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Tomato leaf disease diagnosis based on improved convolutional neural network

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***Abstract*---**Tomatoes are one of the world's most important and tasty crops. This is a high-value crop, and the nation grows a lot of them. Every year, pests and diseases cause more metric tonnes of tomato crop loss in India. Tomato leaf disease is a severe issue that costs farmers a lot of money and threatens the entire agricultural business. As a result, it is critical to precisely diagnose and characterise these diseases. A variety of diseases impede tomato production. Early diagnosis of these diseases will reduce the disease's impact on tomato plants and increase crop yield. Various novel ways of recognising and categorising certain ailments have been widely used. The purpose of this research is to help farmers identify diseases in their early stages. The improved Convolutional Neural Network (CNN) is used to appropriately define and categorise tomato diseases. Kaggle is used to undertake the dataset study, which includes 18160 images of tomato leaves affected with nine distinct diseases and a healthy leaf. The following is a breakdown of the complete procedure: The collected images are first pre-processed. Second, the improved CNN model is used for image feature extraction and classification. Finally, improved CNN is compared against CNN using accuracy and loss measures. According to the experiment results, the improved CNN model achieves high accuracy of 95% and 96% in the training and validation phases, respectively.

***Keywords*---**tomato, disease, network, metrics, evaluation, images.

Introduction

Agriculture is among the most important human activities that contribute to the growth of a country. Due to population growth and the need to fulfil their food needs to improve their lifestyles, large activities in the agricultural and food industries have recently taken place. Agriculture is critical to the country's

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economic growth because it not only offers raw resources and food but also produces employment chances [1]. Plant pathogens and insect outbreaks are generating a 40% reduction in the worldwide food supplement industry each year. Plant diseases have historically been the most significant barriers to long-term agricultural progress. The ecosystem has a regular impact on the quality of the crop since it is a popular vegetable and a key source of revenue [2]. Tomatoes are the most often eaten vegetable in India. Tomatoes contain all three primary vitamins and anti-oxidants. Potassium, a vital nutrient for good health, is present in a variety of foods. With an approximate 3,50,000 hectares of agricultural production and 53,00,000 tonnes of tomato production, India is the world's third-largest tomato producer. Illness has been rampant in the tomato crop at all stages of growth due to the plant's sensitivity to the environment. According to data gathered by the United Nations Food and Agriculture Organization [3] tomato disease is the leading cause of the global tomato output reduction.

Leaf infections are a major source of productivity loss in the tomato business, resulting in significant financial losses for producers. Example, early blight is a common disease in the world and has a large influence on productivity. Late blight, a destructive disease, also impacts crops. To avoid illness, tomato crops must be protected, increasing both the quantity and quality. Consequently, the Initial detection of disease drives the selection of a suitable therapy to avert major harm. In agriculture, early diagnosis of plant disease is crucial. Because the original structure of the leaf varies depending on the sickness, this is the most frequent approach for identifying the existence of plant disease. The capacity of an expert to detect disease just by looking at the crop demands extensive expertise and knowledge of disease sources. Furthermore, the professional should be able to clearly describe the disease's signs and symptoms to the patient. Even today, some rural communities employ manual examination, even though the sickness and its variants cannot be reliably recognised. Manual evaluation takes more time and labour on large farms. Because cultivation is a continual process, crops must be checked for disease detection frequently. As a result, a new method based on leaf images is necessary to identify sickness automatically. Early diagnosis of such plant diseases is crucial for preventing severe decreases in yield and total agricultural output. Because of their intricacy and time-consuming nature, plant diseases are difficult to monitor manually. It is vital to reduce the amount of physical labour required for this procedure to produce accurate predictions and create a hassle-free existence for farmers. The work done on disease identification and categorization has been studied and identified the suitable techniques

