Plant Leaf Disease Detection Using Machine Learning

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Abstract - *The situation of any country in the world depends on its agrarian product. Especially India is depending on husbandry. The product gets affected by conditions of the crop. The yield of a crop is always dependent upon the base of the crop's disease. However, the yield will probably increase, If the complaint can be removed. The complaint that caused the crop to decline could be flashed back by the splint of the plant. The system uses Artificial Intelligence grounded on an algorithm we call machine literacy to estimate the superiority of the splint. The factory splint provides us with the most important data to distinguish the complaint of the factory. The development of the Android app gives growers the capability to do this. Identify factory splint conditions grounded on the image of factory splint taken from the Android app camera source. Detecting conditions of the splint of the factory at an early stage gives it the strength to overcome and treat accordingly by furnishing details to the planter, on what preventative measures should be taken. Android mobile operation which can automatically identify the factory's conditions grounded on their splint appearance with some computer vision and machine literacy ways..*

Key Words: CNN, Deep Learning, Disease Detection, Machine Learning, Neural Network, Tensorflow.

1.INTRODUCTION

Tensor flow and machine vision have been widely used in monitoring plants, harvesting, and other stages of plant growth. Tensor flow is usually combined with artificial intelligence like neural networks to detect mature fruits in these cases, the accuracy ranges between 60% and 100% depending on the type of fruit and other conditions. Crop monitoring is another domain where machine vision has been adopted (e.g., for production monitoring, the detection of diseases, or insect invasion)..

The original discovery of a complaint can be grounded on machine vision and tensorflow that will induce an alert if its symptoms are recognized. Molecular analyses have a advanced cost but may be carried out later if a factory complaint has to be formally verified. The factory disease opinion can be grounded on colorful symptoms as described Symptoms can frequently be grouped as underdevelopment of apkins or organs (short internodes, underdeveloped roots, deformed leaves, lack of chlorophyll, fruits, and flowers that don't develop), overdevelopment of factory corridor like apkins or organs, necrosis of factory corridor(wilts, shoot or splint scars, splint spots, fruit rots) and alternations like mosaic patterns and altered achromatism in leaves and flowers. The progression of the disease symptoms can vary significantly. Biotic agents the speed of the symptom progression. There are primary and secondary symptoms of a disease.

For illustration, the root decay can be primary symptom of a tree while the secondary symptom can be the tree tripping over. Secondary raiders that attack the tree in the after stages of the disease may obscure the original disease symptoms making the opinion more complicated. Other data like indecorous pesticide operation can beget analogous symptoms to spots that are present as a result of any contagious agent. Nonetheless, the symptoms caused by pesticide injury appear suddenly and no progression is observed. The spots may also follow the spray patterns of the pesticide. Dressings can also beget splint deformation which may be confused with viral conditions. still, the new leaves are free of symptoms, indicating a lack of symptom progression. further than one problem or pathogen infecting the factory can be present. In this case ,the symptoms may significantly dicer from that of the individual pathogens when they act alone.

2. LITERATURE SURVEY

Factory complaint identification is critical for a comprehensive knowledge of their growth and health. A deep literacy armature model known as CapsNet is suggested in this study that uses factory prints to determine if it's healthy or has a complaint. The suggested armature is put to the test using the Plant Village dataset, which includes over 60,000 images of sick and healthy shops. Capsules outperform CNN models because they integrate exposure and relative spatial connections between distinct factors in an reality. When compared to former factory complaint bracket models, the CapsNet model has shown to be much more accurate in terms of vaticination delicacy.

For splint complaint identification in plants, the authors suggested an enhanced point calculation fashion grounded on Squeeze and Excitation(SE) Networks before processing by the original Capsule networks. With a 64X64 picture size, SE- Alex- CapsNet obtains the maximum delicacy of92.1, compared to85.53 for Capsule Network. The suggested approach may be used to develop a mobile operation with low processing conditions that can be put on low- cost smart phones and used by farmers. For comparison, the bracket accuracies of six cutting-edge CNN models are presented AlexNet, SqueezeNet,ResNet50, VGG16,VGG19, and Inception V3.Deep convolutional neural network (CNN) models are employed in this study to identify and diagnose problems in plants by looking at their leaves. CNN models bear a huge number of parameters and a high cost of calculation. The typical CNN model is substituted in this study by four distinct deep literacy models InceptionV3, InceptionResnetV2,MobileNetV2, and EfficientNetB0. The models are trained and tested using a factory dataset of 53,407 prints. When compared to a standard CNN model, these models are more accurate and take lower time to train.

3.PROBLEM STATEMENT

Plant diseases have turned into a challenge as they can cause a significant reduction in both the quality and quantity of agricultural products. The automatic detection of plant diseases is an essential research topic. It may prove beneficial in monitoring large fields of crops and thus automatically detecting the symptoms of diseases as soon as they appear on plant leaves. The proposed system is a software solution for detecting and classifying plant leaf diseases.

4.PROPOSED METHOD

To reduce the loss chance of the crops, we present one Android app which distinguishes and identify the symptoms of the disease on a plant splint. Our app work on similar plants which are infected by numerous conditions that as fungi, contagions. To describe &classify factory disease by using machine literacy ways. It identifies the factual type of disease and gives its preventative measures and related recovery memos are displayed by using the CNN algorithm. And eventually, we get all information regarding the disease, its symptoms, its preventative medium, and recovery suggestion at the veritably least time and low cost

5.ALGORITHM

CONVOLUTION NEURAL NETWORK(CNN) STEP1:CONVOLUTIONOPERATION:The first step is convolution operation. In this step, we will touch on feature detectors, which serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection and how the findings are mapped out.

