Plant Leaf Recognition using Machine Learning Technique

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ABSTRACT

Since plants provide humans with their energy, they are seen as being very vital. Significant losses in agricultural product output, economics, quality, and quantity can be attributed to plant diseases. Plant disease losses must be managed because the agricultural output of India accounts for 70% of the country's GDP. As a result, leaf recognition is essential in the agriculture sector. Phases including picture acquisition, image segmentation, feature extraction, and classification are all part of the Plant Leaf Recognition system. This project provides an overview of the different kinds of plant labels that indicate whether a leaf is powdery, rusty, or healthy.

1. INTRODUCTION

Manageable horticulture and environmental change are closely related to the problem of ensuring productive plant disease [1]. The results of research indicate that changes in the environment can modify the stages and rates of pathogen development. This can also modify host resistance, resulting in physiological modifications to host-pathogen interactions [2, 3]. The situation is further complicated by the fact that illnesses are spread more widely these days than they have in the last few years. Novel diseases may arise in areas where they were previously unknown and, typically, in places where there is no local capacity to combat them [4-6]. Careless application of pesticides will hinder the pathogens' long-term blockage and severely reduce the ability to fight back.
A plant pathologist needs to be highly perceptive in order to identify distinctive side effects and perform accurate plant disease diagnoses [8]. Basic computerized image preparation techniques, such as shading analysis and maximum level [9], were abused in addition to the process of identifying and characterizing plant labels. These are combined with different preprocessing methods for images to improve element extraction.
The method currently being demonstrated takes a different approach to diagnosing plant infections by using a deep convolutional neural network that has been carefully designed and adjusted to precisely match the plant's leaf data bank, which is compiled independently for various plant labels. The evolution and peculiarity of the developed paradigm rest in its simplicity; solid leaves and background images follow distinct styles, enabling the model to distinguish between sick and healthy leaves or from the earth with the use of sophisticated CNN. A computerized framework has been implemented to detect and classify the maize plant disease. This system makes use of calculations such as chain code networks, leaping box technique, and minute examination.
In order to determine the severity of Rust Malady on maize, the disease area is separated to identify the disease edge, and the remaining infection area and leaf zone are computed to determine the plant illness seriousness. Finally, we will conclude with a few strategies on the most effective way to raise the project's scope and outcomes as well as how it will help the public and industry by providing disease discovery."

The remaining paper is divided into the following sections: Section 2 discusses relevant work; Section 3 offers approach; Section 4 discusses completed results and related discussion; and finally, Section 5 offers conclusions.

2. LITERATURE SURVEY

Following the appropriate management protocols, such as using fungicide products, applying medications specifically for illnesses, and managing instructions for pesticide requests, may result in timely information about harvest health and infection detection. This could promote illness management and boost productivity. In [12], authors discussed, surveyed, and observed the desire to develop a quick, economical, and trustworthy health monitoring system that promotes advancements in the agriculture sector. Following a review of the work and analysis provided by the authors of [13–16], the picture handling illness acknowledgment approach was selected as one of the many methods commonly used for plant disease diagnosis, including occurrence, dual-beached ribonucleic acid testing, nucleic acid testing, and microscopy. The authors of [17] have provided an overview of prominent conventional techniques for include extraction.

2.1 Data Gathering

The project's computer vision system primarily relies on the leaf images. Thus, we made the decision to take a few pictures of leaves and use them to create a model that makes it easier to identify plant diseases. The 13MP camera is used to manually capture the photographs against a white background. There is only one leaf per image. Approximately 600 photos of leaves are taken in total, and these are utilized to train and validate the model. The model, which was constructed using the training data, is tested on 150 photos in total.There are two primary pathogens that affect maize leaves: Cercospora and common rust. A few of the leaf pictures utilized for detection are shown in Figure 1.

Figure. 1 : Images of leaves.

Every picture that is taken is used to train and construct a convolutional neural network model that aids in the identification of the illness. People manually grade the quality of plant leaves at different stages. This method is challenging, labor-intensive, and prone to errors.
The procedure of detecting plant leaf labels must be carried out utilizing a computer or machine-based model in order to get around these problems. The procedure of detecting labels can be completed quickly and easily with this model.

3. Proposed System

A computer vision-based disease detection system is proposed to evaluate the disease of maize plants in order to address the limitations of the existing framework.
The Disease Detection System uses a pre-made model to assess the state of the maize plant. Convolutional neural networks and other artificial intelligence computations are utilized to create the model from recently marked (Common Rust, Cercospora, no malady) photographs of maize leaves. Once a model is generated, it is approved for precise preparation and evaluated utilizing many picture configurations for approval and testing. The client may then identify the disease in maize plants at that point thanks to the model's integration into the user interface.