Many farmers' impressions of the disease are biased since it is difficult to identify patterns with the naked eye. As a result, farmers' disease-prevention measures may be ineffective or even harmful at times. Farmers frequently join together and they employ standard disease protection methods, due to a lack of specialist advice on how to cope with a crop infestation [4]. Crop damage has happened as a result of pesticide over-or under-dosage due to a lack of knowledge or a misunderstanding of the severity of the disease. This is the impetus behind the proposed method for identifying and diagnosing tomato crop disorders. The researchers [5] intend to better forecast the spread of disease symptoms on barley plants by using a Cycle-Consistent Generative Adversarial Network. Instead of a typical RGB image, hyperspectral images are utilised to train a model, resulting in a more informative output. One of the study's contributions is a weekly prediction for one week. The authors put healthy and powdery mildew-inoculated barley leaf samples to the test. Images of the leaves were captured using a hyperspectral microscope every day from the 3rd to the 14th day after inoculation. Give two methods for comparing the expected time series to the reference time series. A Transfer learning-based Crop diseases categorization system that relies on the Xception framework can correctly detect plant diseases and recommend a strategy to eliminate or prevent disease spread when given an image of an afflicted region as input [6]. In addition to the Xception, InceptionV3, on which the prior model is based, was included in this study. Because of their small size and low computational needs, they were appropriate for our job. Using Xception's architecture, an accuracy of 97.5% was achieved. These models were trained using a dataset containing 38 types of plant diseases.

The author believes that the most difficult issue in farming is the precise and timely diagnosis and treatment of crop diseases. In his research [7], he used the transfer learning method to improve the overall efficiency of the MobileNet V2 classification network. Experiment results show that the Modified MobileNet V2 design detects plant leaf sickness more consistently than previous CNN. The study [8] provides a segmentation technique employed for autonomous diagnosis and classification of leaf diseases, and also a review of several disease classification approaches that may be employed for disease identification. The detection of plant leaf diseases is mainly reliant on image segmentation, which is achieved utilising genetic algorithms. This research into the automated diagnosis of plant illness is crucial because it reduces the amount of labour necessary to monitor vast agricultural fields and discovers disease signals at an initial stage when they were first appearing on plant leaves. In the study [9], an AI-based image processing system is used to identify illnesses on a chilli crop using leaf images. The suggested technique concentrates on image separation using the k-means grouping technique and comparing multiple classification methods. The features of simulated images are obtained and used to classify these images. To compute different SVM classification techniques, variables and kernel functions are used. The outcome was used to identify healthy and diseased plants. The purpose of this article [10] is to present a simple and effective IoT-based disease recognition system for detecting and classifying banana and sigatoka infections in hillside banana trees. Combining computer vision and IoT, the proposed system evaluates plant images and derives textural characteristics. The Random Forest Classification (RFC) technique is used to classify the GLCM features at the monitored location, and agricultural specialists analyze data to offer suggestions. Environmental factors of the agricultural area, like temperature and moisture, should be observed. These values were gathered with the help of a Raspberry sensor. The proposed disease detector has a 99% successful detection rate.

The architecture of the paper contains the study of previous research on this domain in 1st division, the flow of the research takes place in division 2, division 3 gives the detailed view of data, the deep learning (DL) techniques used and its results are elaborated in division 4 and 5. Finally, division 6 analyse the best technique to identify the tomato disease based on leaf image.

Process Flow

The process flow of the research is detailed in this division. First, the data for tomato leaf disease is collected from the internet. The image data is taken rather than numeric data. The image data is resized and rescaled to reduce the complexity of the upcoming process. In resize the size of the image i.e., height and width are changed and in rescale technique the pixel value of the image is altered.

