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Automated Plant Disease Diagnosis Using Deep Learning Model

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Abstract— With the world's population growing, it is vital that food crops and medicinal plants are required to be developed in large quantity. A model that can help us understand the process more comprehensively will be explored. Based on a thorough understanding, we are exploring a model that will enable us to extract the precise information and in-depth knowledge we require. There are many plants that contract lethal diseases every year, including food plants. This reduces their output rates. We must employ automated methods to locate the issue inside the facility if we do not want manufacturing prices to rise. The detection of plant diseases can be automated through robotics and image processing. As a result of recent technological advancements, we now have the ability to simplify our artwork. A deep learning and image processing approach can increase the efficiency of detection processes. A great deal of progress has been made in diagnosing plant diseases. An artificial intelligence model was trained to assist in diagnosing flora disorders. Based on the photo information (leaf), the model can be controlled. Identifying the problem and discovering the condition in this study, we propose the use of computer vision technology combined with fuzzy logic to detect and grade leaf diseases. GLCM is performed to extract texture features, and fuzzy logic is applied to grade the disease. K-means clustering is applied for determining defected areas; GLCM is used to determine defected areas; and fuzzy logic is used for diagnosing diseases. About 70% of classifications are accurate according to the model. By using Speed Up Robust Features (SURF), DENSE, and Bag of Visual Words (BOVW) in addition to the global features, the accuracy of the system can be enhanced.

A treatment program will help people better understand the illness if one is offered.

Keywords — Machine Learning, Plant Disease, Disease Detection, CNN, Deep Learning.

I. INTRODUCTION

Different ways can be found to identify disease based on the way a plant's leaves appear. Experts can assess the health of a plant by inspecting its leaves, branches, or fruit. In order for this strategy to be effective, a substantial number of respondents must be selected. With today's technology and automation, we would greatly benefit from developing an automated system of detecting ailments in plants. The gaps have been filled through various research projects in the past. Machine learning strategies are commonly employed for this purpose.

Images of plant leaves are used as part of our strategy, as is that of other studies. In addition to detecting sick plants, plant disease detection systems can detect the type of illness carried by both sick and healthy plants using computer vision. Herb diseases can be detected automatically with the help of this tool. Farmers rely on these species for their livelihoods. There are many challenges involved in the production of crops around the world [2]. The establishment of health, however, is dependent on plants [3]. Protection of vegetation is a high priority worldwide, despite the fact that humans can't live without plants.

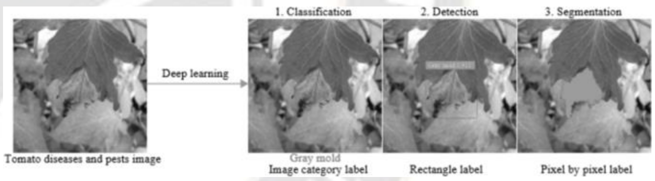

Fig. 1: Identification of Plant disease

Computer vision tasks such as classification, detection, and segmentation are relatively generic compared with plant diseases and pests [9]. Essentially, its needs can be categorized into three categories: what, where, and how. Computer vision classification is equivalent to "what" in the initial step.

As shown in Fig. 1, the group to which it belongs is labelled. This step, called categorization, consists of merely providing information on the image's category. In computer vision, the positioning of the second stage is the exact feeling of a detection, and the concept of "where" is what refers to this stage in the second stage. Pests and illnesses are displayed in the picture, along with their locations.

This step not only indicates what kinds they are but also where they are positioned. As shown in Fig. 1, a rectangular box indicates the area of gray mould on the plaque. In what ways is this comparable to stage three of machine learning, where segmentation is the challenge? By pixel-by-pixel separating the gray mold lesions from the background, a series of information can be obtained, including the length, area, and location of the lesions. Plant diseases and pests can be evaluated at a higher severity level with this information.

The local description of an object in a given image is the focus of object detection, whereas object detection determines whether a particular type of object exists in that image by using feature expression. Through classification, the object detection algorithm determines whether an object exists in a particular position in the image. It is therefore obvious that object classification differs from object detection in addition to feature expression. Research in feature expression primarily focuses on object classification, while research in structure learning primarily focuses on object detection. There is no need to separate the three steps involved in detecting plant diseases and pests because they all have multiple purposes and goals.