3.1 Modules of System

The functions of the components that make up the Leaf Detection System are as follows:

1. Plant leaf handling module

The following are components of the Plant leaf handling system: PC and camera. The computer serves as a server for the photographs that are taken by the camera and uploaded. The photos are then stored by the computer. The disease identification module is used to evaluate these pictures.

2. Disease Detection module

The following processes make up the Disease Detection module: Pre-process, Feature Extraction and Selection, Classification, and Return Results. The disease detection method is shown in Figure 2.

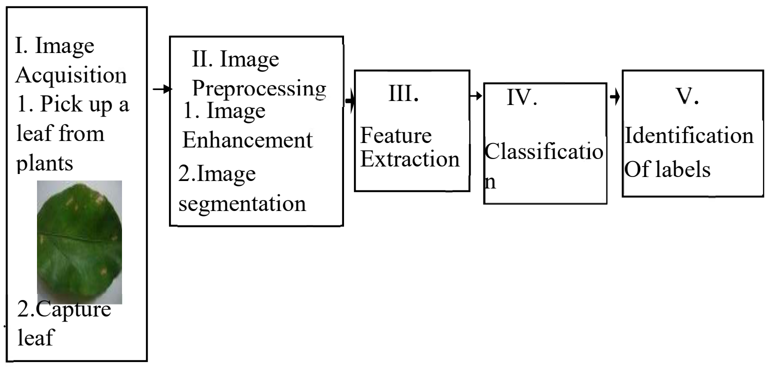

Figure 2: The plant leaf recognition system's architecture

The photos are evaluated by the Label Detection module. After pre-processing the photos, neural networks are used to extract the images' features, such as color, shape, etc. It then categorizes the plant leaves as disease-affected or healthy using the data that was gathered. Subsequently, the outcomes are transmitted back to the plant leaf handling system for display to the user.

4. IMPLEMENTATION AND EXPERIMENTATION

The following are involved in the Leaf Detection System's implementation:

1. Environment: Python is the primary programming language used by the Leaf Detection System, along with numerous additional Python dependencies. Installing the Anaconda Navigator software allows you to correctly handle all of the Python language's dependencies. establishing the necessary dependencies and installing all the software, including NumPy, Matplotlib, Keras, TensorFlow, and PIL (Python Imaging Library),

2. Pre-processing: The photos that were taken with the camera and sent to the leaf detection system resemble those in Figure 3, which is seen below.

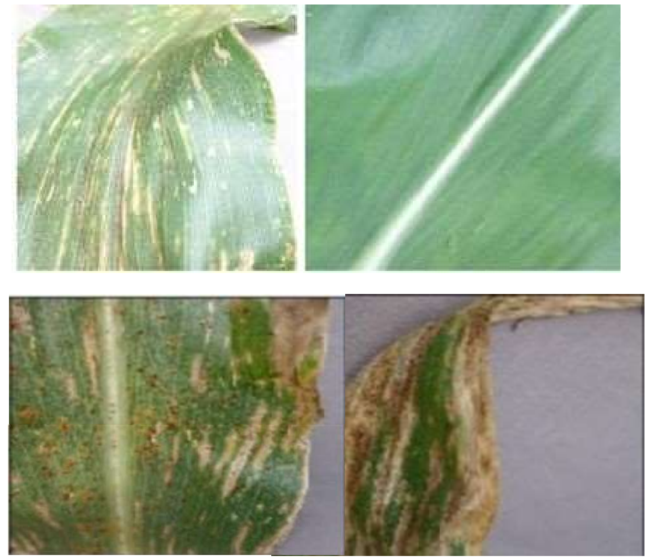

Figure 3: Images of leaves before pre-processing

For quicker image processing, the extra background image can be cropped while the label Detection system evaluates the leaves. The photos that were taken could resemble the one seen in Figure 4.

Figure 4: Images of Leaves after croping

These resized photos are placed into a 250 x 200 graph, dividing the photos into training block segments for the model. However, the images are presented in Figure 6.2 exactly as they are, coupled with an axis that makes it easier to grasp that the image is divided into 250 X 200 blocks. The pre-processed photos in the figure have the labels "good" (0.0) and "bad" (1.0), respectively. The photos with labels are displayed in Figure 5. The labeled, 250 by 200 pixel photos of the leaves represent the pre-processed photographs' ultimate product. These measurements perfectly match the neural network's input dimensions.