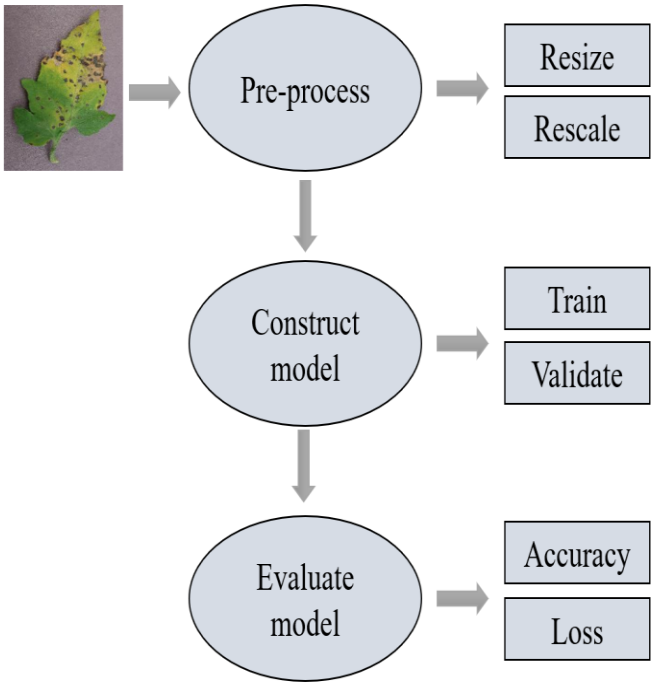

Fig. 1. Process flow of tomato disease identification

Next, the two models are constructed like CNN and improved CNN. Both models are trained and tested with the help of 80% and 20% data. The best model is identified by employing the evaluation method. The metrics that come under evaluation are accuracy and loss. The process flow for automatic identification of the tomato disease using a DL network is shown in figure 1.

Data collection and Processing

The images of tomato leaf disease were contributed by Plant Village [11]. A python script was used to generate the images for the ailments. The collected dataset contains around 18160 images divided into ten unique classifications. This database contains information on every major leaf disease that might affect a tomato crop. The images were stored in the RGB image by default and were preserved in the unprocessed JPG file type. Figure 2 depicts an example image from each disease.

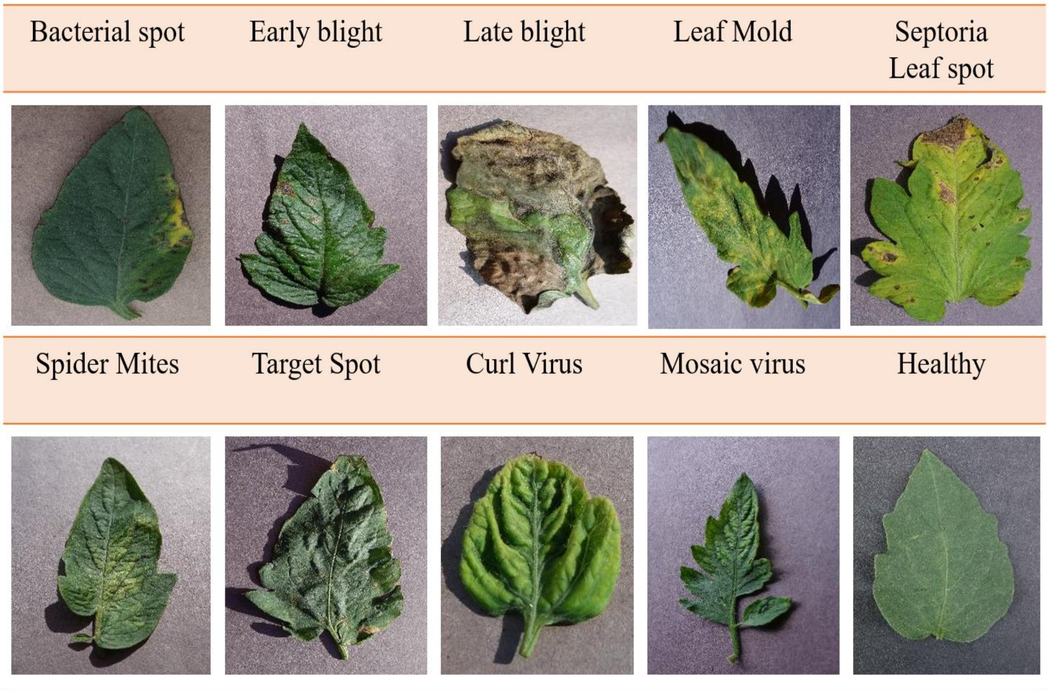

Fig. 2. Tomato disease with sample imagesPre-processing is a common term for activities that involve images at the most basic abstract level. These iconic images, like the original sensor data, are just matrices of image density function encoding an intensity image. Although geometric modifications to images are classified as pre-processing techniques [12], the purpose of pre-processing is to enhance image information by dampening or boosting specific visual aspects that are important for further processing. In this study, image processing methods like resize and rescale are used. Because the acquired dataset consisted of images with little noise, suppression was not required as a pre-processing step. To quicken up the learning process and make the learning algorithm computationally feasible, the images in the dataset were shrunk to m*m resolution. Rescaling either the source or output variables has the effect of speeding up the learning process. This is accomplished by improving the statistical state of the optimization process. It is also examined to see whether the various starting and ending default values are appropriate.

