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CNN Based Early Detection of Leaf Disease

Dommati Vaishnavi*, Thiruveedula Bharath Chandra and Elma Shrenitha

Deprtment of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Vardhaman College of Engineering, Hyderabad, Telangana, India

***Correspondence to:**
Dommati Vaishnavi
Deprtment of Computer Science and Engineering (Artificial Intelligence and Machine Learning),
Vardhaman College of Engineering,
Hyderabad, Telangana, India.
E-mail: dommativaishnavi2002@gmail.com

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Abstract

Majority people depend on agriculture. Improper management leads to the loss of agricultural products. So, it is salient to identify the diseases that are prevalent in the leaves of plants. The term disease refers to the destruction of plants. Diseases that affect plants affect their growth. Disease detection helps reduce crop loss. This paper presents an approach for identifying the type of disease attacked by tomato plants using convolutional neural networks. Convolutional neural networks (CNN) is a subset of deep learning that is used for signal processing, picture segmentation, and other commonplace tasks like image classification, etc. Various parameters such as batch size, dropouts, and various epochs were used to assess the model's effectiveness. The dataset contains 18345 train images and 4585 test images. CNN are used for improving model accuracy. Plants are the food source of the earth. Plant infections and diseases are therefore a major threat, the most common diagnosis consists primarily of examination of plants and presence of visual symptoms. The proposed model achieved about 95% accuracy.

Keywords

Convolutional neural network, Image processing, Image segmentation, Feature extraction, MaxPooling, Conv2D, Dropout

Introduction

In India, the majority of people depend on agriculture for their living. The agricultural sector has a great impact on people's lives and human economic height. India has ranked second in farm yield globally [1]. In 2018, agriculture has given employment to 50% of the employees contributing to 18 - 20% of GDP. The issue of effective pest control is closely linked to the issue of sustainable agriculture. Inexperienced use of pesticides can lead to severe deterioration of the immune system in the case of long-term resistance to pathogens.

In view of the increasing population, there is a large necessity of increasing agriculture production. It is crucial to identify the problems faced in the agricultural sector. To increase production the crops must be healthy.

In order to increase production and help the farmers from crop loss. There is a great need to identify the diseases that attack the plants. On a large scale, it is difficult to examine each and every plant to identify the disease attacked on the crop even after continuous monitoring by experts. In remote areas, it is difficult for farmers to consult an expert for which they may have to travel a longer distance, and also time-consuming. To overcome these problems, one of the successful farming methods is the identification of leaf disease. There are many problems faced by the farmers such as no proper agricultural strategies, inadequate use of fertilizers, and water supply. Major diseases are harmful to the growth of plants. The diseased plants add up to 20% of the total crop deprivation.

Thus, detection of disease and pests in the early stages is essential for the healthier growth of plants. Faster and more accurate predictions of plant diseases can help reduce losses. The progress and development of deep learning have given us the opportunity to improve the performance and accuracy of object detection and detection systems. Deep learning has achieved great results in areas such as image preprocessing and speech recognition etc. The use of convolutional neural networks has resulted in great results. CNN is the best method for object recognition.

The early detection of leaf diseases in plants integrates CNN with advanced nanotechnology. High-resolution images of plant leaves are captured, and nanosized sensors are employed to detect subtle biochemical changes associated with diseases. This innovative synergy of CNNs and nanotechnology presents a robust solution for precision agriculture, enhancing crop management through timely disease intervention. The integration of CNN and nanotechnology not only revolutionizes early disease detection but also underscores the potential for advanced, tech-driven solutions in the agriculture sector. The integration of CNN and nanotechnology signifies a significant leap forward in agricultural disease management. This technology not only revolutionizes early disease detection but also showcases the potential for cutting-edge, tech-driven solutions to address agricultural challenges, ensuring food security and sustainable crop production.