As an example, the "where" in the second phase ties in with the "what" in the first phase, and the "how" in the third phase may address the "where" in the second phase. It is also possible to accomplish the objectives of the second and third phases using methods learned in the first stage. Accordingly, in the text that follows, we will refer to the problem as "detecting plant diseases and pests". Network topologies and functionalities differ only when the terminology is used.

We organize this paper as in Section II, the related works are explained with the help of proposals to identify defective regions using segmentation techniques as well as using textures and colors as characteristics to differentiate them; in Section III, deep learning-based technologies are explained to detect plant diseases and pests. in Section IV, the data sets are used to test accuracy and loss; and finally in Section V, conclusion and future work is explained.

II. LITERATURE SURVEY

The importance of plants in human life and the necessity of our existence depends heavily on them. It is classified as a botany branch of science and plays a key part in the food chain cycle. Increasing production through inorganic production also destroys food quality and health and destroys plant genomes.

Sprayed poisons on plants are poisoning the environment, and it is necessary to find a way to prevent plants from dying. As part of this pathway, researchers are proposing solutions and making proposals to resolve this issue. There have been some proposals to identify defective regions using segmentation techniques, as well as using textures and colors as characteristics to differentiate them. As a result, neural networks are being used here [1].

The Hu’s moments are used as a separating characteristic during snake segmentation in another technique [2].

A BPNN classifier is used to address class issues, and an active contour model is used for limiting the intensity within the infection zone. A categorization rate of 85.52 percent is determined on average [3].

To grade the severity of the condition, fuzzy logic is used along with K-means clustering to divide the defective region, and GLCM is used to extract textural information [4].

In order to determine how seriously affected the sick leaf is, they used artificial neural networks (ANNs) as classifiers. Based on the RGB to HSV conversion of extracted colour histograms, Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Sigatoka Disease [5] is performed.

Max tree is constructed from peak components, and classification is accomplished through area under the curve analysis and five shape parameters. They employed Naive Bayes, Decision trees, Random forests [6], Extremely Randomized Trees, Nearest Neighbors, and SV classifiers. Randomized trees produce a high score in seven classifiers and provide real-time information that allows the application to be flexible. The Multiple Classifier System [7] describes how colour characteristics are encoded in RGB to HIS and how, using GLCM, seven invariant moments are used to determine shape parameters.

In order to detect diseases in wheat plants offline, they used support vector machine (SVM) classifier with MCS. The technique of segmenting the defective region and using colour and texture as attributes is used in the classification of pomegranate diseases based on back propagation neural networks [8].

Neural networks are limited to a few harvests in this scenario, so they are not suitable for this application. One work aimed at minimizing the mortality risk in plants family disease classification is also utilizing Hu's moments, such as the author [9]'s proposed BPNN classifier. It utilizes the active contour model to address the various classification problems. This method works by limiting the flow of blood within the infection area. 85.52 percent of the data are categorized on average.

In this study, we propose the use of computer vision technology combined with fuzzy logic to detect and grade leaf diseases. GLCM is performed to extract texture features, and fuzzy logic is applied to grade the disease. K-means clustering is applied for determining defected areas; GLCM is used to determine defected areas; and fuzzy logic is used for diagnosing diseases.

To determine the severity of the diseased leaf, the researchers used an artificial neural network (ANN). An automated vision-based diagnosis of banana bacterial wilt and black sigatoka disease is rendered "Color histograms are converted from RGB to HSV and RGB to L*a*b.

For classification, the area under the curve analysis is used with peak components to create a max tree with five shape attributes. The classifiers employed nearest neighbours, decision trees, random forests, extreme random trees, Nave Bayes, and SV classifiers. It is also possible to detect plant diseases using NMR or magnetic resonance imaging. Magnetic resonance scanning (nuclear magnetic resonance) is distinguished by its large magnets.

By polarizing and further excitating individual water molecules that are present in tissue, these magnets are useful for excitations of a concentrated proton. An encoded spatial signal provides a quantitative measurement of the body's dimensions. MRI machines produce radiofrequency (RF) pulses that are only capable of binding oxygen. Using this method, a pulse is first created, which is then transmitted to the targeted body part. The spin of the particles changes once the energy has been absorbed.

