

Tomato Leaf Disease Detection using Convolutional Neural Networks

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Abstract: *One of the most important crops that is grown in enormous amounts and has an excellent market value comprises the tomato. They are grown and eaten in large quantities not only in India but also globally. Disease is the primary factor affecting the quantity and quality of this crop's production. In earlier research, the plant's leaves solely were taken into account for disease identification; however, in many cases, the illness only affects the fruit, leaving the other plant parts healthy. Using the unaided eye to diagnose a disease can occasionally lead to a prognosis that is off, meaning the wrong pesticide is applied and the plant may get spoiled. The farmers find it challenging to diagnose the disease because specialists are scarce in many of the affected areas.*

It's an expensive and time-consuming process, even though professionals are accessible in certain sectors. Early disease detection would lessen the impact on plants and increase agricultural yield. As a result, it is essential to recognise these illnesses accurately and use the appropriate pesticide. These issues can be resolved by an automated system. We have developed a system to tackle this problem, which employs a convolutional neural network (CNN) to detect the ailment and recommends a pesticide to aid in its eradication. Since CNN offers its highest level of accuracy, our system incorporates it.

Keywords: CNN, Feature extraction, Pesticide suggestion, Disease detection.

I. INTRODUCTION

In nations like India, the vast majority of people rely on agriculture for their livelihood. Agriculture is essential to the economy of every country. Technology has been and will continue to be incredibly helpful in the agricultural industry over the years. Fulfilling the need of an ever-growing population is the primary objective of agricultural advancement. Modern agriculture is required if it is to survive in the current climate. Crops can suffer from bacterial and fungal illnesses. This seriously impairs farmers' production. For optimal yield, crops should be in excellent health. Diagnosing diseases through eye inspection will never be easy. The farm needs to be continuously observed in order to do this. This method takes an excessive amount of time and can also be quite expensive if the farm is massive.

With this intricacy, even experts in agriculture find it difficult to diagnose the illnesses and find a way out. A technology that could identify plant illnesses automatically would be very beneficial to the farmers. By the help of this technology, the farmers will be able to take the required safety measures and receive alerts at the right times. Plant diseases can damage any part of the plant, including the leaves, fruits, seeds, and beyond. Certain plant segments are more prone to various types of illnesses. The leaves of a plant are its most significant part. An infection on a plant's leaf will immediately interfere with the plant's life cycle. Diseases caused by bacteria, fungi, and other agents are commonly observed in leaves. Thus, it is important to find plant diseases early.

II. REVIEW OF RELATED WORK

In paper[1], the authors have used deep learning to build a system for disease detection. To categorise tomato leaf disease, CNN-based models such as Google Net and VGG16 were used. VGG-16's accuracy rate was 98.00%, however Google Net's accuracy rate was greater at 99.23%. The illnesses with 10735 photos are identified using the Plant

Village collection. Using photos of tomato leaves, they have determined which disease is present. By computing various performance evaluation metrics, such as TP, TN, FN, and ACC, the two models' performances were assessed. In paper [2], the authors described how the recognition accuracy of picture classification and object detection systems has significantly increased when deep learning is applied to plant diseases. They offered a thorough study of current studies on the application of deep learning to the diagnosis of illnesses affecting plant leaves. Large datasets with high variability are gathered, transfer learning is carried out, data is enhanced, CNN activation maps are displayed, and the significance of hyperspectral technologies for illness detection is discussed in order to increase the accuracy of classification.

In paper [3], the writers talked about leaf disease detection methods using machine learning. The Support Vector Machine (SVM) algorithm, a supervised machine learning system, is used in the identification of diseases. The basic steps in the methodology used to detect diseases are as follows: first, take an input image; next, preprocess it; after preprocessing, extract any relevant features that are important for the image's classification; finally, train the model with both healthy and infected images; finally, cluster and classify the images.

The Internet of Things (IoT) is used by the suggested system in the paper [4] to identify illness. Using segments and characteristics from the SVM result robot, the system efficiently detects the disease and applies the pre-defined insecticides. This study's studies all made use of a rose leaf that had a bacterial illness. The Camera module, which is intended to communicate with the Raspberry Pi module, is used by the system to take pictures of the illnesses. The Raspberry Pi 3 Model, L293 Module, electrical relay, sprinkler motor, ultrasonic sensor, motor drive, and OpenCV are the parts that are used.