STEP1(B):RELULAYER

The next part of this step will involve the Rectified Linear Unit or ReLU. In this step, ReLU and explore how linearity functions in the environment of Convolutional Neural Networks.In this, we will have the 5 layers to display better results.

STEP2:POOLING

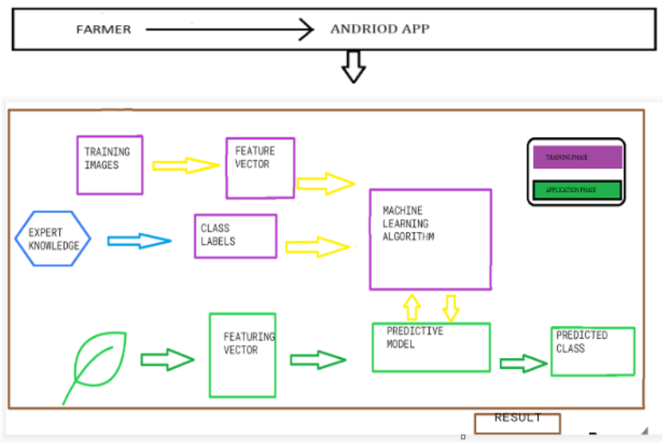
In this part, we'll understand pooling and will get to know exactly how it generally works. Our nexus will be a specific type of pooling; max pooling. We'll cover various approaches having mean (or sum) pooling.

STEP3:FLATTENING

It is a brief breakdown of the flattening process and how we move from pooled to flattened layers while working with Convolutional Neural Networks (CNN).

6.ARCHITECTURE

Farmer can capture the particular leaf acquired using an android camera after successfully installation of this app, then machine learning technique is applied to the acquired image to extract useful results that are necessary for the analysis. basic procedure of the proposed plant leaf disease experiments and evaluations on different segmentations, feature extractions and classification methods were done to find the most effective approach and identification based detection algorithm is used in this model. Farmer can get result is which disease infected by the plant like fungus, viruses



7.PROJECT DESCRIPTION

This project is to develop a complete system comprising a trained model on the server, as well as an application for mobile phones that display recognized diseases in fruits, vegetables, and other plants based on photographs taken from the phone camera. This application will aid farmers by facilitating the recognition and treatment of plant diseases in a timely manner and help them make informed decisions when utilizing chemical pesticides. Also, future work will involve spreading the use of the model across a wider land area by training it to detect plant diseases on aerial photos from orchards and vineyards captured with drones, in addition to convolution neural networks for object detection.

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8.RESULTS

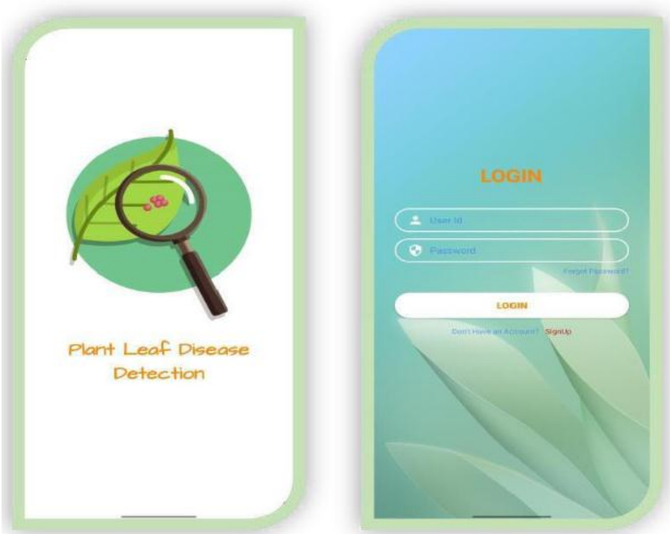

Fig: Flash and Login Screen

Fig: Register and Main Screen

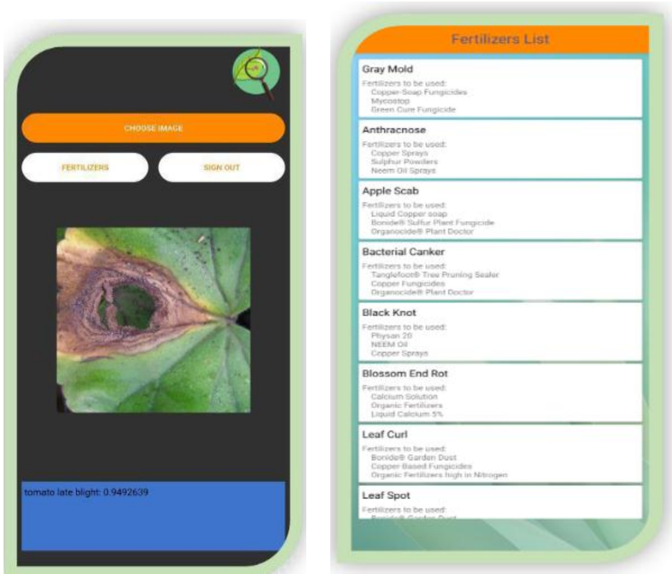

Fig: Disease Detection & Fertilizers List

9.CONCLUSION

This project proposed to find out the disease in the leaf with a union of shape, texture and color feature withdrawal. Firstly, the farmers have to send the diseased leaf image of a plant and these images are read and processed automatically and the results were displayed. The output of this project is to get hold of relevant results that can spot out diseased leaf of certain commonly caused disease to plants. Initially, healthy and diseased images are composed and pre-processed. Later, attributes like shape, color and texture are grasp out from these images. Based on the classification and type of disease a text is showed to the user by this project.

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