MRI is characterized by a resonance process. A hybrid biomedical imaging approach characterized by light acoustic imaging makes use of the photoacoustic effect. The system is capable of imaging diffusive regimes using optical absorption contrast, which is one of its advantages, as well as ultrasonic spatial resolution, which is another. According to a recent study, optical acoustic imaging can be used to detect disease, visualize brain activity, map blood oxygen content, and analyze tumors that are growing.

In a similar way, Tomography involves the creation of a tomogram by imagining a certain plan or object. Different types of tomography methods include linear tomography, polytomography, zonography, computed axial tomography, and positron emission tomography. Plant pathogens cause disease in plants.

There has been a study on the use of various sensors, such as thermography, chlorophyll fluorescence, and hyperspectral sensors, and comparisons have been made. Because hyperspectral devices record a lot of data, different approaches are required to achieve the best results. Among the thermographic parameters, temperature is one of the most important.

There is still a lot of potential left in these technologies. As well as reading sensor data, interpreting it can be challenging. Several classification methods are examined in this essay (Fang and Ramasamy, 2020). As examples of a direct approach (enzyme-linked immunosorbent assay), PCRs, immunofluorescences, FISHs, flow cytometers, and FCMs can be cited. Techniques that use indirect methods include hyperspectral imaging and fluorescence imaging .

In spite of the fact that direct techniques are simple to use, they require the services of highly trained personnel, sophisticated implementation, and a lengthy data processing process. Several tests cannot be conducted with them as well. There is no specificity for diagnosing each type of disease using indirect methods.

The advent of nanotechnology has led to the development of highly sensitive biosensors, and enzymes, DNA, and antibiotics can be used as detection agents to increase their specificity. Study equivalences spectroscopy and imaging technologies for assessing the health and diseases of leaves using spectroscopy-based imagery techniques.

It is possible to identify pant diseases accurately with the help of these gadgets. Plant disease monitoring systems challenge themselves with discovering the optimal cure for each disease and automating the process for continuous monitoring.

III. METHODS & MATERIALS

The model uses CNN and ANN to identify the diseases in the plants. The following steps are performed:

Step 1: Splitting The Dataset into Training and Testing

The project is using a database that has around 68101 images in it. Other than this the project has the ability to predict any image which is fected to it. The images are then divided into two parts. The parts are divided as follows: 80% and 20%. After splitting the data we are using four different variables. These two categories of data have parameters. The parameters are data and labels. The variable data comprises the images, and the label data contains the indexing of each particular image in the dataset. When we are using the 80% data to train our model, we are first going to label each image using the label variable. This would help us to pass the data in different functions easily.

Step 2: Splitting The Data Using Train Test Split Function

This function is predefined by scikit-learn module and by using this function we can create splits in our dataset. Those splits are used as the training dataset and testing dataset. In our model, the splitting takes place with shuffling the data and the splitting function will take arguments like data array (Image Array) and the target (Label) array with a test size value in between 0 and 1.

Whenever we train a model from real-world data, it should be provided in a non-sequential format. Labeling the data would enable us to provide unsequential data to the training model. We would use a random function which would generate unsequential labels of images present in the data set.

For the 80% dataset which is used for training, there are two variables, X_train and X_test, which would be used to store those images and labeling. We also have defined the different 38 categories which we are going to apply to classify the images provided to the model.

Step 3: Data Conversion

After splitting the data into 80% for training we would have 54480 images for our training purpose. These images are then stored in a variable so that they can be decoded into a similar format. If we have an image that doesn't match the required format, we can easily convert it. All the 80% images which are used for training are converted into jpeg format. To reduce complexity and the amount of data so that the training can be done easily we are going to change all the images to gray scale using a function which is already built in the python library. All the other functions which are used are also present in the libraries. After this we are going to change all the images into a floating point format.

In a simpler form, we can say that the data which is provided by an image is always in the form of integers. But for our own use we have to change all the data from integer to float format. It's important to follow all steps so that the data can be transformed into a readable form that can be passed to the next step.

Step 4: Load Img Function

This function is a major function which we will use in the training pipeline the load the images on the go. The TensorFlow training works in a manner that it will load the data when the data is needed so this generator functionality of the TensorFlow pipeline need the unique identification for each image to load its pixel values. We will use image name as a unique identification value. So, this function will take image name and image label as the arguments and return the pixel matrix of the image with respected label. This function is applied on each image name one by one.

