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Machine Learning Approach for Crop Yield Improvement Using Plant Leaf Disease Detection

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ABSTRACT - *Agriculture gave birth to civilization .India is an agrarian country and its economy largely based upon crop production. Agriculture is the backbone of every economy. In a country like India which has ever increasing demand of food due to the raising population, advances in agriculture sector are required to meet the need. The agriculture sector needs a huge up-gradation in order to survive the changing conditions of Indian economy. Some highly technical method is needed for periodic monitoring of crop so that the crop is healthy and give optimum yield. The presence of disease on the plant is mainly reflected by symptoms on leaves. So, there is a need of an automatic, accurate and less expensive Machine Vision System for detection of diseases from the image and to suggest a proper pesticide as a solution.*

Key Words: **Plant Diseases, Pre-processing, Machine Learning, AlexNet Algorithm, Classification model**

1. INTRODUCTION

Crop disease is one of the major factors which indirectly influence the significant reduction of both quality and quantity of agricultural products. A number of varieties of pesticides are available to control diseases and increase the production. But finding the most current disease, appropriate and effective pesticide to control the infected disease is difficult and requires experts advise which is time consuming and expensive. Plant diseases are generally caused by pest, insects, pathogens and decrease the productivity to large scale if not controlled within time. The proposed system provides the solution for regularly monitoring the cultivated area and automated disease detection. The objective of the proposed system is to early detection of diseases as soon as it starts spreading on the outer layer of the leaves. The main goal of this project is to detect and classify different types of sorghum leaf diseases. This system is used to identify the disease in the leaves and notify to the farmers so that they can give the corresponding pesticides to that leaves. It decreases the affection of nearby leaves in a short period of time. We can easily spot the affected area in the leaves using image processing . Reduction in oversized work of watching in huge farms of crops and to detect the symptoms of diseases at terribly early stage itself detection of disease through some automatic technique is helpful.

1.1 Plant Diseases:

Following are the diseases caused to plants due to various reasons:

• Leaf blight:

Fig - 1.1.1: Leaf blight

The fungus Excerohilum turcicum causes Leaf blight . This fungus also causes Northern corn leaf blight. The disease is most readily identified by large cigar-shaped lesions on the leaf with reddish or purple margins. Within the lesion, there are often noticeable black conidia formed by sporulation of the fungus giving the lesion an ashy gray to dark olive appearance. Like many foliar pathogens, the conidia are blown or splashed to neighboring leaves or other plants and will infect when free moisture is available on the leaf. Some hybrids are resistant to the fungus. Resistant reactions have lesions that are smaller, often no larger than a purple fleck, with little to no sporulation. The fungus survives as mycelia on plant residue, buried in the soil, or on the surface.

• Sooty stripe:

Fig - 1.1.2: Sooty Stripe

The fungus Ramulispora sorghi causes Sooty stripe. The disease can occur at any time during the growing season and be severe on susceptible hybrids. Sooty stripe first appears as nondescript lesions on the lower leaves of the plant. During warm, humid weather, conidia form in the lesions and spread to healthy tissue. Sooty stripe is best controlled with resistant hybrids. Fungicides labeled for control of foliar diseases of grain sorghum may offer some control when applied prior to significant disease development. In instances of no-till or reduced tillage, the disease may be more severe.

• Zonate leaf spot:

Fig - 1.1.3: Zonate Leaf Spot

Gloeocercospora sorghi causes Zonate leaf spot. The fungus causes a relatively large alternating purple and tan banded concentric lesion, thus the "zonate" name. The lesions are often large, 1-7 cm in diameter, and can encompass the entire leaf width. Lesions can also be found on the leaf sheath. In Arkansas, the disease has been prevalent in certain years but has not caused yield loss. During the season, the fungus spreads, producing pink or salmon colored spores (conidia) that are either blown or splashed to neighboring plants from within the lesion. Sclerotia are formed in dead sorghum tissue and can germinate and infect new growth or plants in the next season. Some evidence suggests the fungus may be carried on seed.

• Rough leaf spot:

Fig - 1.1.4: Rough Leaf Spot

The fungus Ascochyta sorghina causes Rough leaf spot. It is readily identified by purple lesions with raised black pycnidia, appearing as black globe- like grains that are rough to the touch in the entirety of the lesion, sometimes a well defined dark margin is present around the lesion. The lesions begin as small purple specks on the leaf as disease progresses can encompass the entirety of the leaf.