A method for classifying diseases using a convolutional neural network (CNN) and learning vector quantization (LVQ) algorithm is presented in the study [5]. The system was able to categorise the data into a preset number of classes when evaluated on a dataset that included 400 training photos and 100 test images of tomato leaves. It works well for resolving small issues.

Research on different plant leaf disease detection methods utilising leaf images is presented in Paper [6]. The authors have provided many methods for detecting plant diseases here. Based on several datasets, they have provided a tabular overview of many identification, segmentation, and classification methods along with their benefits, drawbacks, and accuracy. A Multilayered Convolutional Neural Network's ability to recognise important elements without human intervention by deviating from its models is one of its advantages.

The writers of a research study by reference [7] analysed many convolutional neural network (CNN) designs with a focus on tomato leaf disease classification. For assessment, they have made use of the PlantVillage dataset. This collection includes 14529 photos of tomato leaves in ten different classes, showing both healthy and damaged leaves. Of the 14529 photos, 2905 were used for testing and 11623 were taken into consideration for training. The article uses multiple CNN models to classify illnesses in tomato leaves. The models used were Alex Net, VGG16, Google Net, ResNet-101, and DenseNet-121. All the models performed well, they concluded, while DenseNet-121, the smallest model, had the highest accuracy. They claimed that the research can be extended to identify and diagnose disorders in addition to working on creating a lightweight, mobile-friendly model. The dataset can be enhanced to increase performance.

III. CNN

CNNs, or convolutional neural networks, are deep learning network architectures. There are scenarios when they have tens or even hundreds of layers in them. A CNN's layers are made to recognise and identify unique patterns or features in images. Convolutional neural networks (CNNs) use a variety of resolution filters on each input image during the training phase. Next, the convolved images that arise are fed as input to layers that follow. These filters learn more intricate qualities over time, which aid in the unique definition of the objects being classed. Initially, they identify simple aspects like brightness and edges. CNNs can be trained to do tasks such as object detection, segmentation, scene categorization, and image processing.

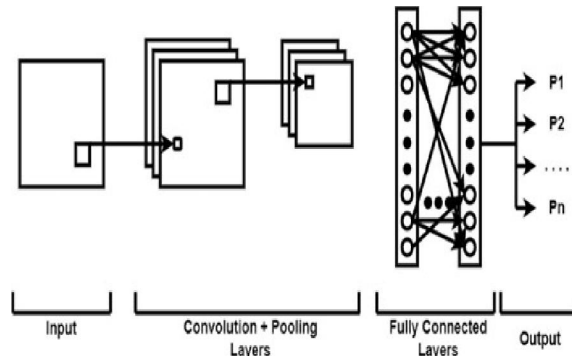


Fig. 1. A general CNN Architecture

CNN consists of four components:

Convolution

In image processing and computer vision, convolution is a fundamental procedure that makes it possible to extract local features from a picture. To put it another way, the network picks up particular patterns in the image and learns to recognise them across all images.

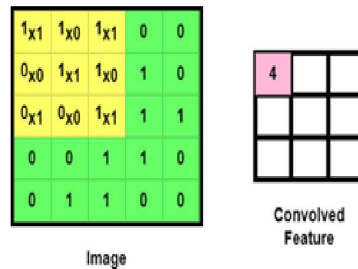


Fig. 2. Convolution on 5x5 image and 3x3 filter

Convolution is a multiplication of elements one by one. The procedure entails scanning a portion of the image, usually 3 by 3, then multiplying it by a filter to accomplish a convolution operation. The result of multiplying elements-by-wise is a feature map. Until every image is scanned, this process is repeated. Convolution reduces the size of the image.

Non-Linearity (ReLU)

To account for non-linearity, an activation function is applied to the output following the convolution process. The standard convent activation function is the Relu. Negative values are replaced by zeros in any pixel.

Pooling Operation

In convolutional neural networks, pooling is used to reduce the input image’s spatial dimensionality. The actions are performed to reduce the operation’s computational complexity. The neural network has fewer weights to compute when the dimensionality is reduced, which lessens the possibility of overfitting. Right now, it’s important to specify the stride length as well as the size. A common technique for pooling the input image is to use the maximum value of the feature map.

Fully Connected Layers

Building a traditional artificial neural network is the last step. In neural networks, one typical technique for image classification problems is to connect all of the neurons from one layer to the next. It is common practice to apply the softmax activation function to allow the network to classify incoming images.