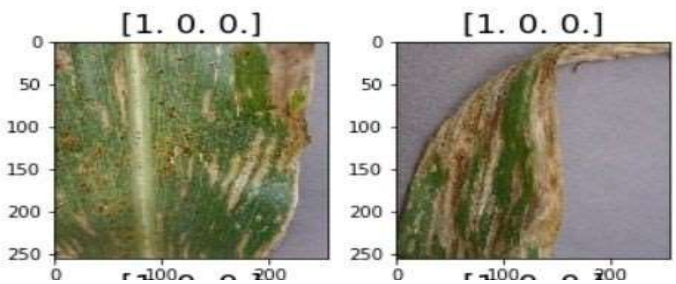

Figure 5: Pre-Processed Images After Labelling

3. Model Development

One way to improve the model is to display a system of artificial neurons, or neural networks, together with the image data, or info. At that time, the neural network has learned every highlight in the images and is able to arrange them in a certain order based on those highlights. Picture data containing named maize leaves is a contribution to the neural system for the enhancement of the Leaf Detection Networks model. Following learning, the nervous system will be able to predict leaf labels.
A convolutional neural network computation, which consists of multiple layers and capacities performing a scientific process on the data and its marks provided, is used to do this. All-connected convolutional neural network.

4. Defining the Neural network

Adding every function to a network is the process of defining a neural network. One input

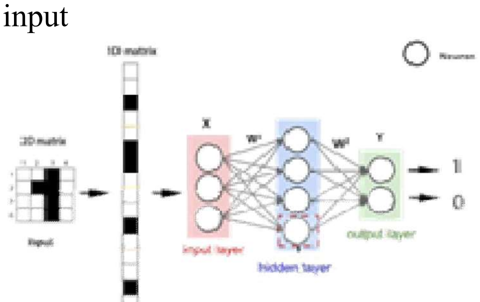

Figure 6 : 2D CNN

layer, three cryptic layers, and one outcome layer define the neural network. As the leaf Detection System evaluates the leaves, the output activation function utilized is sigmoid, which produces the output as 0s and 1s.

5. Supplying Data to Neural Network The neural network is fed data that includes pre-processed photographs of leaves as input. A data generator is made to assist in moving data from the directory to the neural network throughout its classification learning process. The input data is kept in a directory. Next, utilizing the picture data, a model is created once the neural network has been trained.
After generation, the model is saved as a file with the extensions json and h5. Every time an image prediction is needed, this model is loaded. These files are kept on the server and are accessed as needed.

5. RESULTS

The Figure 7 displays the results. After training is finished, the accuracy of the model is validated. Figure 8 displays the correctness of the validation process for the model, which is tested


```
In [12]: model.evaluate_generator(validation_generator, nb_validation_samples)
Out[12]: [0.04825590588418772, 0.9959532374100719]
```

on 550 photos.

Figure 8 : Training accuracy

After the prototype has been developed, the model is next evaluated for overall accuracy. Figure 9 illustrates the prototype's precision. The 53 photos of maize leaves are used for the testing.

```
loaded_model.evaluate_generator(test_generator, nb_test_samples)
[1.150555618331308, 0.8670886029422534]
```

Figure 9 :: Over all Model accuracy after testing

Confusion Matrix

An overview of the likely outcomes for an order problem is called a confusion matrix. Check values are used to outline and divide the number of right and off-base expectations by each category. This is the path that leads to the chaotic grid. The perplexity framework identifies the ways in which your gathering prototype becomes confused during the forecasting process. It gives us insight into not just the faults a classifier makes, but also—and perhaps more importantly—the kinds of mistakes that are produced. The Leaf Detection System's disarray network is shown below. Table 1 displays the information that may be obtained from the perplexity grid. It includes information about the test's exactness, review, f1-score, support, and precision.

Table 1 : Confusion Matrix

Original \ Predicted	Positive	Negative
Positive	39	2
Negative	4	8

Precision: The ratio of accurate positives to the total number of true positives + erroneous positives is known as precision.
True positives / (True positives + False Positives) equals precision.
Recall: Recall is precisely defined as the number of true positives divided by the total number of true positives + false negatives.
True Positives / (True Positives + False Negatives) equals recall.
F1-score: The following equation, which takes into consideration both metrics, yields the F1 score, which is the harmonic mean of precision and recall:
F1 is equal to 2 * (Recall * Precision) / (Recall + Precision).
Support: The quantity of each class's occurrences is its support. With an accuracy of 99.4%, the model has evaluated the disease detection of leaves. Given that it correctly identified 49 of the 50 excellent leaves, this model can be regarded as reasonably good.

5. CONCLUSION

While there are a number of automated or PC image plant disease detection and characterization techniques, this research area is still lacking at this time. Furthermore, aside from those managing plant species identification based on photos of the leaves, there are still no commercial preparations accessible. As of right now, a novel approach that makes use of a profound learning strategy has been researched in order to subsequently classify and diagnose plant leaf labels using leaf photos. The developed model could identify 13 distinct conditions that could be examined externally, as well as leaf proximity and sound leaf recognition. The entire plan was shown in detail, starting with the collection of the images used for approval and preparation, moving on to the preprocessing and enlargement of the images, and concluding with the process of setting up and optimizing the deep neural network.

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