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Machine Learning for the Detection of Tomato Leaf Disease

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A B S T R A C T

The plant diseases are a factor in productivity loss, although they may be controlled with ongoing observation. Monitoring plant diseases manually is time-consuming and prone to mistakes. Artificial intelligence (AI) and computer vision can be used to identify plant illnesses early on, reducing their negative consequences while also overcoming some of the limitations of constant human monitoring. In this study, we thoroughly examined how well ResNet18, MobileNet, DenseNet201, and InceptionV3 classification network architectures performed on 18,162 photos of plain tomato leaves to identify tomato illnesses. India, a sizable agricultural market, offers the ideal atmosphere for a wide range of crops. The tomato crop, which has significant commercial value, is one of the widely produced essentials on the Indian market. In terms of tomato production, India is one of the major nations. However, it is a sad fact that several illnesses that harm the crop are causing the quantity and quality of tomato crop output to decline day by day. The farmer suffers severe losses as a result. It is crucial to have perfect control over the crop's development in order to reduce this loss. These tomato leaves are severely harmed by a number of diseases, including Late Blight, Bacterial Spot, Early Blight, Septoria Spot, Mosaic Virus, etc. Therefore, finding a way to stop these illnesses before they start is essential. Only if we can identify the illness in its early stages will this be possible. Leaf disease diagnosis may be done extremely simply and more accurately with the use of various ML algorithms, producing excellent results. Convolutional neural networks (CNN) and Res Net 50 are used to analyze the dataset in this study. The accuracy displayed by CNN is the highest of the two used algorithms. Machine learning technic is very useful to detend tomato disease.

1. Introduction

Being an economic powerhouse, India has almost 65% of its population employed directly in agriculture or related industries. Plant diseases cause farmers to lose a lot of money. The majority of tomatoes are grown on well-drained soil. Nine out of every ten farmers are known to plant tomatoes on their fields. In India, there are around 3, 50,000 hectares of land used for tomato farming, and about 53,000 tons of tomatoes are produced annually. Many gardeners also cultivate tomatoes in their gardens so they may have fresh ones that are tasty. However, those farmers and gardeners frequently fail to see the whole growth of the produce. The likelihood of contracting infections rises as a result. The evolution of agriculture thousands of years ago resulted in the domestication of the majority of today's food crops and animals. Food insecurity is one of the biggest issues facing humanity today, and plant diseases are a key contributor to this problem [1]. One estimate places the worldwide crop output loss attributable to plant diseases at about 16% [3]. For wheat and soybeans, the potential worldwide loss from pests is estimated to be between 50 and 29 percent [3]. Fungi, fungus-like organisms, bacteria, viruses, viroids, virus-like creatures, nematodes, protozoa, algae, and parasitic plants make up the primary families of plant pathogens. Computer vision, machine learning, and artificial intelligence (AI) have all significantly aided a variety of applications, such as the prediction of electricity from renewable resources [4, 5]. With a per capita consumption of 20 kilos per year and 15% of the average global vegetable intake, tomatoes are a significant food crop worldwide. While Europe consumes 31 kilograms of tomatoes per person per year, North America consumes 42 kilos of tomatoes annually [5, 6]. It is essential to develop methods for increasing crop output and early identification of pests, bacteria, and viruses in order to fulfill the demand for tomatoes on a worldwide scale. In several studies, artificial intelligence-based strategies have been used to increase tomato plants' longevity through early disease diagnosis and subsequent disease control. It is essential to develop methods for increasing crop output and early identification of pests, bacteria, and viruses in order to fulfill the demand for tomatoes on a worldwide scale. In several studies, artificial intelligence-based strategies have been used to increase tomato plants' longevity through early disease diagnosis and subsequent disease control. Manpreet et al. [8] classified seven tomato illnesses with a 98.8% accuracy using a pre-trained CNN-based architecture called Residual Network, also known as ResNet. To diagnose Bacterial Spot, Late Blight, and Septorial Spot disease from tomato leaf photos, Rahman et al. [9] developed a deep learning-based fully-connected network and achieved an accuracy of 99.25%. To categorize 10 illnesses from photos of tomato leaves, Fuentes et al. [10] took into account three primary groups of detectors. Amrita S. Tulshan and Nataasha Raul presented a study in 2019 on the identification of plant diseases. When they used K Nearest Neighbor classification to forecast plant leaf diseases, they obtained an acceptable accuracy of 98.56% [11]. In a study report on the identification of leaf disease that was given in 2013 by Arti N. Rathod, Bhavesh Tanawal, and Vatsal Shah, they detailed numerous methods for identifying diseased leaves using image processing techniques [12].