Resize

With the rapid development in display device diversity and flexibility today, digital media is being presented with new challenges. Image scaling, which is one of the most essential and commonly used techniques in related disciplines, has been significantly improved [13]. Because neural networks only accept inputs of the same size, all images must be resized to a specified size before being fed into a CNN. For larger fixed sizes, a lesser quantity of shrinking is required. With less shrinkage, the image's details and patterns are less distorted. Figure 2 is an example of how the to resize operation in image works. The raw image with dimensions n*n is shown on the left, while the rescaled image with dimensions m*m is shown on the right.

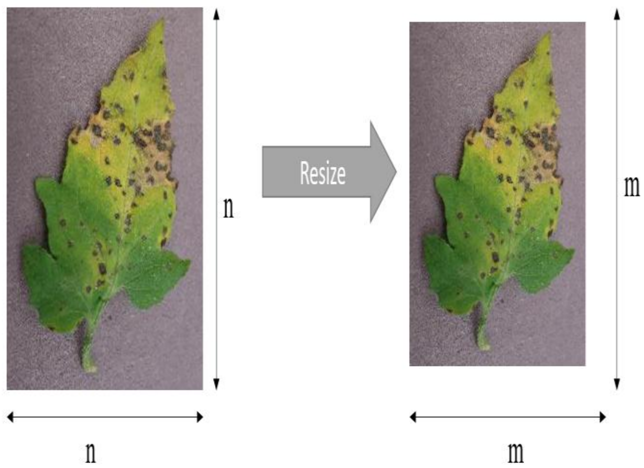

Fig. 3. Resizing of raw image

Rescale

Before any further analysis, the dataset will be amplified by a rescaling factor. The goal of input rescaling is to maintain the weight range as minimal as feasible. In principle, you shouldn't have to rescale any input because a proper interpretation of the weights would compensate. A varied range of weights is critical from a practical standpoint. Because our model (at a normal learning rate) cannot handle the elevated RGB components in the raw tomato leaf images, we employ a 1/255 multiplier to reduce them to a range between 0 and 1. The image rescaling approach is seen in Figure 3. The pixel value of the scaled image before rescaling is shown on the left, and the pixel value after rescaling is shown on the right.

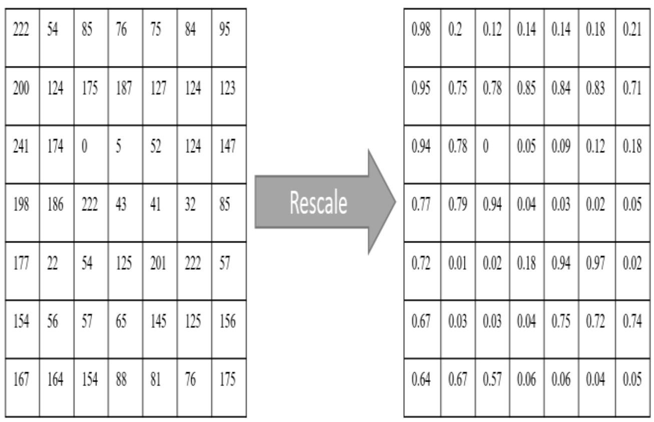

Fig. 4. Rescaling of resized image

Deep Learning

As DL has gained popularity in recent years, some scholars have begun to use DL in computer vision applications. In 2012, the study employed a multilayer CNN to classify images by using a commonly applied huge ImageNet dataset [14] for image classification, with excellent performance. Later, several studies have resulted in better network designs and increased CNN performance.