2. BLOCK DIAGRAM

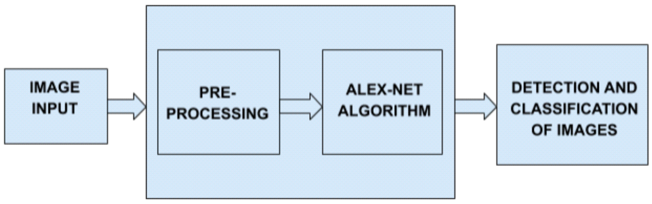

Fig - 2: Block Diagram

3. WORKING PRINCIPLE

1. Pre-processing:

Pre-processing means transformations applied to our data before feeding it to the algorithm. Data Pre-processing is a technique to convert the raw data into a clean data set. Contrast stretching, global thresholding, histogram equalization, log transformations and power law transformations, etc. are some of the point processing techniques. Some mask processing techniques are averaging filters, sharpening filters, local thresholding, etc.

Fig - 3.1.1: RGB to Grayscale conversion

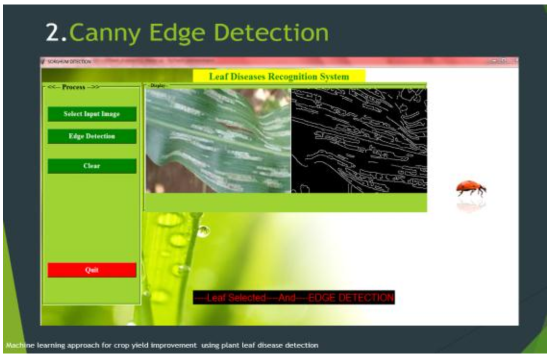

Fig - 3.1.2: Canny Edge Detection

Fig - 3.1.3: Threshold Conversion

2. AlexNet :

Alex-Net is a Deep Convolutional Neural Network for image classification. Alex-Net has 8 layers. Alex-Net consists of first 5 Convolutional layers and the last 3 fully connected layers. In between there are some layers called pooling and activation. Interesting features in an image are extracted by Multiple Convolutional Kernels (filters). There are usually many kernels of the same size in a single convolutional layer. The first Convolutional Layer of AlexNet contains 96 kernels of size 11x11x3. The depth is the same as the number of channels and width and height of the kernel are usually the same. The Overlapping Max Pooling layers follows the first two Convolutional layers .The convolutional layers third, fourth and fifth are connected directly. The Overlapping Max Pooling layer follows the fifth convolutional layer, the output of which goes into a series of two fully connected layers. The softmax classifier with 1000 class labels is fed by second fully connected layer. After all the convolution and fully connected layers, ReLU nonlinearity is applied.

a) The Architecture Of AlexNet:

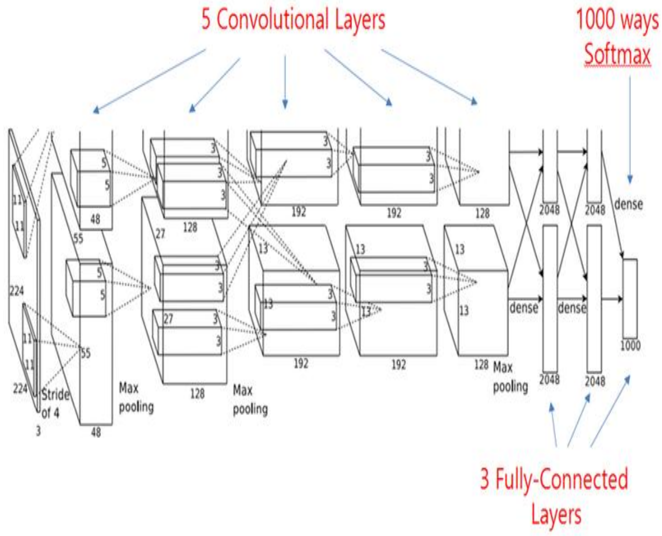

Fig - 3.2: Architecture of Alexnet

The 224×224×3 input image is filtered by the first convolutional layer with 96 kernels of size 11×11×3 with a stride of 4 pixels (this is the distance between the neighboring neuron's receptive field centers in a kernel map).The input to the second convolutional layer is (response-normalized and pooled) output of the first convolutional layer and filters it with 256 kernel's of size 5 × 5 × 48. The convolutional layers connected to one another without any intervening pooling or normalization layers are third, fourth, and fifth layers. There are 384 kernels of size 3 × 3 × 256 in third convolutional layer connected to the (normalized, pooled) outputs of the second convolutional layer. There are 384 kernels of size 3 × 3 × 192 in fourth convolutional layer, and the fifth convolutional layer has 256 kernels of size 3 × 3 × 192. The fully-connected layers have 4096 neurons each.