Ten different types of tomato leaf diseases that are the main prominence of the suggested model for leaf disease detection. CNN are used to implement the model. The accuracy of the model was estimated to be around 95% after training and testing.

Plenty of work and research is in progress in the area of automated leaf detection to identify the plant's species. In this article, some related works are discussed here. Gulhane and Gurjar did feature extraction on the color and shape of holes using unsupervised self-organizing feature map technique and artificial neural network (ANN) classifier on the cotton plant [2]. Kutty et al. categorized the watermelon leaf diseases of Downy Mildew and Anthracnose with 75% accuracy using an ANN-based system. A few of infected leaf samples were collected and they were captured using a digital camera with specific calibration procedure under controlled environment [3]. Ranjan et al. distinguished the healthy and diseased samples of leaf diseases using ANN with 80% accuracy. By combining several image processing techniques with an ANN, the author provided a method for the quick and accurate diagnosis of cotton leaf diseases [4].

Miller et al. did a spectral reflectance evaluation of apple blemishes to recognize varied patterns in different apple Unimodal Gaussian, multi-layer backpropagation, K-nearest neighbor (KNN), and nearest cluster algorithms with 85% accuracy [5]. Prasad et al. worked on plant leaf recognition using a Support Vector Machine (SVM) with 95% accuracy. After image pre-processing, color feature and texture feature plant images are obtained, and then SVM classifier is trained and used for plant images recognition [6]. Gayathri Devi and Neelamegam classified the leaf disease and non-disease plants using multi-class SVM with 98.63% accuracy. First, the affected region is discovered using segmentation by K-means clustering, then features (color and texture) are extracted. Lastly, classification technique is applied in detecting the type of leaf disease [7].

Asraf et al. classified nutrient diseases in oil palm leaves using SVM with 95% accuracy. Initial results show that the recognition of oil palm leaves is possible to be performed by SVM classifier. Based on the best performance result, polynomial kernel with soft margin is capable of classifying nutrient diseases accurately [8]. Joshi and Jadhav classified rice diseases using the KNN, and minimum distance classifier with 89% accuracy [9]. Jhuria et al. categorized diseases using morphology, texture, and color feature vectors of apple and grapes using neural network with back-propagation with 90% accuracy [10]. Mohanty et al. detected plant disease using deep CNN with 99% accuracy. The proposed depp CNN model was trained in the multi-graphics processing units' environment for 1000 epochs. The random search with the coarse-to-fine searching technique was used to select the most suitable hyperparameter values to improve the training performance [11].

To pinpoint the area of the disease that is impacted, this study is divided into two sections. Edge detection-based picture segmentation is used at first, followed by CNN for image analysis and disease categorization. The purpose of this research project is to use image analysis to locate the tomato leaf spot that has the disease.

Experimentation

Proposed methodology

The proposed model is based on Python and provides about 95% accuracy. The proposed model helps users predict plant leaf disease. Diagnosis is one of the most important aspects of training for phytopathologists. Disease control operations can be time- and money-consuming and result in significant crop loss if disease and antibody identification is not done correctly. Therefore, correct disease detection is important. Therefore, this system can be used to easily detect tomato leaf disease and ultimately prevent crop failure. This system is trained by the CNN algorithm and helps maximize the accuracy of disease detection.

Methodology

Dataset

The tomato dataset [12] was used to extract images of tomato diseases. The dataset contains images of many tomato leaf diseases. Bacteria disease, healthy disease, early morning disease, late morning disease, leaf mold disease, septoria leaf spot, spider mite disease, target spot disease, mosaic virus disease, and yellow leaf curl disease (Figure 1).

Labelling

In order to offer the context for the machine learning model to learn, labelling the data entails recognizing the original image and adding accurate and insightful labels.

