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Crop Disease Detection Using Neural Network and Machine Learning Algorithms

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Abstract: *Diseases in crop cause major production and economic losses as well as reduction in both quality and quantity of agricultural products. Now a day's crop diseases detection has received increasing attention in monitoring large field of crops. Farmers experience great difficulties in switching from one disease control policy to another. The naked eye observation of experts is the traditional approach adopted in practice for detection and identification of crop diseases. In this paper we review the need of simple crop leaves disease detection system that would facilitate advancements in agriculture. This paper proposes a smart and efficient technique for detection of crop leaf diseases with the help of image processing and neural networks. The proposed system is able to detect 14 diseases of 11 common crop with 98 percent accuracy for 24 classes from a total of 34236 images.*
Key Word: *Disease Detection, Image acquisition, pre-processing, features extraction, classification, symptoms, neural network, machine learning, accuracy.*

I.INTRODUCTION

India is an agricultural country wherein most of the population depends on agriculture. Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure, with increased profit. Agricultural production system is an outcome of a complex interaction of soil, seed, and agrochemicals.

Vegetables and fruits are the most important agricultural products. In order to obtain more valuable products, a product quality control is basically mandatory. Many studies show that quality of agricultural products may be reduced due to crop diseases. Diseases are impairment to the normal state of the plant that modifies or interrupts its vital functions such as photosynthesis, transpiration, pollination, fertilization, germination etc. These diseases are caused by pathogens viz., fungi, bacteria, and viruses, and due to adverse environmental conditions. Therefore, the early-stage diagnosis of crop's disease is an important task. Farmers require continuous monitoring of experts which might be prohibitively expensive and time consuming. Therefore, looking for fast, less expensive, and accurate method to automatically detect the diseases from the symptoms that appear on the crop's leaves are of great realistic significance. The objective of this paper is to concentrate on the crop leaf disease detection based on the texture of the leaf. Leaf presents several advantages over flowers and fruits at all seasons worldwide.

In our research we have employed various neural network models on the chosen dataset which is refined using various data cleaning and augmentation techniques. We have used image processing to detect various abnormalities in the crop by analyzing their leaves. Image Processing is a procedure to change over an image into digital shape and play out a few operations to get an enhanced image and concentrate valuable information from it. The neural network models used by us are CNN, VGG16, VGG19, Alex Net model, ResNet50 and InceptionV3.

II.MATERIAL AND METHODS

Lot of work has been devoted to the detection of leaf diseases using image processing in the history and it continues to attract research to carry out their research work in this field. Automatic crop disease de- t action using image processing and machine learning has been gaining prominence in recent years. In [1] a philosophy for identifying plant diseases early and precisely, utilizing different image processing techniques and counterfeit neural network (ANN). The framework created here is for plant diseases acknowledgment, the advancement of good classification techniques and exact components is critical keeping in mind the end goal to run the framework continuously. In this way proposed approach which depends on Gabor channel for highlight extraction and ANN classifier for classification showed signs of improvement results and acknowledgment rate up to 91%. An ANN based classifier is embraced which utilizes the mix of shading and surface components to perceive and characterize distinctive plant diseases. The outcomes are empowering and guarantee the advancement of a decent machine vision framework in the zone of acknowledgment and classification of plant diseases.

In[2] a system to perceive the disease of two plants. This examination has been done on two grapes plants and two wheat plants to enhance exactness utilizing image processing techniques. Back propagation (BP) networks were utilized as the classifiers to distinguish grape diseases and wheat diseases, individually. The outcomes demonstrated that identification of the diseases could be successfully accomplished utilizing BP networks. While the magnitude of the element information were not decreased by utilizing principal component analysis (PCA), the optimal acknowledgment results for grape diseases were gotten as the fitting precision and the expectation exactness were both 100% and that for wheat diseases were acquired as the fitting exactness and the forecast exactness were both 100%.

