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Hibiscus Plant Disease Detection Using CNN

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ABSTRACT

Ensuring plant health and productivity is critical in modern agriculture. The hibiscus plant, which is prized because of its colorful as well as decorative blossoms, is prone to a number of diseases that can negatively affect both its growth and appearance. In this project, the use of convolutional neural networks, also known as CNNs, for hibiscus plant disease detection is investigated. CNN is a good option for automating plant disease identification because of their impressive performance in picture classification tasks. Images of hibiscus plant leaves, divided into two groups to represent various leaf varieties, make up the dataset. There are three sets of the dataset: training, validation, and testing. including random flipping and rotation, are applied to the training dataset to artificially increase its size and enhance the model's ability to generalize. Additionally, the images are resized and rescaled to a standard size. The CNN model is defined with multiple convolutional and pooling layers, followed by a flattening layer and fully connected layers for classification. The training process is monitored for accuracy and loss, and the results are visualized using Matplotlib. Finally, the results are displayed along with their confidence scores.

I. INTRODUCTION

Plant productivity and health are of utmost importance. One of the major sources of income for India is hibiscus cultivation. The Malvaceae family includes the hibiscus plant, which is prized for its colorful and decorative blossoms.These flowers come in a variety of colors and are typically quite stunning. However, the primary issue with hibiscus plant cultivation is that illnesses on the leaves of the plant will hinder its growth. Plant diseases are caused by several pathogens, including bacteria, fungus, and viruses. Climate change and a lack of awareness on detection and recognition are causing significant financial losses for the agriculture sector.In order to identify the plant disease, domain experts typically use a visual assessment approach on the spot. This kind of detection method typically calls for expensive equipment in addition to a significant quantity of human labor. Moreover, it does not ensure successful outcomes. One of the most popular Deep Learning-based classifiers is the Convolutional Neural Network (CNN), which is utilized in many different domains including audio processing, human action identification, picture classification, pattern recognition-related issues, and leaf disease detection.

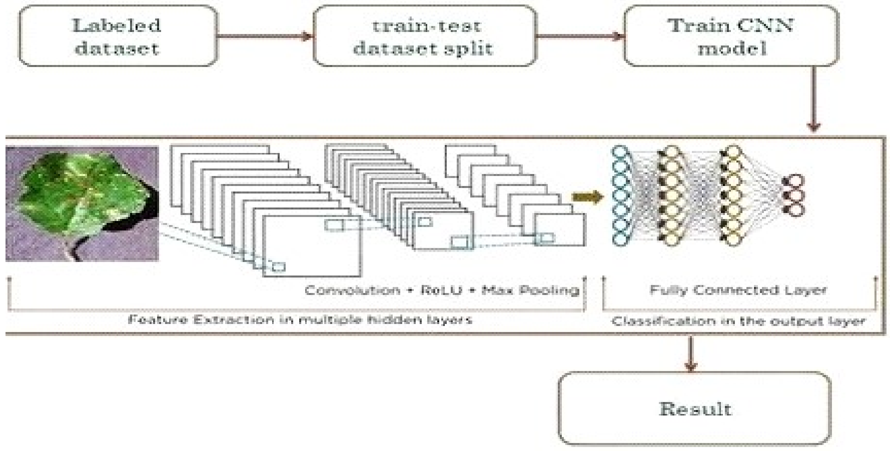
II. LITERATURE REVIEW

The author used a Convolutional Neural Network (CNN) model with an optimized activation function in[1] to create a plant disease detection and classification system. They used the Raspberry Pi and the computer vision package OpenCV to construct this model in TensorFlow, a well-known deep learning framework, and enable it to process real-time data.

The author created a method in[2] to classify and identify illnesses in plant leaves. By examining the form and texture of afflicted leaf photos, they employed machine learning techniques such as FFNN (Feed Forward Neural Network), RBFN (Radial Basis Function Networks), and LVQ (Learning Vector Quantization) to identify diseases.Their system's ability to recognize and categorize plant leaf illnesses is proven by the simulation results they obtained. This work could serve as the basis for the creation of a machine.

The author of [3] suggested a method for dividing up the flaws using a clustering algorithm. The picture was divided into a number of clusters, of which one or more were determined to include only portions that were contaminated. The K-means clustering scheme in this study used the squared Euclidean distance.

III. RESEARCH WORK



3.1 Labeled Dataset

Initially, a collection of photos of hibiscus plants is gathered. Both healthy and diseased hibiscus plants should be included in this collection; the dataset should be labeled as healthy or unhealthy based on the photographs. Preprocessing methods for images usually involve scaling them to a consistent size, normalizing pixel values, and enhancing the dataset using methods like flipping, rotation, and brightness modifications. Data augmentation improves the model's ability to generalize.

