Basil Leaf Diseases Detection using Deep Learning architectures

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***Abstract*— An important role played by plants on earth is unquestionable. In both the ecological and medicinal fields, every plant organ plays a crucial role. On Earth, however, we have a wide variety of plant species. Different plants have different diseases. Therefore, it is needed to identify the plants and their diseases to prevent loss. Now to identify the plants and their diseases manually is very time consuming. In this research an automatic plant and their disease detection system is proposed. Training and testing of high-quality leaf images is permitted for experimental purposes. Our study used color-based and region-based thresholding techniques to detect the diseased and healthy areas of the leaf. The Gabor texture feature selection and the Random Forest method were applied for feature selection. The final two classification methods used were Random Forests and Support Vector Machines, which were used for binary and multi-label classification. 98.7% accuracy is obtained using Random Forest and Support Vector Machines for feature selection. A graphic user interface was made so that all users could understand the automated system. Using computer vision and artificial intelligence (AI) to detect plant diseases early can reduce the adverse effects of disease and reduce labour costs. We have used edge detection algorithms that are based on Canny and Sobel models to detectthe infected one not by its color, but rather by its shape. Image resizing and grayscale conversion were performed prior to passing them on to machine learning models to speed up processing time. In addition, mini-batch techniques were used to speed up the processing time of NN and LR. 800 images of holy basil leaves are included in the dataset, including 400 images of healthy leaves and 400 images of infected leaves. As a result of the experiments, it has been shown that the proposed method is effective in detecting the curling leaves on holy basil.**

Keywords*— *agriculture, crop recommendation, voting, K-Nearest Neighbor

I. INTRODUCTION

In addition to places where we live, plants also exist elsewhere. A great deal of information about humans can be gleaned from these plants. In addition, humans and plants are inextricably linked. A plant also creates circumstances and produces products that are valuable to human beings. Unfortunately, the incredible progress of human civilization has disrupted this balance to a greater extent than anticipated. Among human beings' most important duties is securing the plants from various dangers. So, it is necessary to restore the biodiversity of the plant community and make it into a balanced ecosystem. Numerous plants are in danger of extinction. Numerous plants are in danger of extinction. It is therefore very important to create a database for plant protection. We believe that educating a computer about classification is the first step.

Researchers have studied the curl leaf disease classification issue extensively [1,2]. In the reports, it was found that the previous systems do not detect diseased leaves if they do not change color. A novel method of identifying holy basil leaves characterized by green curls is presented in this paper. There are three major steps in the proposed methodology: data collection, pre-processing, and classification. We collected images of basil leaves in our laboratory in the first step. A pre-processing model was then used to resize the images to 300x200 pixels. Using Canny and Sobel models, gray scaling and edge detecting are performed as part of the pre-processing step. After the images are pre-processed, the classification model is run.

Plants are one of the most important forms of life on this planet. Gardening of useful plants is horticulture, a part of agriculture. Daily life necessities are fulfilled with those plants that are used in horticulture, like flowers, fruits, and vegetables. Therefore, it is critical to have a comprehensive understanding of these plants and their diseases. It is possible to prevent leaf loss and poor crop quality by detecting plant diseases in their early stages. In the past, it was difficult to detect plant diseases manually, but with the development of technology, it is now quite simple to detect diseases and monitor them. This type of technology gives more accurate results when used with computer vision. A region-based thresholding method and color based thresholding technique are used for image segmentation in this automatic plant diseases system. These techniques greatly simplify the process of determining disease-affected and healthy leaf areas. To determine which leaves are diseased or healthy, a classification algorithm is applied.

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II. LITERATURE SURVEY

Other research papers analyse different methods for detecting disease in agricultural plants, and a detailed analysis of their classification is also presented [4]. Researchers proposed an improved convolutional neural network model for detecting apple leaf disease based on deep neural networks. Based on real-life and laboratory images, they create a dataset of apple leaf diseases. In order to discover diseases, the researchers use a deep neural network as well as Google's interception and Rainbow concatenation. Their model can detect five diseases on apple leaves.