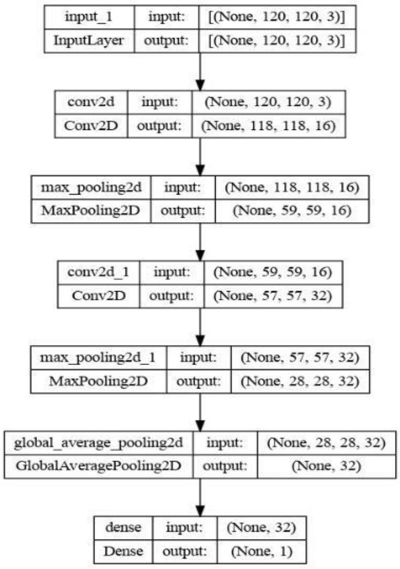
While the measurements of the element information were lessened by utilizing PCA, the optimal acknowledgment result for grape diseases was acquired as the fitting exactness was 100% and the forecast precision was 97.14%, and that for wheat diseases was gotten as the fitting exactness and the expectation precision were both 100%.

In [3] a system to distinguish diseases of plants utilizing image processing. This goes under automatic plant disease identification. There are number of colors for disease set apart as a dark spot and intensity for color segmentation. RGB image can be utilized for color segmentation. In this paper an examination of the result of CIELAB and HSI color space during the time spent disease spot identification is finished. Image smoothing is finished by middle channel. Otsu technique on color component to distinguish the disease spot can be connected for limit values. An algorithm which is autonomous of background plant sort, noise and disease spot color was produced and examinations were passed out on various "Monocot" and "Dicot" family plant leaves with both, noise free (white) and noisy background.

The model developed is based on Image processing and Machine Learning. A comparative analysis of various Neural Network models is done to find out which model is the most accurate.

A particular class of neural network called a convolutional neural network (CNN)[4] is made to cope with data that has a grid-like structure, like an image. They process the data using a mathematical procedure called convolution, hence the term "convolutional".[5] In a convolutional neural network, the neurons in the network are arranged in three-dimensional grids, with each neuron connected to a set of local inputs from a subset of the overall input data.[6] This arrangement allows CNNs to effectively learn spatial hierarchies of features, which makes them well-suited for tasks such as image classification and object detection.[7]

The dataset has been taken from “plant village dataset.” The data consists of total 11 crop species and 14 disease types and total 70113 images.



S.no	*Crop*	*Name of Disease*	*Number of Images*
1.	Apple	Apple scab, Black rot Cidar Apple rust	2541
2.	Blueberry	Healthy	1502
3.	Cherry	Powdery Mildew	1906
4.	Corn	Cercosporin leaf spot Common rust Northern leaf blight	3852
5.	Grape	Black rot Esca Leaf Blight	4062
6.	Orange	Hangdogging	5507
7.	Peach	Bacterial Spot	2657
8.	Bell Pepper	Bacterial Spot	2475
9.	Potato	Late Blight, Early Blight	2152
10.	Soybean	Healthy	2592
11.	Raspberry	Healthy	372

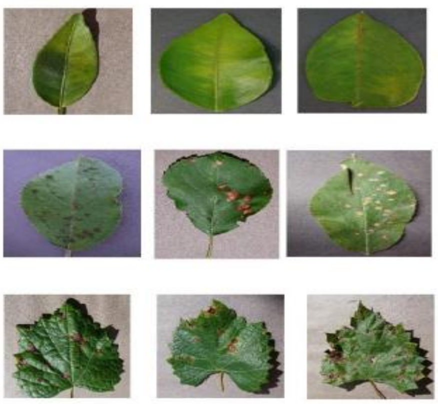


Fig 3. Image Dataset

Data augmentation is used to increase the size of training set and to get more different image. Through Data augmentation we can prevent overfitting, this refers to randomly changing the images in ways that shouldn’t impact their interpretation, such as horizontal flipping, zooming, and rotating.

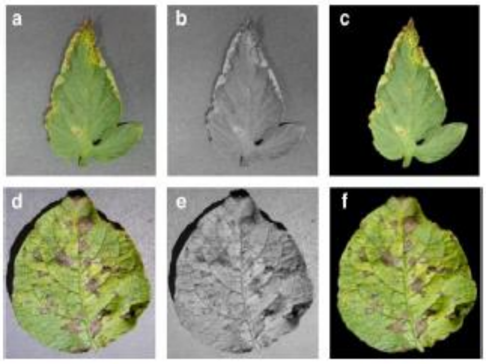


Fig 4. Grayscale Augmentation

As a part of image processing, the sample images are resized to 224 × 224 pixels to maintain equal size throughout the experiment. Resizing the image, rotating it at various angles, and flipping it vertically or horizontally are just a few of the numerous pictures enhancing.

