. Plant Disease Detector is an automatic plant disease diagnostic device focused on computer vision, which uses machine learning methods to accurately distinguish disease and stable plants, including the type of disease. An image-based deep learning network such as Convolution neural network (CNN) can be used to accomplish this. CNN is used to remove characteristics from images, such as horizontal borders, vertical borders, RGB values, etc. CNN is the best deep learning neural network to extract visual features. The CNN-based network can be learned to diagnose disease in plants by supplying a large amount of images of healthy and sick plants, and a developed model can be used in the future to predict disease in plants by images of leaves.

II. <u>RELATED WORKS</u>

→***<u>Plant Disease Classification</u>***

Until the issue of the detection of crop diseases can be overcome, the issue of the identification of different species of plants needs to be discussed. Luckily, a lot of work has already been done in this problem field. In the research paper, A Model of Plant Identification System Using GLCM, Lacunarity, and Shen Features, researchers have gone through a variety of pre-processing steps that can be done to extract important features for binary class classification. Photos are transformed by using the Polar Fourier Transform to achieve translational and rotational invariance. Color characteristics, such as mean, standard deviation, skewness, and kurtosis, are seen on the pixel values of the leaves. Finally, the study paper introduced features that derived from the Gray Level Co-Occurrence Matrix (GLCM). The GLCM functions characterize the texture of an image by measuring how often pixel pairs of unique values and in a given spatial relationship occur in an image, generating a GLCM, and then extracting statistical measurements from this matrix. While crop disease detection is moving away from hand-engineered features such as SIFT, HoG, and SURF, there are still a number of techniques that allow deep learning networks to extract important features such as history. It's segmentation. The method used in the experiments will be explained in the section on the methods. In the study paper Plant Leaf and Disease Identification Using HSV Features and SVM, researchers suggested using a neural network to assess whether or not a leaf was infected. If the leaf was contaminated, the images were further analyzed by a neural network, where a genetic algorithm was used to maximize the SVM failure to assess the type of disease. This approach is very unique in that it breaks down the detection of the disease mechanism in two steps. It's going to be interesting to compare and contrast with More recent reports, in which safe leaves are viewed as yet another class name. As a consequence, classification is achieved in a single stage. In addition, the study paper proposes a framework for maximizing the loss function using a genetic algorithm that can be compared to the natural selection where only strong hyperparameters can survive. I need to do more studies on how genetic algorithms compare to other types of computing failure, such as Adam, RmsProp, and so on. Ultimately, similar to the article, A Model of Plant identification. Method Using GLCM, Lacunarity, and Shen Characteristics, the emphasis was on defining essential features of the picture to aid in the classification process.

→***<u>Plant Disease Classification using Convolutions</u>***

Other study has progressed towards the use of convolutionary networks to boost performance. Convolutional Networks are a group of Neural Networks that have proved to be very effective in fields such as image detection and classification. ConNets have been effective in recognizing faces, objects, etc. And road signs rather than control vision in robotics and self-driving vehicles. ConvNets takes its name from the "convolution" operator. In the case of ConvNet, the primary objective of Convolution is to remove features from the input image. Convolution retains the spatial relationship between pixels by using tiny philters to learn image functionality.

Some of the important parts of Convolutional Neural Networks are: -

- ➔ Depth
- ➔ Stride
- ➔ Zero-Padding
- ➔ Non-Linearity
- ➔ Spatial Pooling

III. <u>METHODOLOGY</u>

Deep learning is a versatile machine learning approach that has mitigated the conventional machine learning headache of function engineering. No domain knowledge is required now, and all credit goes to deep learning. Artificial neural network (ANN) is the core of deep learning. Artificial neural networks are mathematical structures that reproduce their neurons and synapses, interconnecting them with the general concepts of brain function. One of the most standard libraries to build a neural network is TensorFlow. Provides all libraries applicable to the artificial neural network. With the support of TensorFlow, both text and image classification tasks can be done.

→*Convolutional Neural Network*

Convolution Neural Networks (CNNs) are used to diagnose disease in the leaves of the plant. CNN is a simple ANN evolution that gives a better picture result. That the pictures involve repeated patterns about a single object. Convolution and pooling are two essential features of CNN. Convolution is used to identify pattern edges in an image and pooling is used to minimize the size of an image. CNN architectures added to the problem are as follows:

(a) Basic CNN,
(b) VGG,
(c) InceptionV3.

