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Leaf Illness Prediction for Smart Agriculture

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I. INTRODUCTION

Disease causing pathogens can have an adverse effect on plants. Timely and accurate diagnosis of plant diseases is critical to prevent unnecessary waste of monetary and other resources, appropriate and timely disease identification including early prevention is important. To identify a plant sickness at exceptionally starting stage, utilization of programmed illness location strategy is favorable. Distinguishing evidence of leaf infections is one technique to avoid mishaps in the agrarian item's yield and quantity. The investigations of plant diseases mean the investigations of outwardly perceptible examples noticeable on the plant. wellbeing following and disease identification on the plant is extremely basic for feasible agriculture. It's far exceptionally difficult to screen plant infections physically. It requires a terrific quantity of labor, know-how in plant sicknesses, and also calls for immoderate processing time. Hence, picture processing is used for the detection of plant illnesses. ailment detection entails the stairs like image acquisition, photograph pre- processing, photograph segmentation, function extraction, and type. This paper discussed the techniques used for the detection of leaf disease. This paper also attempted some segmentation and characteristic extraction set of rules used in leaf disease detection.

II. RELATED WORK

Liu, Bin, et al. "Identification of apple leaf diseases based on deep convolutional neural networks”. In this paper [1], Liu proposes another model of profound convolution networks for exact expectation and distinguishing proof in apple leaves. Model Proposed in the Paper can consequently perceive the different person exchanges with an extremely undeniable degree of precision. A sum of 13,689 pictures were made with the assistance of picture handling innovations like PCA wavering. Aside from this new AlexNet based neural organization was additionally proposed by carrying out the NAG Algorithm to streamline the organization. In future work to anticipate the apple leaf illness, different Models of Deep Learning like F-CNN, R-CNN, and SSD can be executed. This article [2] proposes a better approach to characterize leave utilizing the CNN model and assembles two models by changing organization profundity utilizing Google Net. We evaluated the viability of each model in light of staining or leaf harm. The acknowledgment rate accomplished is over 94%, regardless of whether 30% of the leaves are harmed. In future assessment, we will attempt to recognize leaves attached to branchesto encourage a visual system that can reflect the methodologies individuals use to perceive plant species This Paper [8] also depicts different systems for Extracting the idea of tainted leaves and arranging plants Disease. Here we are utilizing a Convolution Neural Network (CNN), Which comprises of different levels that are utilized for determining. That the total technique is depicted in light of the pictures utilized for preparing and pretreatment testing and Image improvement and afterward a preparation strategy for CNN profound and enhancers. Utilize these pictures We can unequivocally decide the handling strategy and separate between

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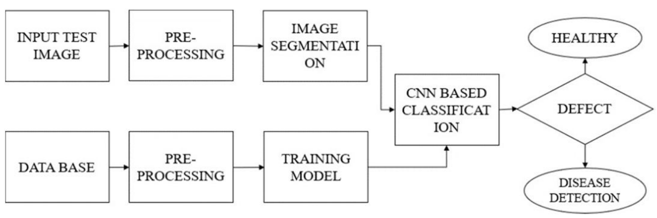
various plant illnesses. The purpose of this paper [10] survey proof of foliar illness warm, advanced, and hyperspectral imaging review with different grouping strategies. The division technique is applied to distinguish the necessary regions. The technique disengages the ideal region from the foundation. In view of the edge Value, grayscale picture, shading picture division strategy unique. Used to separate highlights just as different strategies, for example, grayscale the framework is utilized for related qualities, histogram force, and so forth To Classification of illness propagation from occasions, counterfeit neurons maintenance vector organizations and machines are utilized in support the vector motor gives the most acceptable outcomes to each kind Picture. On paper [8], RGB pictures are changed over to grayscale pictures utilizing shading transformation. Different upgrade procedures, for example, histogram arrangement and difference change are utilized to further develop picture quality. Various sorts of characterization qualities are utilized here, for example B. Characterization as indicated by SVM, ANN, and FUZZY. When separating capacities, various kinds of trademark esteems are utilized; B. Surfaces, structures, and mathematical components. The ANN and FUZZY characterizations can be utilized to recognize sicknesses in unpeeled plants B.