Data pre-processing

Before data is transferred to the network, it can be altered

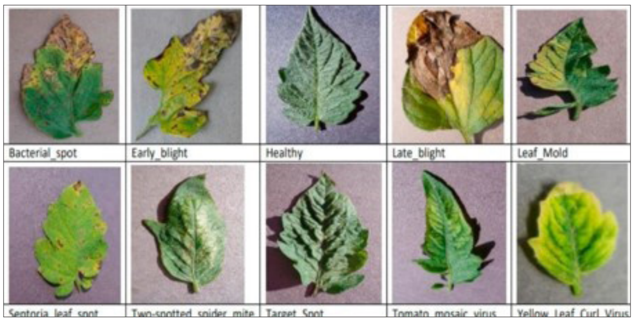

Figure 1: Shows the different tomato leaf diseases.

or deleted using data pre-processing. During CNN's training, this procedure is used to prevent bias for any given class. The size of the images is 64 x 64 (Figure 2).

Model building

In this case, CNN was used to construct the model. The algorithm is guided by input data (CNN). A sequential iteration, this one. Convolutional, pooling, dropout, flatten, and thick layers have all been used in this model (Table 1).

Conv2d

The foundational element of the CNN design is this. The layer's input is transformed along with the convolution kernel it produces to create the output tensor.

MaxPooling2d

It is used in part to combat overfitting by giving the representation of an abstract form. Additionally, it provides basic translation unvarying for the internal representation and lowers enumerating overhead by lowering the number of parameters to learn.

Dropout

The dropout layer is a mask that removes the contribution of certain neurons to the next layer and leaves all others intact.

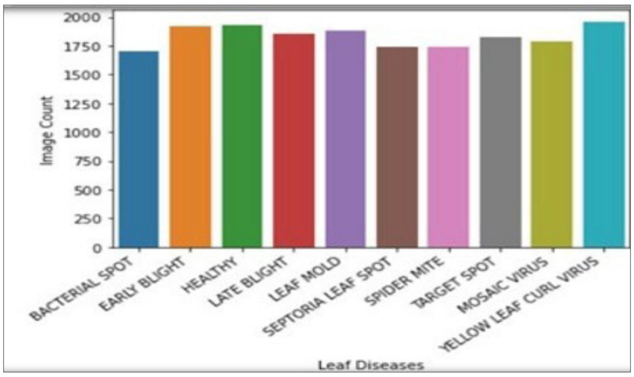

Figure 2: Shows the image count of different diseases in the dataset.

Table 1: Shows the parameters and the corresponding values.

Parameter	Value
Epcohs	75
Hidden layers	05
Accuracy	95% approx.

Flatten

Flatten layer transforms data into a one-dimensional array for input to the next layer.

Dense

Each neuron in a dense layer receives all of the outputs from the preceding layer, with each neuron sending an output to the following layer. The most fundamental component of neural networks is this one (Figure 3).

Results and Discussion

The majority of prediction models for freestanding disease diagnosis perform less well when applied to novel real-world situations. It is claimed that it is difficult to enhance performance for the perception and classification of plant leaf disease. The importance of collecting large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification accuracy are discussed. To improve the final classification process's recognition rate, more effort can be done to develop hybrid algorithms and neural networks. The amount of disease present in the leaf must also be calculated. Several pre-trained neural network designs were used in the study's experiments as feature extractors, and the higher dimensional layers were calibrated to learn characteristics specific to the dataset. The