CNN

After researching neurons in monkey cortexes associated with local sensitivity and orientation selection, Hubel and Wiesel postulated the first CNN in the 1960s. CNN employs weighted distribution, subsampling, and backpropagation connection approaches to significantly lessen the number of needed variables and the complexities of the CNN architecture. Classical feature extraction methods have indeed been suited to the properties of modern CNN. Furthermore, CNN's decrease the need for costly image pre-processing even though they may be using the real images as input.

Fig. 5. Architecture of CNN

The majority of CNN is composed of convolutional (conv), pooling, and fully connected (FC) layers. A fundamental element of CNN is the conv layer. This layer should retrieve important features from input images. Each conv layer may have many conv kernels, each of which is used to generate a unique feature map. The conv layer is determined using the following formula:

$$x_j^l = f\left(\sum_{i \epsilon M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right) \qquad [1]$$

Here,

x_i^{l-1} → Characteristics map
x_j^l → jth Conv layer output
$f(.)$ → Activation function
M_j → Input feature map subset
b_j^l → offset

Improved CNN

An improved CNN method used in this work is a dual-channel convolutional neural network (DCCNN) for multiclass image labelling. DCCNN is constructed by merging deep learning and multiclass image labelling, solving the difficulties of inadequate training and the adverse labelling impacts of underweight images owing to data imbalance. To increase annotating quality, the suggested framework employs two channels for input and one channel for output generated by CNN with customizable variables. One input channel is trained using the entire dataset, while another uses only the low-frequency (LF) elements. The combined data sample's training weights for LF words are enhanced by training the LF datasets twice. These are two different channels. Throughout the testing process, a combined judgement is made based on the findings of both input channels, resulting in the greatest possible annotation impact. Each image may be associated with several annotated words in the context of the image annotation issue, and each of these annotated words may relate to a particular disease. Certain scenarios are related to a huge number of images, showing that the annotation words, such as the names of 10 illnesses, are often used. Inadequate training of rare annotated words may arise from uneven input data, resulting in a poor recognition rate. The purpose of this work is to construct a DCCNN model that will increase the accuracy of identification and overall recognition efficiency for LF annotated words.

Fig. 6. The architecture of improved CNN

Using specialised training channels, the model increases the training weight of the LF input. To accomplish sample equalisation, the training samples are initially handled individually. During the recognition process, the two channels, therefore, collaborate to determine the ultimate labelling result. Because the LF channel is educated predominantly with LF data, its properties are more adapted for identifying LF data, reducing the labelling influence of training with a small number of LF samples.

Result and Discussion

The CNN and improved CNN are evaluated and identify which network is best with the help of metrics. The results obtained by both methods are discussed in this division. The accuracy and loss obtained by CNN and improved CNN in each epoch from 0 to 19, using 80% of collected data are shown in figure 7. This accuracy is called training accuracy similarly loss is represented as training loss. The first two plot in the graph shows the CNN and improved CNN accuracy at the training stage. Then the two plots at the bottom represent the CNN and improved CNN loss at the training stage. The value of the CNN accuracy plot at the 19th epoch is nearer to 95% and the improved CNN accuracy is 97%. Then the loss attained by CNN and improved CNN during the training phase are 13% and 8%. From this metrics comparison, the improved CNN gives satisfactory results for training data. The metrics of each model in the graph are differentiated using the colour code. Each parameter is represented using various colour and the legend is also mentioned in the graph.