III. Proposed Method

Plants are defenseless to different infection related issues and convulsions. There are various reasons that might be represented by their effect on plants, unsettling influences because of ecological conditions, for example, temperature, moistness, unnecessary or lacking food, light and the most widely recognized infections, for example, bacterial, viral, and parasitic sicknesses. In the proposed framework, we utilize the CNN calculation to recognize illness in plant leaves on the grounds that with the assistance of CNN the greatest precision can be accomplished assuming the information is great.

A. System Architecture



B. Dataset

We use Kaggle Dataset. The Kaggle dataset comprises of 11030 sound and unfortunate leaf pictures isolated into 14 classes by species and sickness. We dissected in excess of 10,000 pictures of plant leaves with conveyed marks, and we attempted to anticipate the class ofsicknesses. We scale the image to 256 x 256 pixels and use it to perform progression and model expectations.

TABLE I. Dataset Details

Class	Plant Name	Disease Name	Causes Virus Name	Type of Disease	No. of Images
C1	corn	Healthy	-	-	10
C2	corn	Cercospora leaf spot	Cercospora zeae-maydis	Fungal	10
C3	corn	Common rust	Puccinia sorghi	Fungus	10
C4	corn	Northern Leaf Blight	Exserohilum turcicum	Foliar	10
C5	Tomato	Healthy	-	-	10
C6	Tomato	Bacterial spot	Xanthomonas perforans	Bacterial	10
C7	Tomato	Early blight	Alternaria'sp.	Fungal	10
C8	Tomato	Late blight	Phytophthora infestans	Fungal	10
C9	Tomato	Leaf Mold	Lycopersicon	Fungal	10
C10	Tomato	Septoria leaf spot	Septoria lycopersici	Fungal	10
C11	Tomato	Spider mites	Tetranychus spp.	Pest	10
C12	Tomato	Target Spot	Corynespora cassiicola	Fungal	10
C13	Tomato	Tomato mosaicvirus	Tomato mosaic	Viral	10

C. Data Augmentation

Image data augmentation is a technique for artificially inflating the size of a prepared dataset by altering the renderings of the images in the dataset. Image data augmentation is Change of pictures are finished by applying different tasks like Image flip, Image turn, picture shift, Image brilliance and Image Zoom. These changes are upheld by means of Image Data Generator Class.

Fig 3.1 Augmentation of corn leaf

D. Data Processing

After increase every one of the information have various heights and widths. Our model requires a proper pixel for all information pictures. We resize all information in a fix goal of 256x256 for our model. The image processing is done using Keras applications. We have used VGG architecture and InceptionV3 architecture.

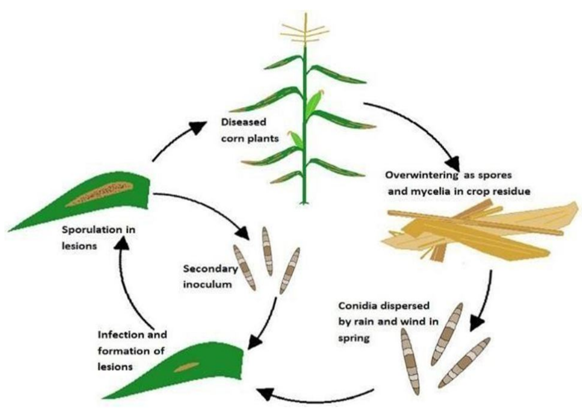


Fig 3.2 Data Processing of corn leaf

E. Training Model

To train the model Transfer Learning method is used. Transfer Learning is interaction of taking a model prepared on an enormous dataset and move its insight to a more modest dataset. For object acknowledgment with a CNN, we freeze the early convolutional layers of the organisation and only train the last couple of layers that create a forecast. After Data increase and Processing, preparing of the model starts. Each progression randomly selects 8 images from the preparation set, identifies their elements, and feeds them into the final layer to generate forecasts. These forecasts are then used to refresh last layer's weights After adding new layers these layers of the model are also trained using the same train dataset.

F. Performance Evaluation

After all the training steps are done, the substance runs a keep going test accuracy appraisal on a lot of pictures that are put something aside for testing reason and precision of the model is evaluated using the condition:

$$\text{Accuracy} = \frac{\text{Samples correctly classified}}{\text{Total number of samples}}$$

After training the last layer of the pre trained model and testing it, the model has a testing accuracy of 0.94 which is the best accuracy. After adding a new layer and training that layer again to extract in-depth features of currency the accuracy of the model for same testing data has raised from 0.96 to 1.0 which is a drastic increase and more efficient.