Step 5: Data Scaling

This step is provided with the data from the preceding step. The data of the images was changed in the last step to float format. so the float formatted data will we complied and divided by 255.

example : img = [1,100,400,255]

divided by 255

[0.00392156862745098, 0.39215686274509803, 1.5686274509803921, 1.0]

Step 6: Visualizing Data

These are the 6 images which we have taken to seen the dataset. The images have gone under some step of changing the images to black in white. The leafs are shown in Fig 4

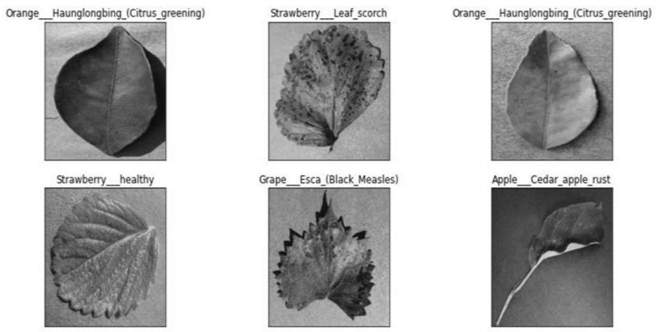

Fig. 4: Normal images of the leaf

After all the images are converted to float format then the we are able to see that how the images from the dataset are converted for future steps. The images are then displayed with the help of matplotlib_pyplot. The plotted images then can be seen easily.

The output of each image in Fig. 4 differs from the input image since they look the same as input. In this case, the probability filter applied at the initial level determines the output. These filters are designed to enhance the quality of the input data by extracting useful information.

The gradient descent and backpropagation allow us to track this loss all the way to the filter weights, which can then be adjusted to achieve the minimum loss.

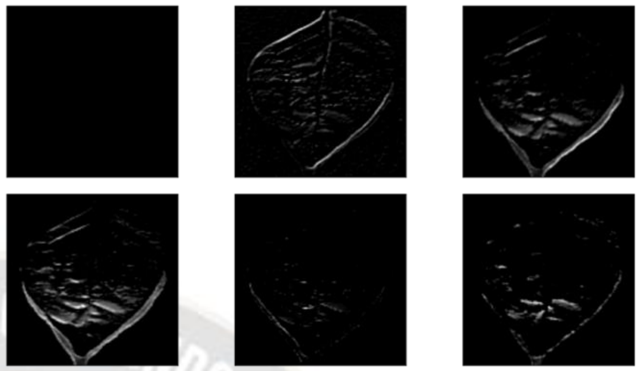

Fig. 5: Images after getting any kind of disease

After the model is trained, the filter weights are adjusted to get the minimum loss and to get the most useful information from the input image. Fig. 5 illustrates that the images now mainly show the edges and the diseased parts. Most of the useless information is lost.

This image is most likely to give the most likely likelihood in comparison to images with random information. Images that we get from one convolutional layer will be forwarded to the next convolutional layer. The next convolutional layer helps to extract even more useful information and it will try to remove the useless information.

A very accurate prediction result was obtained after training our model.

The class images displayed here vary according to the class. There are not just images of diseased or unhealthy individuals being shown--there are also images of healthy individuals.

Using this method, we are also able to determine whether an image is healthy or not. A peach, tomato, grape, etc., are just a few of the basic plants that are categorized.

There is a difference in the number of samples in different categories. In order to make the model as accurate as possible, it is necessary to take a number of samples. Our model can learn equally from every data sample if the number of samples per category is the same.

Our model will predict more images from a particular category if samples from that category are higher than those from other categories. A total of 38 categories/classes are included in this dataset.

IV. RESULTS & DISCUSSION

An input batch consists of a number of images with dimensions (batch size, number of pixels in x direction, number of pixels in y direction, and number of channels). A convolutional layer is created based on this input image. Gaussian distribution-based convolutional filters are applied to

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this layer.
The purpose of this custom training look is to initialize the losses and optimizer. We have defined a variable called num_step, which will store the length of the images stored in the variable x_train. In addition, X_train is divided by 32 to produce batches of 32 images.