A model for identifying plant leaf diseases was proposed using image processing and machine learning. A variety of image processing tools are used to pre-process the image, and GLCM feature extraction is used to extract leaf features. Using K Nearest Neighbour, you can detect leaf diseases. According to the proposed implementation, 98% of leaf diseases can be detected. In many countries, holy basil is an important economic crop because it is used to make a variety of foods and traditional medicines. Detecting curl leaf disease in holy basil leaves is particularly important since theleaves are the main ingredient that we use. Nevertheless, manually monitoring basil leaves is a time consuming and challenging task. In previous studies [3, 7], plant diseases have been analysed by removing image features, pre- processing color images, and classifying leaf diseases based on those features. Gopal et al. [4] proposed using Neutrosophic approach computer vision to identify and classify leaf diseases. As part of their research, five classes ofdiseases were classified based on the analysis of basil leaves,including gray mold, fusarium wilt, bacterial leaf spot, and downy mildew. After undergoing pre-processing, the leaf dataset was converted from RGB to CMYK color space, segmented, features were extracted, and classification was performed. In the present study, the color space model was used to determine the classification of disease leaf traits. In the event that the color of leaf does not change, the system can detect curl leaf disease.

The authors analyzed 19 studies using Convolution Neural Networks (CNN) to identify automatic crop diseases. A disease profile, CNN implementation techniques, and a performance evaluation of the techniques are described in this study. They provide a framework for improving CNN research in the future [7]. The authors examine different machine learning classification techniques for detecting leaf diseases in plants in another paper. They describe their performance and discuss the different algorithms [8].

III. PROPOSED WORK

Dataset Collection

Data set contains the soil attributes and the crop yield that was produced. The dataset features were: Rain, temperature, soil pH value, moisture, Crop type and Crop yield are shown in the Fig 1. Among its health benefits are the minerals and micronutrients found in basil, a common and ancient medical plant. The symbolism of basil appears throughout both science and theology. Several high amounts of the anti-inflammatory compound (E)-beta-caryophyllene (BCP) were found inside the Swiss Federal Institute of Technology. BCP is expected to help manage arthritis and inflammation. With 40 images each, it contains images of three classes of leaf diseases: Bacterial leaf blight, Brown spot, and Leaf smut. The training and testing datasets that are taken from these classes provide 70 and 30 percent of the training dataset, respectively.

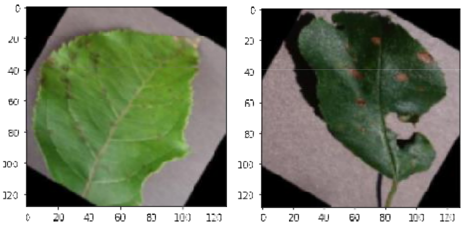

Fig 1- Diseases of basil leaves

Pre-processing

Resizing the dataset images to 300x200 resolution reduced noise and speed up the training process. To extract useful features for further analysis, we applied image-processing techniques to the images. In order to detect edges of images, this algorithm extracts useful structural information from images. It consists of five steps: smoothing images, calculating gradient intensities, eliminating spurious responses, and determining potential edges. Gaussian filters achieve smoothing of images by removing noise, which can interfere with edge detection. To reduce the effects of obvious noise on the edge detector, it is necessary to removenoise from the images

Segmentation

One of the most important steps in image processing is segmentation [12-13]. A critical component of this technique involves dividing the input image into similar type areas and extracting the area of interest. Segmenting images using thresholds is a common and simple method. Regions are used to segment images. One type of thresholding method isGlobal thresholding, while the other type is Local thresholding. The input image is divided into two main regions using the Global Thresholding process: 1) background and 2) region of interest. Using this method, the input image is segmented at a single thresholding level.Local thresholding divides the input region from the background based on multiple thresholding levels.

Global thresholding is employed in this experiment. Optimal threshold values are selected globally for segmentation. For leaf images, the backgrounds are darker, which allows a more effective segmentation effect. The calculation is therefore much simpler and faster for leaf images.