In addition, the training of these models is performed using the Jupyter notebook and the TensorFlow Keras API. Keras is a high-level API tensioner for developing and training deep learning models.

→*Dataset and Features*

Two datasets are used to diagnose plant diseases. The first dataset consists of 15 classes and the second consists of 38 classes. Both databases provide a number of photographs for each plant. The first dataset has a limit of 2952 images. The final results of this work are on the dataset of PlantVillage, which includes 38 groups of different plants. It is also freely accessible on the Internet. Each class comprises around 2,000 pictures. There are 14 different plants present in this data collection. Good as well as diseased photographs of leaves are possible for any herb. Some of the photos refer to the plants of Tomato and Apple. The least photos are from the Raspberry, Soybean, and Squash classes. Below, the graphic displays several images of the various leaves that are available in the dataset.

a) Sample Images

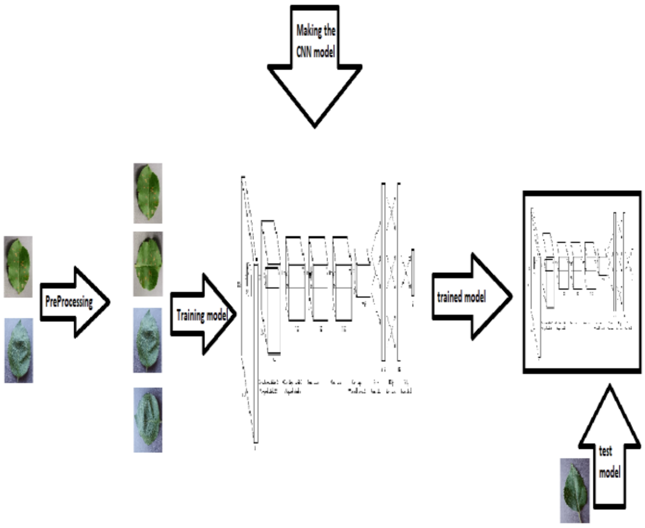
→*Model Description*

Next, some pre-processing is added to the dataset in the form of an improvement in the scale of the dataset in order to ensure greater accuracy. Then the resolution of the images is limited by 256x256 pixels. After this, a convolution neural network-based model will be generated with several pooling and convolution layers and a dense prediction layer. Five convolution layers with a 3x3 philter and five MaxPooling2D layers with a 2x2 philter are included. Batch Normalization is also used for this model. Batch normalization is used to scale data on a particular scale, but the distinction is that it does so only on the input layer, but also on other hidden layers. At last, the model is conditioned on the dataset of PlantVillage.

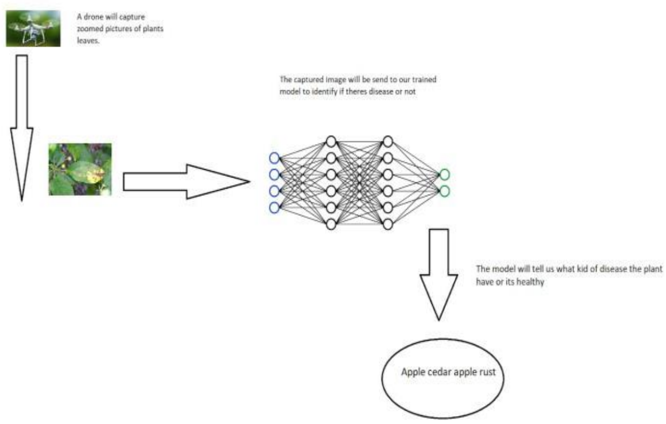
b) Training Parameters

Parameter	Value
Epochs	25
Batch Size	35
Activation (Middle Layer)	Relu
Activation (Finals Layer)	SoftMax