3. Detection and Classification of Image:

In Machine Learning Decision Tree is one of the predictive modelling approaches used in statistics. An algorithmic approach that identifies ways to split a data set based on different conditions is used to construct decision tree. Regression or Classification models in the form of a tree structure are builded by decision trees .Tree structure breaks down a dataset into smaller subsets and finally associated decision tree is developed . A tree with decision nodes and leaf nodes is the final result.

4. FLOWCHART

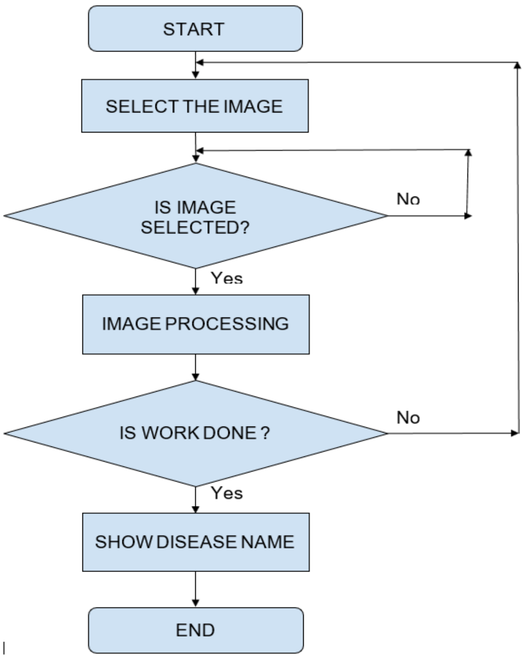

Fig - 4: Flowchart

5. RESULTS

Fig - 5: Results

6. CONCLUSION

Sorghum crop diseases can earn tremendous amount of loss in agriculture if sufficient attention is not given. Early notification of disease can be provided by an automated system using computer and communication technologies. ALEX-NETs is a valuable pattern-recognition method both in theory and in application. In this paper, we proposed an innovative technique to enhance the deep learning ability of ALEXNETs. The proposed ALEX-NETs based model can effectively classify common diseases through images recognition. The application to the Sorghum leaf disease detection shows that the proposed ALEX-NETs model can correctly and effectively recognize Sorghum leaf diseases through image recognition. ALEX-NETs are very good feature extractors. This means that we can extract useful attributes from an already trained ALEX-NET with its trained weights by feeding your data on each level and tune the ALEX-NET a bit for the specific task. In this study we have implemented techniques of the image processing and machine learning that have been used sorghum leaf disease detection and classification.

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REFERENCES

[1] Dhakate, Mrunmayee, and A. B. Ingole. ”Diagnosis of pomegranate plant diseases using neural network.” Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2015 Fifth National Conference on. IEEE, 2015

[2] M. Reyalat,Al Hiary, Bani Ahmad,Braik and Z. Rahamneh, “Fast and Accurate Detection and Classification of Plant Diseases”

[3] Smith J S., Camar+go A., “An imageprocessing based algorithm to automatically identify plant disease visual symptoms”

[4] Sulaiman, N., Mustapha,“K-means clustering to improve the accuracy”.

[5] David Mount,Tapas kanungo, “An Efficient k-means Clustering Algorithm: Analysis and Implementation”

[6] Ford A., Robert, “Colour Space Conversions.”

[7] C M Procopiuc, P. K.Agarwal, “Exact and Approximation Algorithms for Clustering”. Machine Learning Approach For Crop Yield Improvement Using Plant Leaf Disease Detection

• Books

[1] Yang Lu, Shujuan Yi, NianyinZeng, Yurong Liu, Yong Zhang, “Identification of Rice Diseases using Deep Convolutional Neural Networks”, Y. Lu et al. / Neurocomputing 267 (2017) 378–384.

[2] SharadaPrasannaMohanty, David Hughes and Marcel Salath´e, “Using Deep Learning for Image-Based Plant Disease Detection”, Front. Plant Sci., 22 September 2016