System Overview:

Input images will be clicked by the user. Then the images will be uploaded via web applications which will then call the application programming interface where the pre-trained model will compute the output to give results at the maximum accuracy.

Experiment:

Each image is first turned into an array. The input file is scaled to the range [0, 1] from [0, 255] (the image's least and most prevalent RGB values).[10]

The dataset was then divided into 20% for testing photos and 80% for training images. Objects that conduct random rotations, motions, inversions, civilizations, and sections of our picture library are formed as image generators. We have used different convolutional layers to get the output at the utmost accuracy.

We have utilized a 2D convolution layer, which produces a tensor of outputs by winding a convolution kernel with layers of input. Then we have used a Max pooling operation for 2D spatial data. A pooling procedure known as "max pooling" selects the largest element from the feature map area that the filter covers. Therefore, the max-pooling layer's output would be a feature map that featured the standout elements from the previous feature map.[19]

Classification & Architecture:

The techniques such as CNN, VGG-16, VGG-19, Alex Net, Res Net 50 are used for classifying the samples. The CNN is a type of ANN which is designed to process the data. The architecture of CNN includes input (IL), output (OL) and hidden layers (HL), which are multiple in its nature. The HL includes convolutional layers, RELU layer i.e., which performs activation function, pooling, fully connected and normalization. It is having mathematically evident that its architecture is cross correlation rather than a convolution and demonstrates significance for the indices in the matrix. CNN uses convolution operation to process the data, which has some benefits for working with images. In that way, CNNs reduce the number of parameters in the network.

CNN:

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

When compiling the model, we provide objective function (loss), optimization method (adam) and accuracy that we will follow.

VGG16:

VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The “deep” refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG architecture is the basis of ground-breaking object recognition models. Developed as a deep neural network, the VGG Net also surpasses baselines on many tasks and datasets beyond ImageNet. Moreover, it is now still one of the most popular image recognition architectures. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

VGG19:

The concept of the VGG19 model (also VGGNet-19) is the same as the VGG16 except that it supports 19 layers. The "16" and "19" stand for the number of weight layers in the model (convolutional layers). This means that VGG19 has three more convolutional layers than VGG16.

InceptionV3:

The model will be downloaded automatically the first time the command is run to create the model. Assigning the weight parameter to the ImageNet will enable the weights of the ImageNet model to be used. If we want to train something using the Inception mesh, the weight parameter can be set to None, that way the weights will be randomly generated with default values.

Alex Net:

Alex Net is the name of a convolutional neural network which has had a large impact on the field of machine learning, specifically in the application of deep learning to machine vision. It famously won the 2012 ImageNet LSVRC-2012 competition by a large margin (15.3% VS 26.2% (second place) error rates). The network had a very similar architecture as LeNet by Yann LeCun et al but was deeper, with more filters per layer, and with stacked convolutional layers. It consisted of 11×11, 5×5,3×3, convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum. It attached ReLU activations after every convolutional and fully-connected layer.

ResNet50:

ResNet-50 is a convolutional neural network that is 50 layers deep. ResNet, short for Residual Networks is a classic neural network used as a backbone for many computers vision tasks. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers. Deep residual networks like the popular ResNet-50 model is a convolutional neural network (CNN) that is 50 layers deep.

Following table gives a summary of the accuracy/performance of different models resulting from Object Detection and classification algorithms. From Table it is evident that AlexNet has the best performance followed by VGG16 model. ResNet-50 model underperforms and hence is not suitable for classification.

S no.	Model	No. of parameters	Accuracy
1.	CNN	8488185	95.1
2.	VGG16	21143897	97.10
3.	VGG19	26453593	94.66
4.	InceptionV3	23082809	92.55
5.	Alex Net	28104777	99.22
6.	ResNet 50	23587712	60