c) Figure Showing Plant Disease Detection

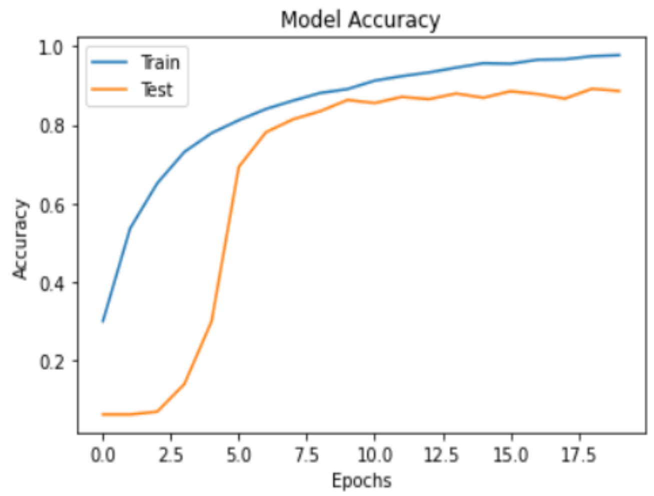


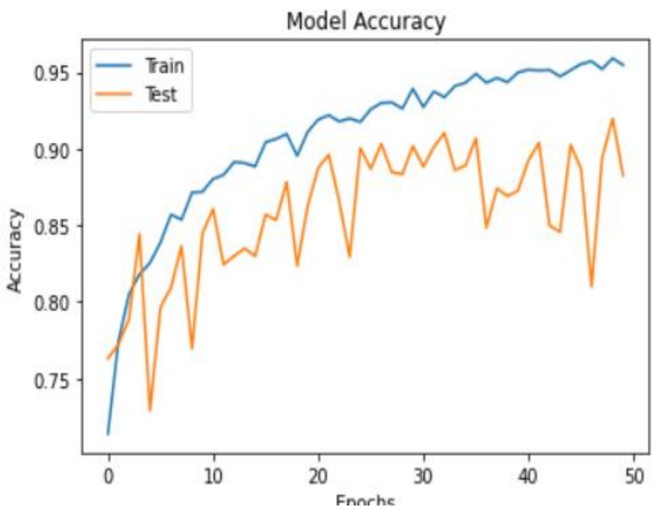
d) Methodology



IV. RESULT

This research demonstrates the importance of the diagnosis of plant diseases in these days. This model was created using Deep Learning in python. 20 percent (14,059) of the photographs from the dataset of PlantVillage were used to test the accuracy of this model. These pictures come from 38 different groups. 20% of each class randomly chosen for research. Any real-time photographs have also been used. These photos have been taken from the surrounding setting. They do not belong to any class that is present in the dataset. But the model gives us more than 95% accuracy on those photos, as well as saying that any leaf is safe and unhealthful. A total of 100 photographs have been used and 96 have been accurately identified. Many of the photographs were taken at night with the aid of flashlight, and some of the photographs had debris so that they were misclassified. Research dataset gives more than 98 percent accuracy. This indicates that 1379 images of 14,059 images have been correctly identified by model. Below is the Training and Validation Accuracy Graph generated by our test dataset model.





e) Training Graphs

Groups such as Corn (Maize) Stable, Tomato Mosaic Virus, Strawberry Stable, and Corn (Maize) General Rust have approximately 100 percent precision. Just 1 to 5 photos misclassified from them. Apple Cedar apple rust, Cherry (including sour) healthy, Grape Black rot and Raspberry healthy classes offer less accuracy than other classes. Below is a picture class table that gives us greater consistency when checking our model.

MODEL	Training Dataset	Testing Dataset	Training Accuracy	Testing Accuracy
CNN	80%	20%	96	95
CNN	80%	Actual	96	95

The above mentioned is the end result and accuracy of the model that is created.

V. CONCLUSION

This thesis used deep learning capabilities to achieve an automated plant disease detection system. This system is based on a simple classification mechanism that exploits the features of CNN extraction. Finally, the model uses entirely linked layers for estimation. The study was carried out using a freely available array of 70295 images and 100 images from laboratory environments and the real world. The device has obtained a cumulative test accuracy of 98 percent on publicly available datasets and has done well on photographs of Sukkur IBA University plants. It is inferred from the precision that CNN is extremely suited for automated plant identification and diagnosis. This system can be integrated into mini-drones to live the detection of diseases from plants in cultivated areas. Although this machine is trained on the dataset of Plant Village of just 38 grades, it could say whether or not the plant has a disease, since somehow the signs are the same in all kinds of plants. In addition, more actual photographs of the ecosystem will be applied to the data collection to boost the precision of real-life photographs of leaves and to identify more plant varieties as well as disease varieties. In the future, this device will also follow a 3-layer approach where the first layer detects whether or not there is a plant in the picture, the second layer tells the plant type, and the third layer tells whether or not there is a disease and what type of disease there is, if any.

VI. REFERENCE

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