Bilateral Filter

It is basically the “root” of the bilateral filter. It transforms a L2 linear diffusion into a L1 nonlinear flow by utilizing a variety of techniques. Both spatial length and intensity distance are dependent on the weight of the bilateralfilter's pixel values in the local area. The vibrations therefore maintain a good outline. Local binary pattern (LBP) is a modified version of central symmetric local binary pattern (CSLBP). This pattern is used to capture image textures and gradients. Algorithms such as this one are computationally simple; they are robust against blurring, illumination changes, and flat image areas. This operator matches the gray levels of the center symmetric pairs of pixels that represent the gradients in the image.

Convolutional neural networks (CNNs) are a special type of neural network. When the input layer outputs are passed to hidden layers, the weights and prejudices of each node are used for point operations (multiplication and addition), and the output values are generated from the activation method. Whether it is a regular neural network or a CNN, the basic operating concept remains the same. Using the back-propagation principle, network parameters are determined in the output nodes and modified after each iteration of training data. CNNs have a relatively high difficulty level, which makes them more difficult to train than other shallow neural networks. The CNN is able to arrange its neurons in the spatial dimensions based on any spatial correlation input structure, such as images. In addition to facilitating the transfer of knowledge, this method significantly reduces the total number of network parameters. A CNN structure is built using spatial information. By applying this theory, CNNs can better define phenomena and recognize them shown in Fig 2 and Fig 4.

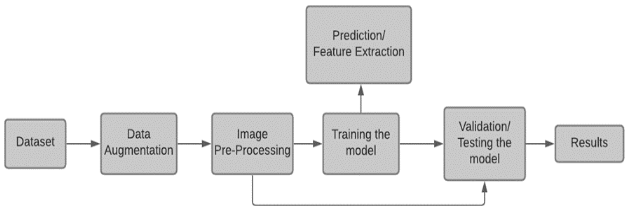

Fig 2- Proposed architecture

An RGB image of size 224x244 is used as input to VGG. For each image on the training set, the average RGB value is calculated, and the image is input to the VGG convolution network. Convolution is performed using a 3x3 or 1x1 filter, and the step size is fixed. 3 VGG fully connected layers, which can range between VGG11 and VGG19 based on the total number of convolutional layers and fully connected layers. There are 8 convolutional layers in the minimum VGG11 and 3 fully connected layers. For the maximum VGG19, there are 16 convolutional layers. +3 fully connected layers. The VGG network is not followed by a pooling layer behind each convolutional layer, or a total of 5pooling layers distributed under different convolutional layers. The following figure is VGG Structure diagram:

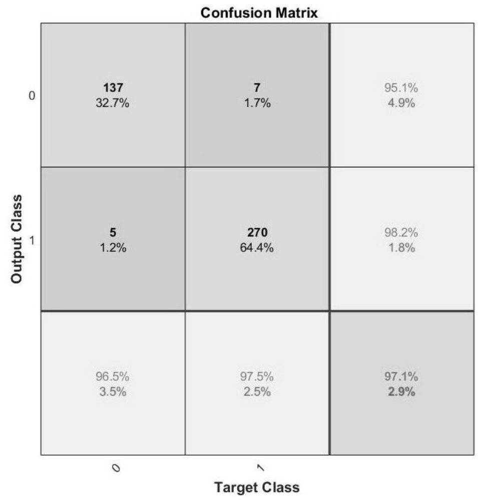

Fig 3- Confusion Matrix

The Fig. 3 shows the confusion matrix obtained after the testing of all the images of basil leaf category.