3.2Test dataset Split:

To evaluate the performance of the model, we must divide our dataset into training, validating, and test datasets. Usually, this is done to make sure the model can effectively generalize to previously encountered data. A train-test split is a popular method in which part of the data is used to train the model and the remaining piece is set aside for testing and validation. In this case, 70% of the data were utilized for training, 20% for validation, and 10% for testing.

3.3 Train CNN Model

3.3.1 Convolutional Layers:

Convolutional layers make up CNN's first layers. These layers pick up on elements and patterns in the photos of hibiscus plants. These patterns could be signals relating to diseases, leaf forms, or textures. Increasingly complicated features are captured by stacking many convolution layers. While deeper layers pick up more abstract elements, earlier layers identify more basic shapes.

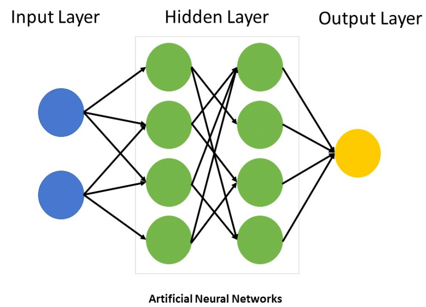


Fig2. Convolutional Layer

3.3.2 ReLU Activation Layers:

An activation function called Rectified Linear Unit (ReLU) is applied after every convolutional layer. ReLU gives the model non-linearity, which enables it to discover intricate links in the data. The functionality replaces negative numbers with zeros to help the network concentrate on pertinent information.

3.3.3 Pooling Layers:

Convolutional layers are followed by pooling layers. A common technique for lowering the spatial dimensions of feature maps is max-pooling. Max-pooling eliminates less significant information while keeping the most crucial information. It also aids in lowering the model's computational complexity.A neural network's pooling layer functions similarly to a data organizer. It takes the data produced by the layer before it, which was often a convolutional layer, and condenses and simplifies it.

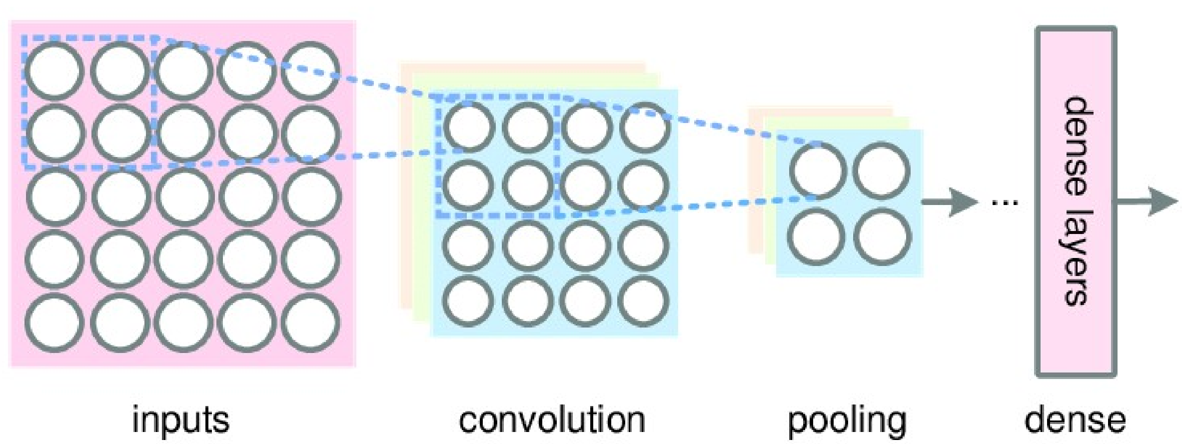


Figure 3 Pooling Layer

3.3.4 Flattened Layer:

A flattened layer is a data transformation step rather than a conventional layer with learnable parameters. The output from the preceding layer is transformed into a one-dimensional vector in this step. When convolutional and pooling layers in convolutional neural networks (CNNs) move to fully linked layers, this is frequently crucial. Convolutional and pooling layers in a CNN take the input data and extract hierarchical features from it, typically producing a three-dimensional tensor (height, width, and channels). Fully connected layers, however, require input vectors that are one dimension only. The flattened layer is introduced to fill in this gap. It essentially "flattens" the multi-dimensional output from the layers that came before it into a single-dimensional vector. The smooth transition from convolutional operations to the fully linked layers is made possible by this transformation.