2. Data Collection

The dataset utilized in the study was obtained from the Kaggle directory [13]. The whole dataset for this study is comprised of the following 10 directories, each of which contains 1000 images:

1. Leaf with Bacterial Spot: This category has 1000 images of tomato leaves with bacterial spots on them.

2. Leaf with Early Blight: This directory has 1000 images of tomato leaves with Early Blight on them.

3. Late Blight Leaf: This category has 1000 images of tomato leaves with Late Blight on them.

4. Mosaic Virus on Tomato Leaf: This directory has 1000 images of tomato leaves with Mosaic Virus on them.

5. Septoria Spotted Leaf: This category contains 1000 images of tomato leaves with Septoria Spot.

6. Target Spot: This collection has 1000 images of tomato leaves with Target Spot on them.

7. Leaf Mold: This collection has 1000 images of tomato leaves with leaf Mold on them.

8. Yellow Leaf Curl Virus: This collection has 1000 images of tomato leaves with Curl Virus on them.

9. Two Spotted Spider Mites: This category has 1000 images of tomato leaves with spider mites on them.

10. This collection has 1000 images of healthy tomato leaves.

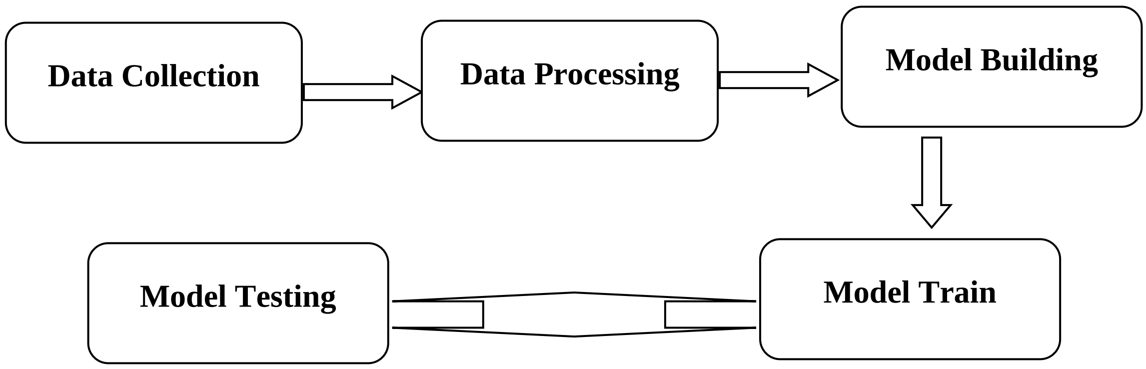

Fig. 1 Dataset collection process flow chart.

Machine Learning Approach with ANN and Resnet-50

An artificial Neural Network is simply a Neural Network that is similar to the biological Neural Network found in the human brain. It is constructed in such a manner that it functions similarly to the human brain. It is made up of millions upon millions of artificial neurons. These artificial neurons serve as the foundation for the ANN model. An Artificial Neuron is made up of Inputs and their related weights. An activation function is chosen to take these inputs, multiply them by their weights, and create the output. Every Artificial Neural Network must have three layers: the input layer, which receives input, the hidden layer, which does all calculations, and the output layers, which provide output. An Artificial neuronal Network (ANN) is a computer model inspired by the neuronal structure of the human brain. It is made up of linked nodes (neurons) that are grouped into layers. During training, the network modifies the connection strengths (weights) to learn from input, allowing it to spot patterns, make predictions, and perform multiple tasks in machine learning and artificial intelligence. The network architecture has three levels: the input layer, the hidden layer (or layers), and the output layer. Because of the various layers, the MLP (Multi-Layer Perceptron) is sometimes used. The hidden layer may be seen of as a "distillation layer," extracting some of the most important patterns from the inputs and passing them on to the next layer for further analysis. It speeds up and increases network efficiency by detecting just the most significant information from inputs and rejecting the superfluous information.

