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Convolutional Neural Network Architectures for Enhanced Tomato Leaf Disease Classification using ResNet-152 and VGGNet Model

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ABSTRACT

Background: Tomato is one of the most extensively grown and consumed crops in the world. Diseases, such as bacterial spots and bacterial specks, cause significant economic losses by reducing both yield and quality. These diseases damage and destroy the leaves of tomato plants, making it difficult for the plant to produce fruit.

Methods: The purpose of this work is to use Convolutional Neural Network (CNN) models to diagnose diseases in tomato plants more quickly and accurately. This paper compares the ResNet-152 and VGGNet models for the classification of bacterially-induced tomato leaf diseases.

Result: An accuracy of 98% is achieved using the ResNet-152 model for disease classification.

Key words: Bacteria, CNN model, Diagnose, Diseases, Tomato.

INTRODUCTION

Tomatoes are one of the most widely cultivated and consumed crops globally, making them a significant part of the agriculture industry (Lugito *et al*., 2022; Vengaiah and Konda, 2024; Hu *et al*., 2024). Unfortunately, tomato plants are susceptible to various diseases, which can lead to significant economic losses due to reduced yield and quality. The process of diagnosing a tomato plant disease may begin with identifying the affected section of the plant. Next, changes in the plant, such as holes and brown or black patches, should be noted and insects should be searched for. Bacterial spots and bacterial specks are a prevalent disease that damages and destroys leaves on tomato plants, making it difficult for the plant to produce fruit.

Tomato leaf disease classification

Abiotic (environmental) and biotic (life-related) factors, such as rain, frosts in the spring, weather patterns, chemical burning, *etc*., were also responsible for the tomato leaf disease. Fig 1 displays the three principal causes.

The primary focus of this study was to know the diseases caused by bacteria. The 200+ different kinds of bacteria that cause tomato leaf disease. Bacterial diseases induced by bacterial pathogens in tomato plants. Tomato plant bacterial diseases need to be identified early, treated promptly and handled completely. To prevent bacterial infections, tomato crops can benefit from cultural techniques, specialised medicines and preventive measures. Sometimes tomato plants can develop Bacterial Spot or Bacterial Speck, two forms of bacterial infections that harm the leaves and/or fruits of the plants (Too *et al*., 2019).

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Bacterial spot

Xanthomonas species cause the disease. Strong winds and extremely high temperatures force crops to lose their leaves (Kodali and Gudala, 2021; Vengaiah and Priyadharshini, 2023). Any portion of a tomato plant that is above ground, such as the leaves, stems and fruit, might get bacterial stains. Bacterial spots on leaves often manifest as tiny (less than $^{1}/_{8}$ inch), occasionally wet-looking, circular regions that have been saturated in

water. Spots start out yellow-green and eventually turn brownish-red as they mature.

Bacterial speck

Bacterial speck is caused by the bacterium *Pseudomonas syringae* pv. tomato. This seed-borne disease can persist through the winter in crop residues, especially in temperate regions. The development and spread of bacterial speck are favored by high relative humidity (above 80%) and moderate temperatures ranging from 64°F to 75°F (18°C to 24°C). Symptoms include small black lesions ($^1/_8$ inch or less), which are more prominent on the undersides of leaves. As the lesions age, they may develop yellow halos. On tomato fruit, the disease appears as small specks that may be either raised or sunken.

Deep learning techniques for leaf disease detection

Over the past 20 years, the agriculture sector has made extensive use of deep learning (DL) techniques. One well-liked deep learning technique that has shown promise in precisely classifying illnesses is the convolutional neural network (CNN). The industry standard for diagnosing problems with tomato leaves is now deep learning. It allows for the sorting of sick leaves and the pixelization of annotated photographs, which provides additional data for study. CNNs are deep learning models capable of automatically extracting features that help in photo categorization (Cho, 2024; Alzubi, 2023a, 2023b). After the characteristics have been collected, the most informative features are chosen for categorization. CNNs' natural learning properties make them perfect for feature extraction and picture classification, which is why they are commonly utilised in deep learning identification. CNN designs have been deeply studied and applied to better understand plant leaf diseases (Hong *et al*., 2020; Agarwal *et al*., 2020; Vengaiah and Konda, 2024). CNN develops the novel and effective properties of sick pictures directly from the source images, as compared to choosing or manually extracting the characteristics, which is a better way, according to those works and studies. This work proposes a tomato leaf image-based image classification system. The accuracy of its classifications and the range of its possible global applications are two important areas where deep learning outperforms machine learning.