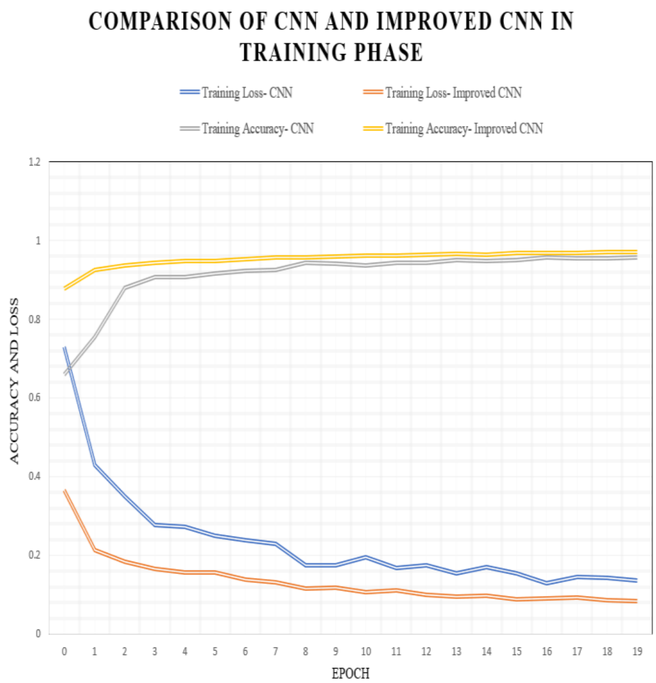

Fig. 7. Comparison of CNN and improved CNN in the training phase

Figure 8 depicts the accuracy and loss gained by CNN and improved CNN in each epoch from 0 to 19, using the remaining 20% of collected data. This is referred to as validation accuracy, while loss is referred to as validation loss. The first and second plots in the graph show the CNN and improved CNN accuracy at the validate stage. Finally, the final two graphs show the CNN loss and the improved CNN loss at validation. The 19th epoch CNN accuracy plot is closer to 92%, whereas the improved CNN accuracy is 96%. The loss obtained by CNN and improved CNN over the training period is thus 32% and 9%, respectively. From the analysis of both graphs, it is shown that the CNN and improved CNN gives almost equal result in the training stage. But in validation, the performance of CNN is very lower than the improved CNN.

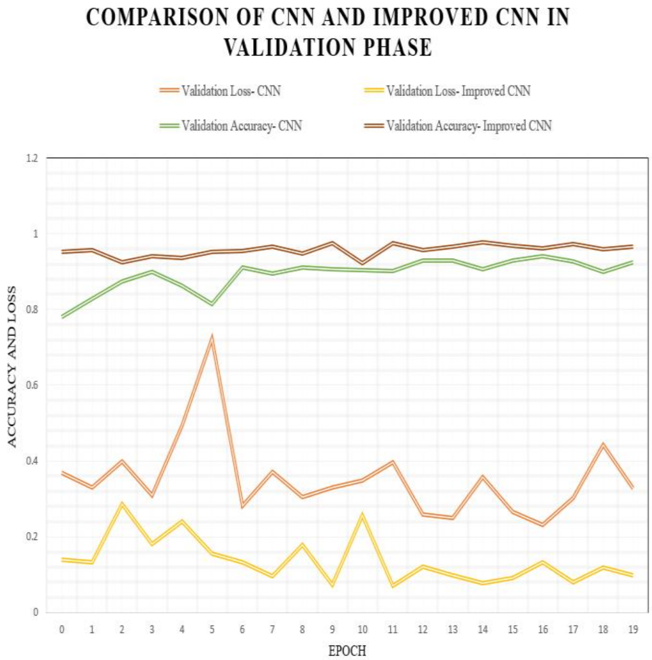

Fig. 8. Comparison of CNN and improved CNN in the validation phase

From the analysis, it is strongly believed that the improved CNN gives better results than the conventional CNN technique. The improved CNN is eligible for identifying the tomato disease with a high accuracy rate and without human intervention.

Conclusion

With millions of hectares under production, the tomato is India's most popular vegetable crop. Even though India's tropical climate is ideal for tomato cultivation, the natural growth of tomato plants is influenced by a range of climatic conditions and other factors. Aside from these environmental factors and natural disasters, plant disease is a severe problem in agricultural production and contributes significantly to economic loss. When employing existing methods for finding the disease in tomato plants, detection times were long and outcomes were unreliable. Early disease detection can produce a better cultivation rate. DL algorithms based on computer vision could be best for detecting the disease earlier. This study examines the disease classification and detection strategies on tomato leaves in depth. This paper also details the study approach, which includes data collection, processing, model construction, model validation, and model comparison to CNN. Finally, our study enables early diagnosis of tomato leaf disease utilizing improved CNN architecture, yielding superior results with high accuracy of more than 95% and a minimum loss of less than 10%.

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