Tomato Leaf Disease Detection Using Convolutional Neural Network

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Contents

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CONTENTS

Leaf diseases pose a significant threat to crop production and profitability, particularly in the case of tomatoes, which are extensively cultivated worldwide. Early detection of these diseases is crucial to prevent significant crop losses. In this study, we propose a novel deep learning-based approach for disease detection and prediction in tomato plant leaves. Convolutional neural networks (CNNs) have emerged as the most effective deep learning algorithm for image classification tasks. Leveraging the power of CNNs, we employed a CNN architecture to detect and identify diseases in tomato leaf samples. The suitability of CNNs for detection and prediction tasks makes them an ideal choice for this study. Our dataset comprised 6,926 images of both healthy and diseased tomato plants obtained from the PlantVillage dataset. By training our CNN model on this dataset, we achieved a promising test accuracy of 98.39%. This high accuracy demonstrates the effectiveness of our approach in accurately predicting the presence of diseases in tomato plant leaves. Through our study, we aim to contribute to the early detection and prevention of leaf diseases in tomato plants, ultimately improving crop productivity and ensuring the profitability of tomato cultivation.

1.1 INTRODUCTION

Tomatoes are a popular crop grown by the majority of farmers, as they can thrive in well-drained soils[1]. Many individuals cultivate tomatoes in their own gardens to enjoy the freshness of homegrown produce in their daily cooking. However, tomato plants often encounter various diseases that hinder their growth and flowering. These diseases primarily affect the leaves and stems of the plants. To identify tomato plant diseases, determine the infected part of the plant and observe any noticeable changes such as brown or black patches and holes, before inspecting for potential insect infestation are essential.

To maintain healthy tomato plants, this is recommended to avoid planting tomatoes and similar vegetables on the same farm consecutively within a three-year cycle[2]. Diseases tend to thrive in environments with high humidity and temperature. Bacteria can rapidly multiply within the plant's water-conducting tissue, leading to the clogging of the vascular system while the leaves may remain green. Infected plants exhibit brown stems and emit yellow substances. In addition, tomato yellow leaf curl, a viral disease prevalent in tropical and subtropical regions, can result in complete crop losses[3]. Farmers typically rely on traditional knowledge to identify plant diseases and often resort to pesticide treatments.

In this paper, we propose a novel method for detecting diseased tomato plants through the analysis of leaf images. This method enables farmers to identify plant diseases independently, eliminating the need to consult plant pathologists. By utilizing this method, farmers can effectively treat diseased plants and produce high-quality tomatoes. Our experiment utilized a tomato leaf dataset obtained from PlantVillage, a platform that has experienced a significant annual growth rate of 250%. The platform reached its two millionth user milestone in the fall of 2015[4]. We developed a convolutional neural network model for image classification with this dataset.

Performance evaluation of the model included metrics such as training accuracy, validation accuracy, testing accuracy, and trainable parameters.CNNs are particularly well-suited for image-based tasks, such as disease detection, due to their ability to learn relevant features directly from the input images automatically. By leveraging the capability of deep learning, CNNs can analyze large amounts of visual data and extract intricate patterns and features indicative of disease presence.

The remaining sections of the paper are structured as follows. Section 1.2 discusses the previously published related works on deep learning-based tomato leaf disease detection. We elaborated methods of this study in section 1.3, which details the characteristic of CNN architectures for leaf disease classification. Section 1.4 describes the results and analysis of the experiment and the results is summarised in section 1.5.