VGGNet

The Visual Geometry Group at the University of Oxford proposed the VGGNet (Visual Geometry Group Network) convolutional neural network architecture. Simonyan and Zisserman introduced this model in 2014, emphasizing its simple and uniform design (Vengaiah and Konda, 2024). The architecture is primarily composed of multiple convolutional layers, followed by max-pooling layers and fully connected layers. The number of weight layers (convolutional and fully linked layers included) determines the depth of the network. One of the main benefits of VGGNet is its uniform design, as seen in Fig 2, where the max-pooling layers have a 2×2 filter size with a stride of 2, while the convolutional layers have all had the same padding and a 3×3 filter size with a stride of 1.

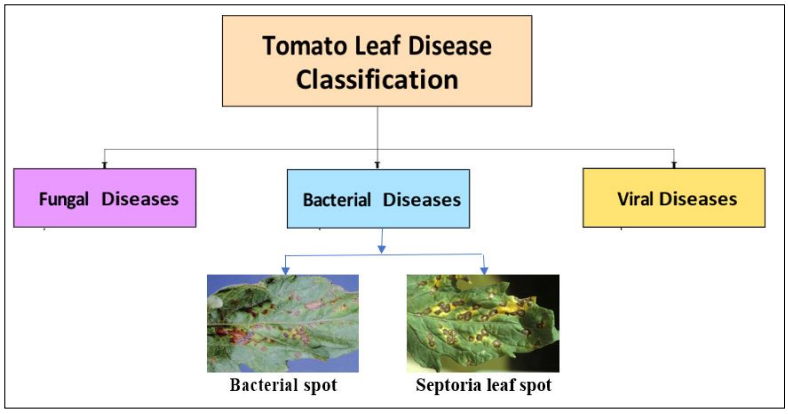


Fig 1: Tomato leaf diseases classification due to bacteria.

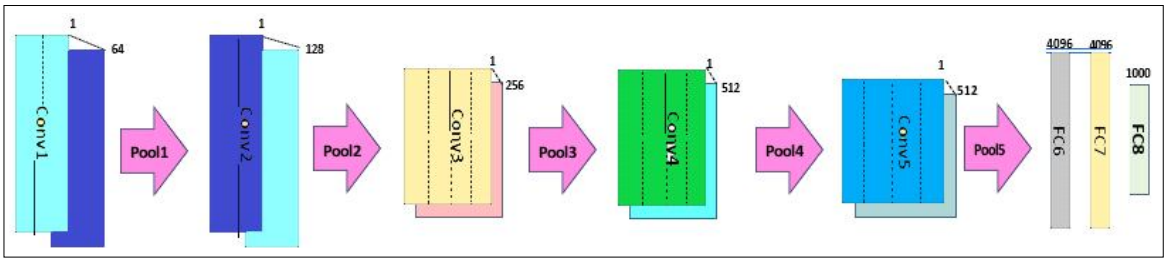


Fig 2: VGGNet architecture (Vengaiah and Konda, 2024).

It can handle input pictures up to 224 by 224 pixels in size by employing its 4096 convolutional features. Tomato leaf diseases were effectively identified by Hassan and Maji (2022) by classification using VGGNet. For accurate disease classification on a dataset of tomato leaf diseases, transfer learning was utilised to improve a pre-trained VGGNet model. VGGNet's deep design with several parameters means that even while it is useful for applications related to tomato leaf disease detection, it has rather high computational and memory needs. Therefore, newer designs that are more computationally efficient like ResNet have outperformed VGGNet in terms of performance.

ResNet-152

ResNet-152 is a member of the ResNet (Residual Network) family of deep convolutional neural networks, introduced by Kaiming He and colleagues (2015). It is an extended version of the original ResNet architecture and is characterized by its considerable depth, consisting of up to 152 layers, as illustrated in Fig 3 (He *et al*., 2015). Skip connections, often referred to as shortcut connections, are used by ResNet-152 to move data straight from one layer to the next without modifying it (Omar and Jain, 2022; Abbas *et al*., 2021; Alkaff and Prasetiyo, 2022).

Image classification, object identification and semantic segmentation are just a few of the image recognition tasks on which ResNet-152 has shown state-of-the-art performance. Deep learning for computer vision is a powerful discipline in that it can successfully learn hierarchical characteristics from input pictures due to its residual connections and depth.

To identify plant diseases, Karthik *et al*. (2020) and Saleem *et al*. (2019) used a variation of ResNet-152. The study found that ResNet-152 performs very well in tomato leaf diseases.

MATERIALS AND METHODS

Experimental setup

An NVIDIA DGX v100 system has been used to run the suggested CNN model. The computer has 1000 TFLOPS speed, 128 GB RAM, 5120 tensor cores and 40600 CUDA cores. The class balancing data augmentation approach has been used since the photos in each class in the data set are distinct.