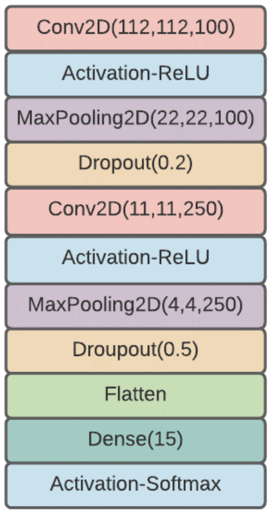

Fig 4- Deep CNN Architecture

IV. RESULTS AND DISCUSSIONS

In order to classify crop species and detect disease on images that the model had never seen before we trained a deep convolutional neural network model on images of plant leaves. By comparing the obtained results with base models, the proposed model is evaluated for its effectiveness in predicting plant leaf disease ttransformations accurately, which causes to enhance its recognition accuracy under several image distortions shown in Fig 5. The proposedmodel shows significant improvement in both classification performance and execution time when compared with other DLL-based approaches.

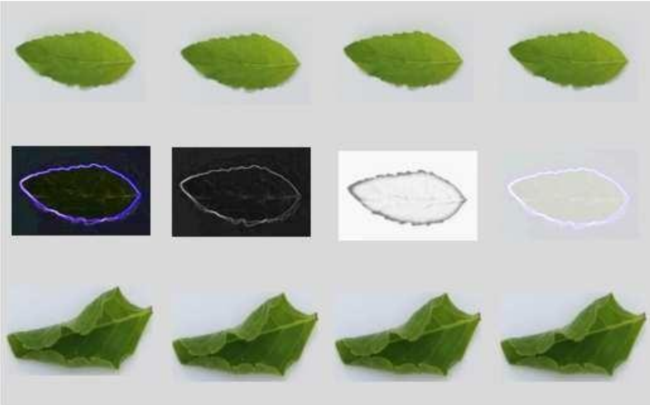

Fig 5- Healthy and Unhealthy Basil Leaf

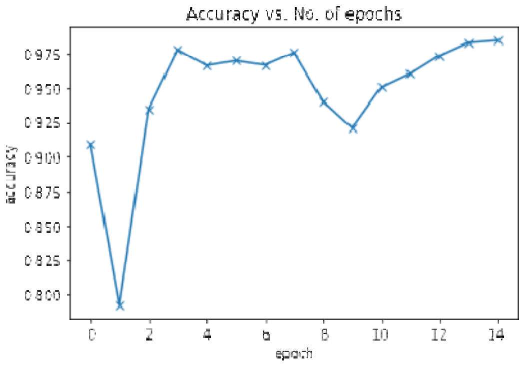

Fig 6- Accuracy of Basil Leaf

Fig. 6 show the images of network training in Python. It can be seen that the training accuracy is 100% for and loss is 0% for guava leaf dataset. Below are the results of a CNN trained to identify healthy and unhealthy Basil leaves. According to the results, the CNN of basil dataset achieved 97.1% accuracy using the proposed model.

By comparing the obtained results with base models, the proposed model is evaluated for its effectiveness in predicting plant leaf diseases. Classification and performance of the presented model is evaluated against other base approaches i.e. VGG-16, ResNet-50 and ResNet-18. The performance of the models are shown in Fig 7.

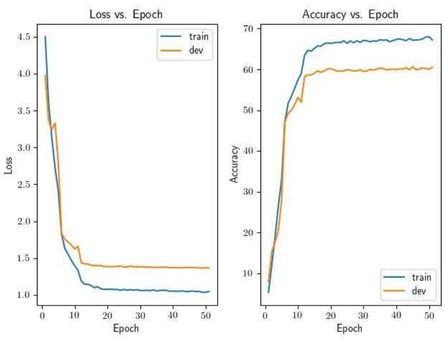

Fig 7- Performance of Comparision models

V. Conclusion

In this paper, we propose an automated leaf detection system. Healthy and diseased leaves can be distinguished from images using region-based thresholding. Healthy and diseased leaves can be distinguished from images using region-based thresholding. We were again able to detect specific diseased leaf areas of a leaf using a colour-based thresholding method. To select features from the input images, HOG and LBP feature selection techniques are used. Healthy leaves and diseases can be distinguished using SVM classifiers as well as their subclasses, leaf names, and diseases. Analyzing the performances of the main classes and subclasses was accomplished using several different classifiers. The result was a graphical user interface for users to view.

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