IV. Result and Discussion

Plant leaf picture is caught by utilizing the camera and picture is saved into the information base. Different types of diseases are considered namely Bacterial spot, Common rust, Mosaic virus, Grey Leaf spot along with the healthy leaves. In this method images are first loaded from the database (different types of leaves) and then images of leaves are enhanced by using the image processing technique of CNN classifier method. When we give an image as input the predicted output is printed as the majority of leaf from which disease the leaf is affected. An epoch implies preparing the neural organization with all the preparation information for one cycle. In an epoch, we utilize every one of the information precisely once. A forward pass and a regressive pass together are considered one pass: An epoch is comprised of at least one clumps, where we utilize a piece of the dataset to prepare the neural organization**.** The accuracy achieved when Epoch with 15 can be

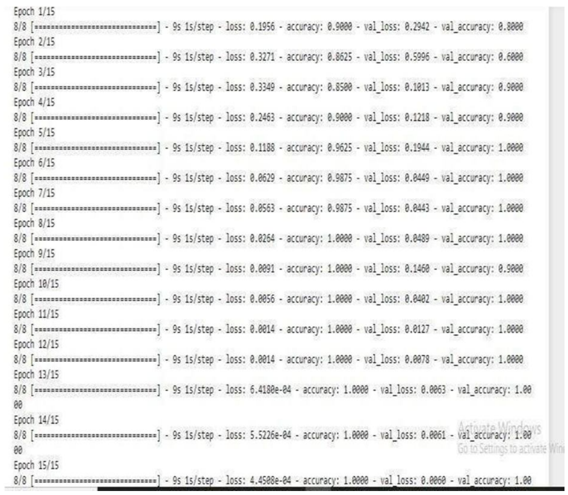


Fig. 4.1 Epoch chart

(i) Corn leaf affected with “common rust” is given as input for disea se detection as given in fig 4.2.

Fig 4.2 Corn leaf (common rust)

Fig 4.2.1 Disease detected with percentage

The result is indicated with the percentage of leaf effected by different diseases and the percentage of leaf that is healthy. The major disease that is present on the leaf is printed as output that is given in fig 4.2.1.
(ii) Corn leaf which is “healthy” is given as input for disease detection as given in fig 4.3.

Fig.4.3 Corn leaf (healthy)

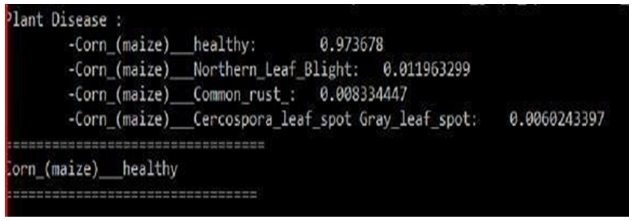


Fig 4.3.1 Disease detected with percentage

The result is indicated with the percentage of leaf effected by different diseases and the percentage of leaf that is healthy.The major disease that is present on the leaf is printed as output that is given in fig 4.3.1.

(iii) Tomato leaf affected with “late blight” is given as input for disease detection as given in fig 4.4

Fig 4.4 Tomato leaf (Late blight)

The result is indicated with the percentage of leaf effected by different diseases and the percentage of leaf that is healthy.The major disease that is present on the leaf is printed as output that is given in fig 4.4.1.

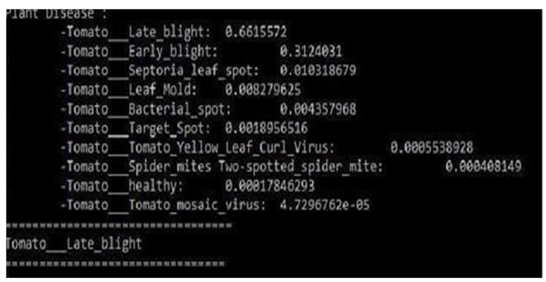


Fig 4.4.1 Disease detected with percentage

V. CONCLUSION

We proposed a model that shows how CNN may be used effectively. Even though the created data set was limited and did not represent a real-world scenario of damaged leaves, it proved to be quite useful throughoutthe experiment. Under the trained model, detecting sick leaves is a simple and quick operation. This also ensures that the model AFCRS can be well-trained and offer accurate results under genuine and huge data sets, which may assist users in determining whether plant leaves are healthy or ill, as well as classifying the type of disease.

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