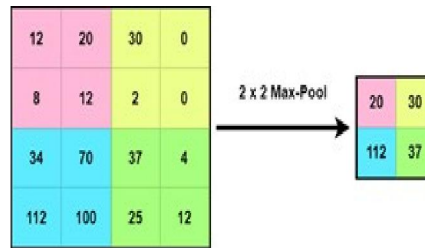


Fig. 3. 2x2 Max pooling

IV. PROPOSED SYSTEM

The system at hand focuses on identifying and categorising diseases using a convolutional neural network. We plan to launch this idea as an online application. The study employed a dataset comprising 1386 photos, which includes photographs of both fruit and tomato leaves. The model has thirteen categories in all, ten of which are based on tomato leaves and three on fruit. Tomato fruit images are gathered from the internet, and images of tomato leaves are taken from the PlantVillage dataset. There are 148 images in the healthy category, some of them feature fruit and tomato leaves. There were 1240 training photos and 146 testing images in the dataset that was used to train and test the models. The JPG format was used for the photos, which were 224 by 224 pixels in width and height. As seen in the picture, the framework consists of several steps that increase the precision of disease detection.

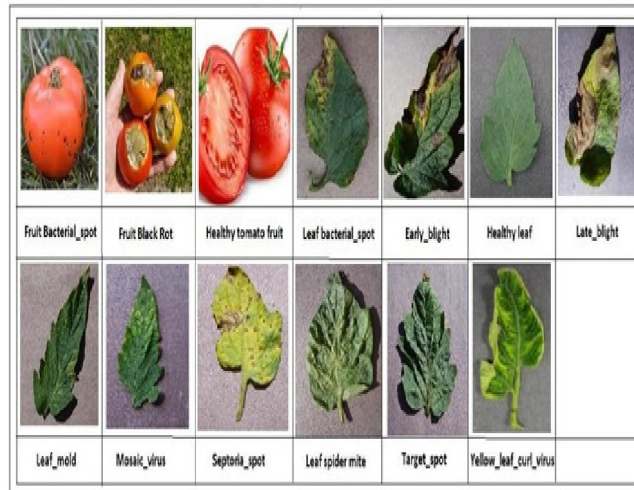


Fig. 4. Class-wise sample image of the dataset

Our system operates as follows:

Step 1 : On the dataset, image preparation procedures are carried out. The preprocessing of the dataset will include reshaping, image rescaling, and array format conversion. In image classification tasks, resizing images to fit the input size of a convolutional neural network (CNN) is a typical preprocessing step.

Step 2 : Data preparation comes before building a CNN model, which is the next stage. The training dataset is supplied to CNN, and the weights are adjusted to correctly detect the disease and differentiate it from the other. CNN uses convolutions to gather pixel information from an image and then uses that information to extract the best possible set of characteristics, including colour, shape, and texture.

Step 3 : Post model training, the fully connected layer uses the features acquired by the previous layers and their corresponding filters to forecast the disease.

Step 4 : A recommendation for pesticides will be given, along with a list of the vendors' locations

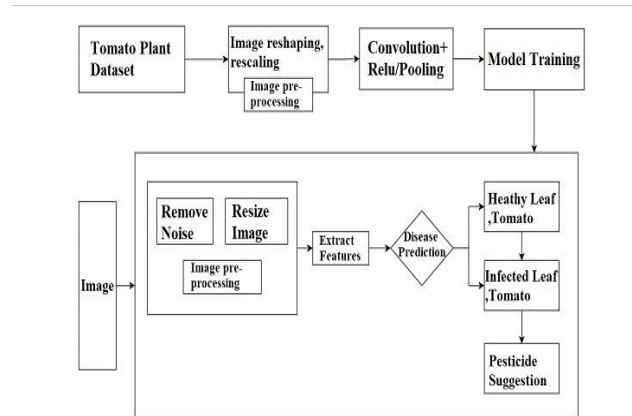


Fig. 5. System Architecture

V. METHODOLOGY

The suggested approach finds illnesses in tomato plants. The method of classifying if a leaf or plant is diseased involves analysing leaf photos, applying image processing techniques, extracting features, and developing a model. To verify the model’s accuracy and dependability, it is tested on a different set of photos after training.

Dataset Collection

The software generated a data set that was used for training that included images of plants with different diseases as well as ones with healthy leaves. There are 1386 photos in the dataset that were utilised in the experiment that show both tomato fruit and tomato leaves.

Dataset Preprocessing

The pre-processing technique is applied to reduce noise and enhance image properties. Prior to picture processing, contrast enhancement is applied. It improves visual qualities by converting input intensity to a new value.