ResNet50 is a Keras Resnet model with 48 convolutional layers, 1 MaxPooling layer, and 1 Average Pooling layer. It can do 3.8 x 109 floating point computations. This is the most practical Resnet model. It may also be utilized for computer vision applications such as picture categorization, object location, and object detection [13]. This technique may also be applied to noncomputational vision applications to save computing costs while providing depth.

In the beginning, raw data is acquired through a website called "Kaggle" [14]. The raw data is then pre-processed, with the data initially shrunk to 150 for CNN and 224 for ResNet 50, followed by online data augmentation to prevent overfitting. Following data pre-processing, the essential features are retrieved and the data is separated for training and testing purposes.

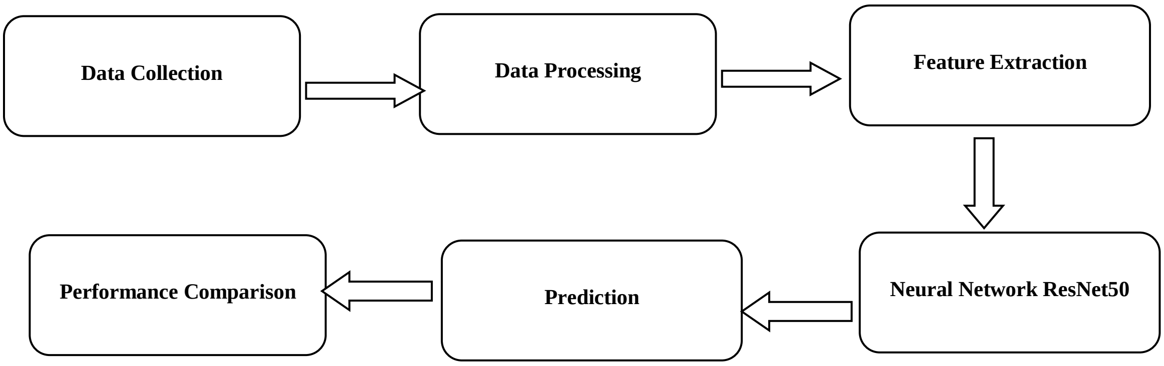

Fig. 2 Proposed Methodology flow chart

Result Analysis

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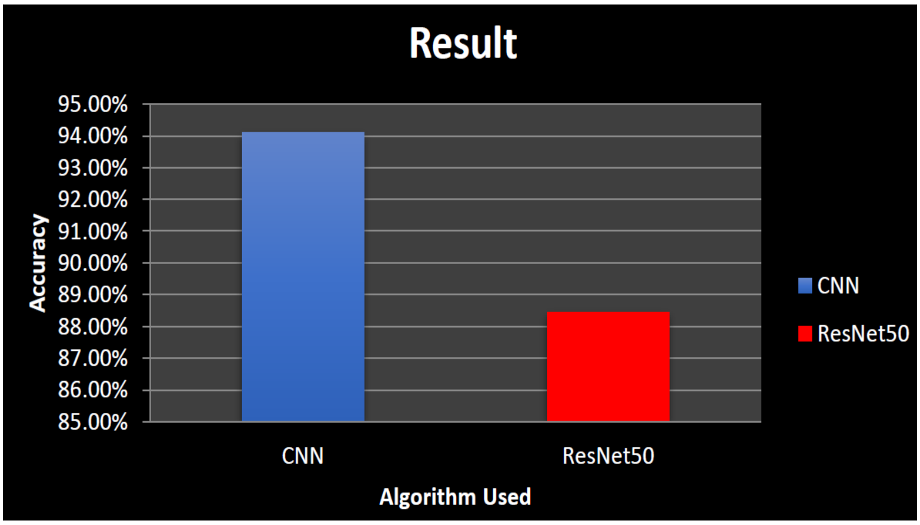

Fig 2 Result Accuracy

When we examine the output of the processed data on different proposed models, we find that the Convolutional Neural Network model has an excellent accuracy of 94.1%, followed by ResNet 50 with an accuracy of 88.44%, indicating that our CNN model can predict more accurately. The above graph depicting the results of the algorithms used in the proposed model shows that CNN has the longest bar, indicating that it has the maximum accuracy of 94.10%, compared to ResNet50, which has a short bar with an accuracy of 88.44%.