III. RESULT

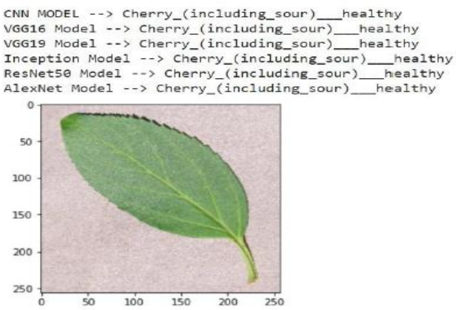


Fig 7. Cherry healthy Detected

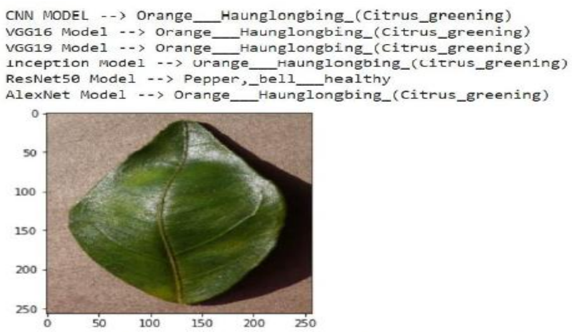


Fig 8. Orange Haunglongbing Detected

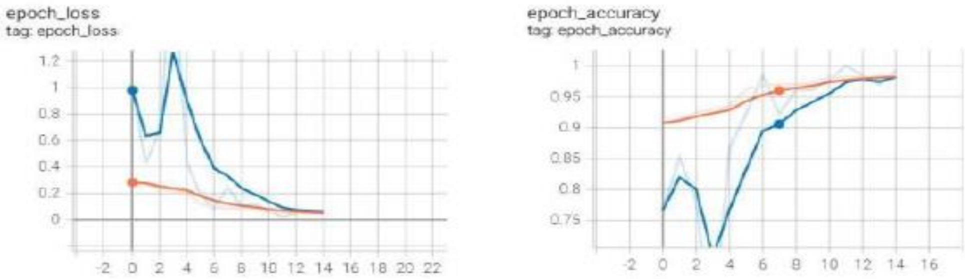
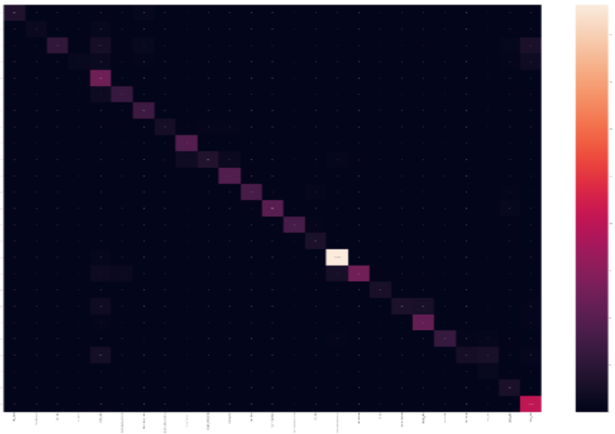


Fig 9. Epoch Loss & Accuracy Graph for AlexNet

Red Line represents **train**
Blue Line represents **validation.**
The results above show that Alex Net performs effectively and can precisely identify Diseased Leaves of crops.

Confusion Matrix:

A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes.



Our project may easily be integrated with our educational system while encouraging alternatives to the conventional blackboard method of instruction because all we need to use the application is a website on the internet.

We have created our web application user interface as simple as possible to allow everyone irrespective of age and mindfulness to use the feature.

Our project may easily be integrated with our educational system while encouraging alternatives to the conventional blackboard method of instruction because all we need to use the application is a website on the internet.

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IV.CONCLUSION

In this paper we have shown the efficacy of using object detection and classification algorithm models like CNN, VGG16, VGG19, ResNet50, AlexNet and InceptionV3 to do leaf diagnosis of crop disease compared with image data, the de-facto automated diagnosis methodology.

Experiments show a significant gain in classification accuracy after data augmentation keeping the issues and challenges (overfitting and underfitting) in mind.

This work has also demonstrated the comparison of performance/accuracy of different classification models. Our research shows that AlexNet model performed the best with a 99.22% accuracy.

V. FUTURE WORK

Particularly of interest is the collection of spectral data from the good part of the leaf which has implications for doing detection of disease in the plants before they are symptomatic. This will form the crust of our future work

There are many interesting experiments which we can do. We can try increasing the Image size and Batch size while training the model. We would also recommend to experiment with Label Smoothing. This helps to deal with cases where the model confidently gives wrong answers or we can say that it might reduce the overconfidence of the Model. We came across a Library dedicated for image Augmentation. Such techniques are widely used in Computer Vision problems.

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