Upon completion of the loop, the total number of steps required to train the training and testing data sets was obtained. In total, there are 1757 steps in the training data set and 439 steps in the testing data set. By adding up all the steps, we are able to determine the total number of steps that were required to train the full data set, including both training and testing images. Visuals in 4.7 and 4.8

Table 4.1: Loss and accuracy table

LOSS AND ACCURACY TABLE				
Epoch	Training Loss	Training Acc	Test Loss	Test Acc
0	1.2277672290802002	0.6355	0.5608615875244141	0.8213
1	0.4316710829734802	0.8607	0.47166067361831665	0.8516
2	0.2709227502346039	0.9103	0.4491407573223114	0.8625
3	0.19171400368213654	0.9354	0.38201186060905457	0.8858
4	0.1533288061618805	0.9467	0.4118884205818176	0.8852
5	0.12551529705524445	0.9564	0.45336252450942993	0.8800
6	0.10155898332595825	0.9665	0.5105146169662476	0.8788
7	0.08817227929830551	0.9707	0.5478593707084656	0.8742

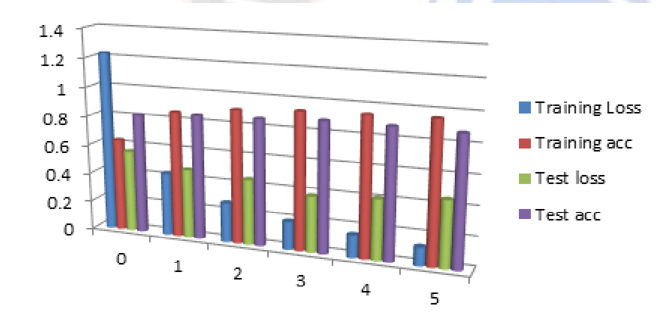

Fig. 6: Loss and Accuracy Graph

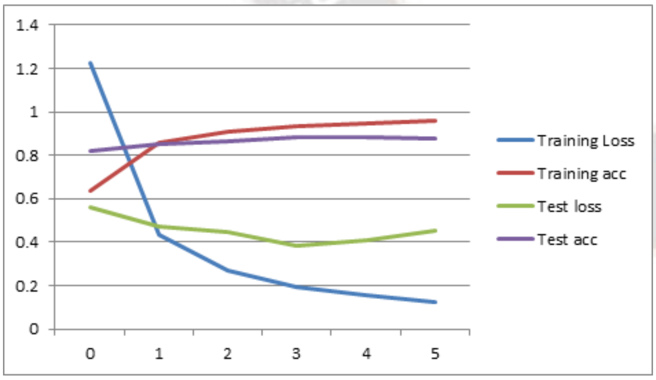

Fig. 7: Loss and Accuracy Plot

V. CONCLUSION AND FUTURE GOALS

To determine whether a leaf is healthy or sick, we will utilize a random forest classifier. In the wild or in greenhouse environments, this algorithm can spot anomalies in plants. A simple background is often used in photographs to prevent occlusion. Other machine learning models were compared to see how accurate the method is.

Photos of leaves were used to train the model, which uses a random forest classifier. About 70% of classifications are accurate according to the model. By using SURF (Speed Up Robust Features), DENSE, and BOVW (Bag of Visual Words) in addition to the global features, the accuracy of the system can be enhanced.

A number of techniques have been developed to detect and categorize plant diseases using computer vision or automated tools, but this field still requires improvement. As well, commercial solutions are not available except for those that detect plant species from photographs of leaves.

In the future, this project will benefit from increased cloud storage of disease detection findings, allowing farmers to apply the appropriate fertilizers based on the diagnosis of that disease.

Cloud storage is a service that lets you keep data on a server operated by a third party and accessible via the Internet or another network. There are many cloud storage options available, from personal storage to enterprise storage, which allows businesses to use cloud storage as a commercially supported remote backup solution where data files can be safely transferred and stored. Personal storage stores and/or backs up an individual's emails, photos, videos, and other personal files.
Human photographers and videographers would not be able to capture pictures and audio/video like that from drones. In addition to their ability to fly, drones can endure harsh conditions because of their small size or their ability to fly. Drone photography makes it feasible to obtain first-person views (FPVs) that would otherwise be impossible.

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