Dataset

Tomato disease photos may be found in the Plant Village collection. Bacterial infections in tomato leaves are often divided into two types: bacterial spot and bacterial speck. 10% are utilised for testing, 10% for validation and 80% of the photographs in the dataset are used for training.

Image data preprocessing

The set of images is initially labelled with the relevant class. After that, to reduce the training time, the images are compressed and converted into 256×256 pixel tensor data. To ensure that convolutional neural networks (CNNs) can train an optimised model, the pictures are scaled and enlarged to get the uniform input dimensionality that they need.

This process contributes to maintaining computational efficiency during the training phase. Image augmentation is the process of incorporating fresh photos into our dataset using a range of techniques, including rotation, flipping, noise addition, shear, shifts, *etc*.

Data augmentation

An array of augmentation techniques is used in this study to add diversity to the original dataset. These methods were rotation, flipping, shifting, zooming and shearing. Rotation added random rotations to the images to simulate different views and orientations, which helped the model identify objects from a range of perspectives-flipping created mirror images in the dataset by flipping images horizontally, which improved the model's ability to recognize objects in any orientation.

Modeling

Convolution layer

To extract features from the image and determine the characteristics and interactions between the pixels in this layer, small squares of input data are utilized. This procedure is performed by convolution of the input image matrix with a filter matrix.

$$[f(t) * g(t)] = \int_{-\infty}^{\infty} f(\tau)\, g(t - \tau)\, d\tau \quad (1)$$

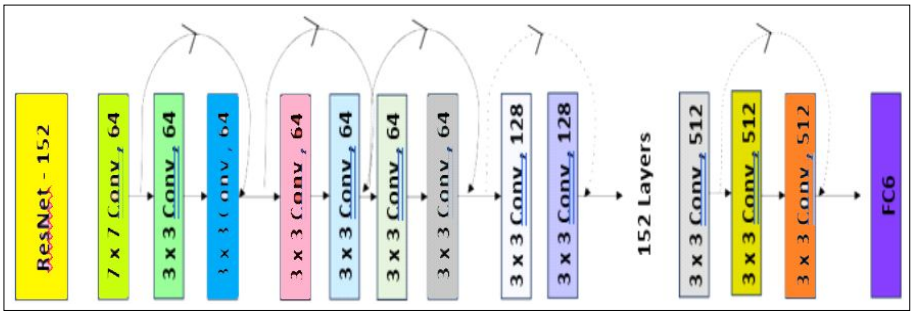


Fig 3: ResNet152 architecture.

Table 1: Precision, F1-score and recall for ResNet-152 and VGGNet accuracy classes summary.

Diseases	Precision		F1-score		Recall	
	ResNet-152	VGGNet	ResNet-152	VGGNet	ResNet-152	VGGNet
Bacterial spot	0.954	0.945	0.959	0.948	0.982	0.983
Bacterial speck	0.962	0.983	0.959	0.981	0.988	0.983

Pooling layer

The use of pooling layers reduces the number of parameters when working with large images. Here, the feature map matrix is subjected to max pooling with a stride value of 2.

Fully connected layer

The three-dimensional image is flattened into one dimension using a flattening layer to determine the probability value. Two fully connected dense layers with an optional activation function are then used for classification.

Accuracy measurements

Precision

It measures the accuracy of positive predictions by dividing the total number of correct positive outputs by the predicted positive labels.

$$\text{Precision percentage (P\%)} = \frac{TP}{FP + TP} \times 100$$

The rate at which the model responds to input data frames is known as sensitivity (True positive rate or Recall). It can be expressed as follows:

$$\text{Recall percentage (R\%)} = \frac{TP}{FN + TP} \times 100$$

F1-score

It signifies the balance between precision and recall, with 1 denoting perfect performance and 0 indicating total failure.

$$\text{F1 - score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

RESULTS AND DISCUSSION

Two models based on convolutional neural networks (CNNs) were created for the proposed study to identify leaf diseases in tomato crops. There are two different illness categories in the dataset. The performance of ResNet-152 and VGGNet is compared using several metrics, including Precision, F1-Score and Recall. The metrics collected for the equivalent models are described in Table 1.

As seen in Table 1 the assessed CNN models of ResNet-152 and VGGNet computed the appropriate assessment parameters depending on each disease.

CONCLUSION

Today's farmers must overcome several obstacles in their fields. Timely and accurate disease diagnostics may contribute to meeting the growing need for tomato output. Thousands of agricultural goods may be precisely and effectively screened and monitored through the use of artificial intelligence in farming to detect illnesses. To identify tomato illnesses, the study compared two CNN models. To produce more effective and high-quality goods with fewer errors, a more straightforward CNN model focuses on delivering faster and more accurate outcomes. In the majority of cases, ResNet-152 outperforms VGGNet in terms of accuracy.

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Disclaimers

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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