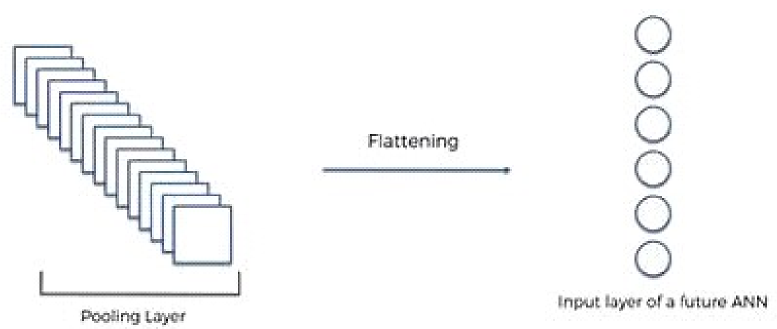


Figure 4 flattened layer

3.3.4 Fully connected layer

The flattened vector is followed by fully connected layers. These layers pick up the ability to integrate the features that the previous layers extracted and forecast. Neurons belonging to disease classes (e.g., healthy, diseased) often make up the output layers in hibiscus plant disease detection.The thick layer, sometimes referred to as a completely connected layer, is essential for encapsulating high-level abstractions and links in the data. Convolutional and pooling layers in the early stages of a CNN are in charge of extracting spatial features and hierarchies from the input data, such as photographs. Nevertheless, the output from these layers is flattened and routed through fully connected layers as the network grows. Every neuron in a fully connected layer is connected to every other neuron in the layer before it.Learned biases and weights are used to parameterize these associations. Usually, an activation function (such ReLU, Sigmoid, or Tanh) is applied to the completely linked layer's output. Because of its capacity to learn intricate, nonlinear patterns and generate sophisticated predictions, fully linked layers are an essential part of the CNN architecture when it comes to tasks like picture classification.

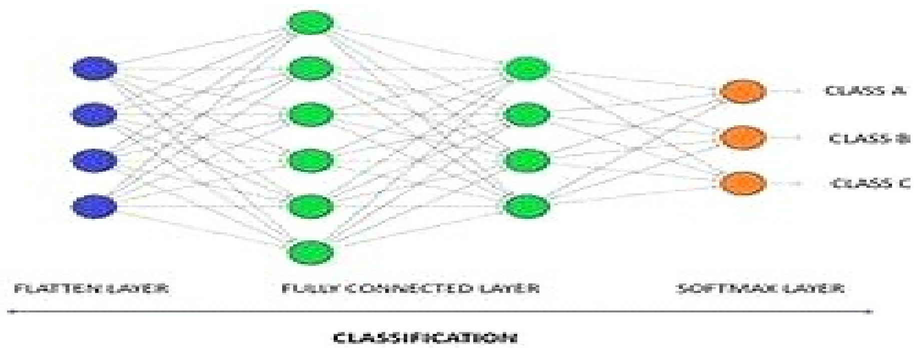


Figure 6 . Trained Dataset

Figure 6 shows the trained dataset used for the CNN model. It consist of 100 leaf images infected with disease. Similarly separate datasets of 100 image each is created for each disease.

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V. EXPERIMENT RESULTS

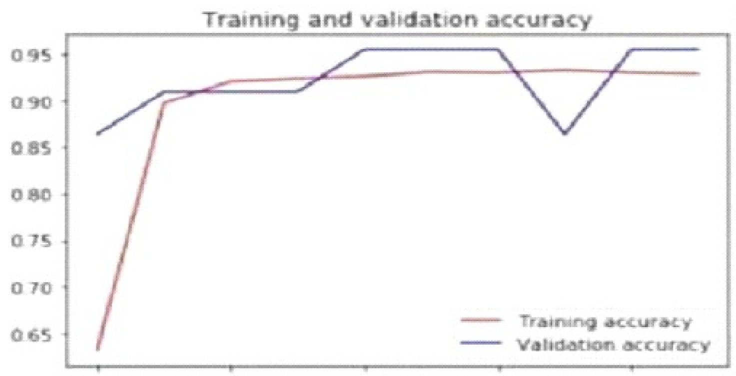

Figure7. Accuracy Graph

Figure.8 Loss Graph

The accuracy and loss plot of plant disease prediction using the suggested activation function are displayed in Figures 7 and 8. The prediction's accuracy rises with the number of iterations. In a similar manner, the accuracy and loss plot of the model can be obtained by testing it.

VI. CONCLUSION

Ultimately, we draw the conclusion that our study of the effective TensorFlow implementation of a Convolutional Neural Network (CNN) model and its 90% accuracy rate is an impressive accomplishment. The system's potential is further enhanced through the employment of the 'Adam' optimizer, which is well-known for its optimization skills. Upon examining different optimizers and activation functions, it is clear that the suggested approach routinely attains an accuracy rate higher than 90%, with the 'Adam' optimizer demonstrating very good performance. We intend to create an agricultural online application in the future. This software can detect whether plant leaves are infected or healthy in real time by taking images of the leaves. Your proficiency with CNN layers will be essential to the success of this application in the farming industry.

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