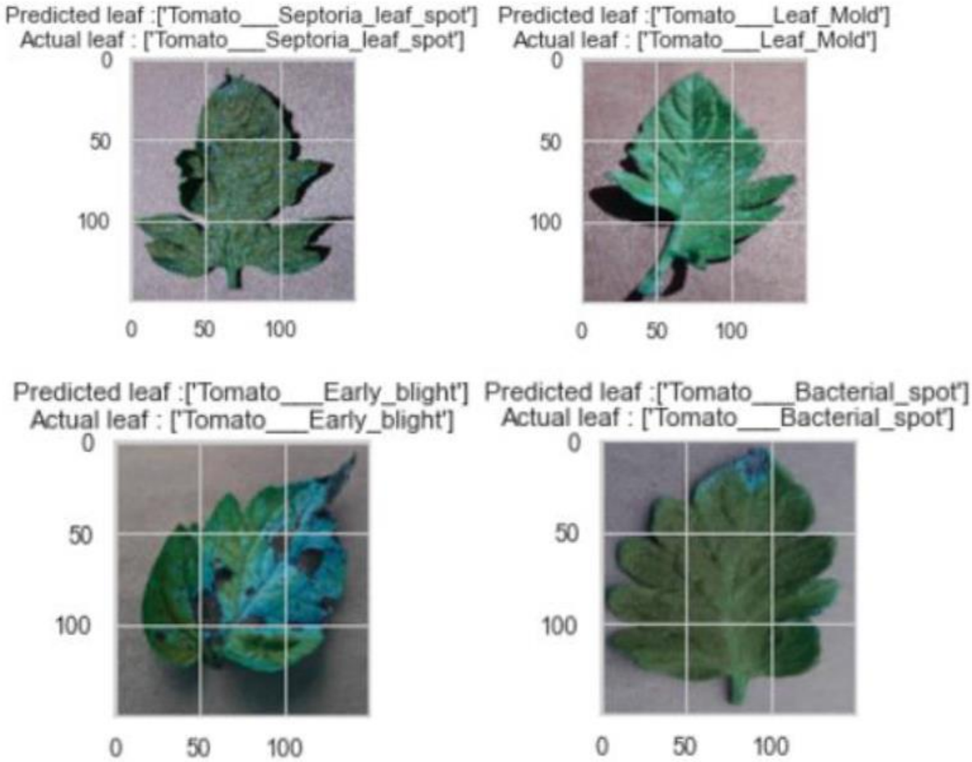

Fig. 3 Output of Actual Vs Prediction

The photographs above illustrate that the anticipated leaf disease is identical to the real one. Our model is capable of making accurate predictions.

Conclusion

Science artificial neural networks, which emerged in the mid-twentieth century, are rapidly evolving. We have now researched the benefits of artificial neural networks as well as the challenges encountered during their use. It should not be forgotten that the disadvantages of ANN networks, which are a thriving scientific area, are being eradicated one by one, while their advantages are growing by the day. It indicates that artificial neural networks will become an increasingly crucial aspect of our life. Timely detection and diagnosis of illnesses that affect the leaves is critical these days since they cause significant damage to crop yield and quality. This study describes a model in which a total of 10000 photos were pre-processed before being applied to a machine learning technique, CNN, and a pre-trained model, ResNet 50, for image processing and prediction tasks. The obtained results revealed that the CNN algorithm had the maximum accuracy. The ResNet 50 Model's accuracy is good, but in the future, we may modify the parameters used to improve the accuracy even further.

As a result, it has been discovered that pre-trained models are not always a viable choice for all datasets under consideration.

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