Model Building

Pre-processed photos are supplied into the CNN model to classify different plant diseases during the training phase.

Feature Extraction

This stage determines how photos are classified. We do not choose the full image; instead, we selectively extract characteristics from the impacted area. Feature extraction, which provides the best restrictions and an acceptable platform, is an important step in the image processing technique. Effectively analysing a leaf image’s shape, colour, pattern, and size is essential for feature extraction.

Categorization

After training, the model is prepared to classify unlabeled plant data. The training and testing photos are compared, and the image is fed into the model. The model’s output includes the plant’s name, the discovered disease, and a recommended pesticide.

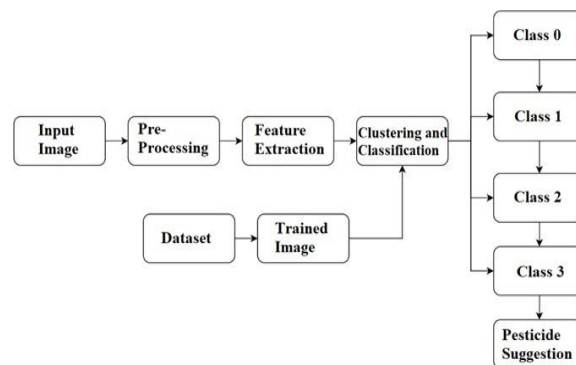


Fig. 6. System Flow

VI. RESULTS

Table 1. Hyperparameters used in the Proposed Model

Hyperparameter	Specification
Count of the convolution layer	3
Count of the max pooling layer	3
Dropout rate	0.5
Activation function	Relu
No. of epoch	5
Batch size	16

These were the hyperparameters used in this system.

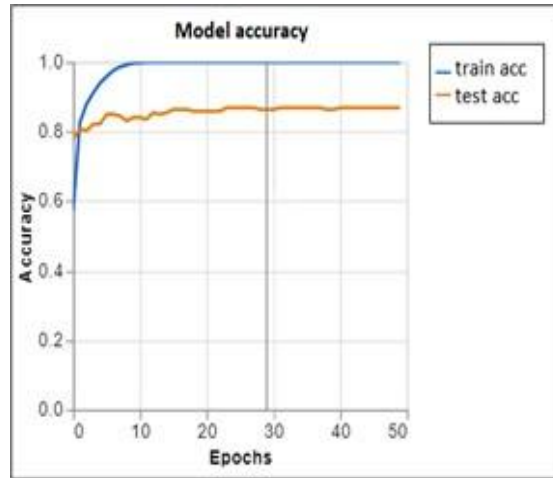


Fig. 7. Model Accuracy

As the graph above illustrates, after 10 training epochs, the maximum accuracy of 99% was attained, and about 90% of validation accuracy was attained

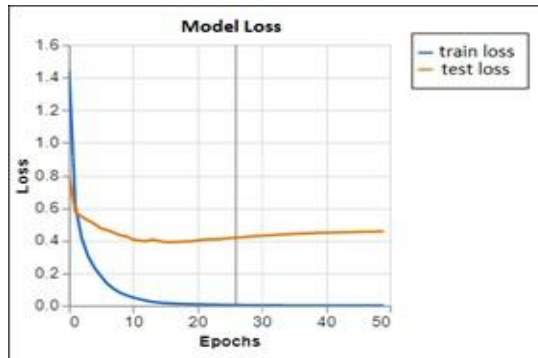


Fig. 8. Model loss

VII. CONCLUSION

One significant industry that has a big impact on society is agriculture. It is crucial for the nation's economy in addition to being necessary. Given their importance, tomatoes need to be produced with extreme caution. There are instances when a plant's fruits are impacted without the leaves showing any signs of harm. Using the incorrect remedies can result from making erroneous observations with the naked eye. Consulting an expert can be expensive and time-consuming.

Because convolution neural networks are so accurate, they are ideal for image recognition applications. As a result, we used it to create this tool, which will assist in reducing the time and expense associated with manual prediction.

It offers remarkably accurate disease identification for 13 conditions. Although occasionally only the fruit is harmed, it categorises diseases based on both the fruit and the leaves. In addition to identifying the illness, it also recommends the brand of pesticide that can be used as a treatment.

VIII. FUTURE SCOPE

By developing an application, this work can be expanded to include the identification of illnesses in plant species other than tomatoes. This technology can be used to create an IOT- based monitoring system. In the future, even greater accuracy can be achieved by substituting new and improved algorithms. A chatbot for farmer inquiries can be included.

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