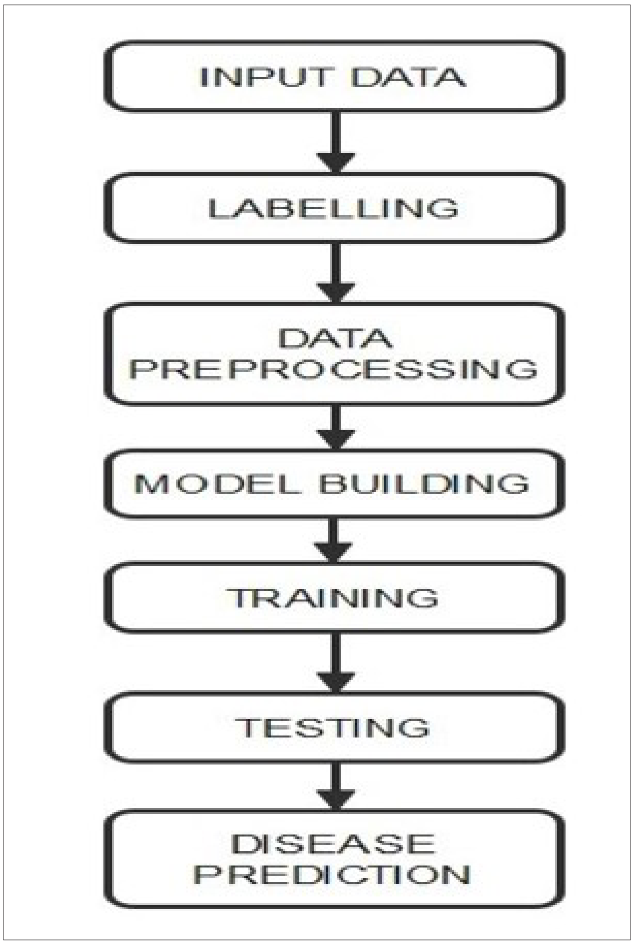

Figure 3: Shows the proposed methodology.

conclusion has come up from the study of machine learning classification models. SVM and neural network were found to give 90% accuracy, which competes with the best machine learning classification models available for classifying high-dimensional datasets.

The self-classification accuracy has been seen to be consistently higher than 93% in each instance. This is because of a number of images for bacterial spots and tomato early blight symptoms. This confuses the model during training. The model's average accuracy of 95% is in line with other researchers' findings (Table 2). The similarity of the photos in the tomato data, which are utilized for both training and validation, can be partly blamed for this high accuracy. The model, however, has the peculiar issue that the average self-classification accuracy only drops to 42.3% when tested with the same photos cropped to include partial leaves or with independent images from the internet. This is in line with other studies that trained their models using images from the tomato dataset and then contrasted their findings to pictures from unrelated datasets (Figure 4).

Table 2: Shows the accuracy of related methods.

S. No.	Reference No.	Accuracy
1	9	75
2	4	80
3	5	85
4	9	89
5	10	90

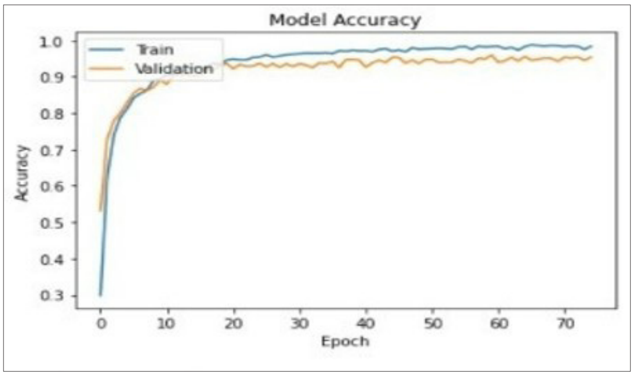

Figure 4: Shows model accuracy.

Conclusion

There are numerous approaches for classifying plant diseases using plant leaves. Yet there is no practical and reliable commercial technology for detecting the disease. In our work, we have applied convolutional neural networks concepts to detect the leaf disease of the tomato plant. We have taken the dataset from Kaggle website it contains 10 different types of diseases attacked on the tomato plant. Various activation functions like relu, softmax are utilized for achieving an effective result. The model has achieved an accuracy of 95% approximately. This model can accurately predict the diseases attacked on tomato leaf and it can be utilized to identify the disease of the plant at the preliminary stage and take preventive steps for the better growth and production of the crop.

Acknowledgements

None.

Conflict of Interest

None.

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