1.2 RELATED WORKS

Tomatoes are the third most widely cultivated crop, following Potato and Sweet Potato. As a result of various types of diseases, both the quality and quantity of tomato harvests decline. Here, we discussed the deep learning-based approach to disease prevention and productivity improvement. Transfer learning is used to minimize the amount of training data, the amount of time, and the computational costs associated with building deep learning, according to Gayakwad et. al. [5] . Five deep network structures were used to extract data features: Resnet50, Xception, MobileNet, ShuffleNet, and Densenet121, Xception. To deaverage the image of the blades, image samples of 224*224*4 pixels are normalized, and grayscale values for G, R, and B are subtracted from the average. By augmenting data, a dataset containing 13112 images for training was created. In addition, the augmented data set contains 41263 images. Hong et. al. [6] use a deep convolutional neural network to identify five diseases. The PlantVillage dataset contained 9,000 images of tomato leaves, which included specimens of five different tomato diseases, including Bacterial Spot, Early Blight, Septoria Leaf Spot, Leaf Mold, and Yellow Leaf Curl Virus, as well as healthy leaves. On a held-out test set, their method achieved 99.84 percent accuracy, proving its viability. Ashqar et al. [7] developed a deep learning technique called LeNet for identifying the type of leaf disease based on images of the diseased leaves. In addition, they obtained their dataset from PlantVillage, where they gathered 18160 photographs organized into ten categories. To make model training accessible to computers and reduce processing time, the resolution of the images in the dataset was reduced to 60×60. The proposed method has an average accuracy rate of 94-95%. Researchers proposed a CNN model to detect and classify leaf diseases in tomatoes. It is comprised of 3 convolutions, 3 max-pooling, and 2 fully connected layers. The proposed model outperforms all three pre-trained models, namely VGG16, Inception V3, and MobileNet, according to experimental results. The proposed model's average precision is 91.2%. In a separate study [8], authors employed a DCNN model. Using images of 14,903 diseased and healthy plant leaves from the PlantVillage dataset, they trained their model to identify the type of leaf. In the performance test, the trained model achieved an accuracy of 99.25%. Geetharamani et. al. [9] present a a nine-layer convolutional neural network approach for plant leaf disease identification utilizing a deep convolutional neural network (Deep CNN). The proposed model is trained on a comprehensive open dataset consisting of 39 distinct classes of plant leaves and background images. By comparing it with popular transfer learning techniques, the authors demonstrate that their model outperforms them in terms of performance on the validation data. Through extensive simulations, the proposed model achieves an impressive classification accuracy of 96.46%, surpassing traditional machine learning methods. To evaluate the performance of their Deep CNN model, the authors conduct a comparative analysis with well-known transfer learning approaches such as AlexNet, VGG16, Inception-v3, and ResNet. Another study [10] proposed a CNN model for detecting diseases on tomato leaf. Before tomato leaf detection, the dataset is separated. Using transfer learning, a trained model (ResNet-50) is imported and modified based on the classification problem. Data augmentation has been implemented to improve the quality of the ResNet model and produce a result that corresponds as closely as possible to the actual prevalent disease. All of these factors were considered during the development of a PyTorch and deep-CNN-based disease detection model for tomato leaf. After processing the testing dataset, the ResNet 50 model's learned parameters are utilized to validate the results. To classify the data, six of the most prevalent diseases affecting tomato crops were utilized. This model achieved a 97% accuracy rate when the data set was expanded to four times its original size. Ozbilge et. al.[11] proposed a compact convolutional neural network (CNN) for disease identification, utilizing a network architecture consisting of only six layers. The compact nature of the network renders it computationally inexpensive in terms of the employed parameters. The implementation of the compact CNN architecture yielded impressive results in disease identification.It demonstrates an accuracy of 99.70% for the F1 score, 98.49% for the Matthews correlation coefficient, 98.31% for the true positive rate, and 98.49% for the true negative rate when tested on the unseen images. . Furthermore, the authors claimed that the proposed model outperforms the pre-trained models due to its compact architecture.

Some researchers [12] recommend image processing techniques, including image acquisition and segmentation, for detecting leaf diseases in tomatoes. Two technical models, Resnet50 and MobileNet, have been implemented using the transfer learning technique of deep learning. These models have produced favorable outcomes. The results have improved with each model execution step.

The experimental results of the Resnet-50 Model fluctuate between 94 percent and 99.81%, whereas the MobileNet predictions correction fluctuates between 95.23% and 99.88%. On the other hand, Wang et. al. [13]presented deep convolutional neural networks and object detection models to develop methods for detecting tomato disease. The proposed architecture uses Faster R-CNN and Mask R-CNN are models, where tomato diseases are identified using faster R-CNN, and the locations and shapes of the diseased areas are detected and segmented using mask R-CNN. The suggested tomato disease detection architectures, however, were unable to identify some tomato disease types or infected areas due to a lack of training images or low image resolutions. A study [14] proposed a deep learning-based method for detecting tomato diseases by employing Conditional Generative Adversarial Network (C-GAN), which can produce synthetic images of tomato plant leaves. The DenseNet121 model was trained on synthetic and real images using transfer learning in order to classify images of tomato leaves into ten categories of disease. They have gathered the dataset from PlantVillage in order to train and validate the model. The proposed method achieved an accuracy of 99.51%, 98.65%, and 97.11% when classifying tomato leaf images into 5 classes, 7 classes, and 10 classes, respectively. Tahamid et al.[15] have proposed a deep convolution neural network (DCNN) model based on transfer learning to detect tomato leaf disease. In this model, disease detection is performed by capturing and storing images of tomato plants in real-time. The tomato leaves dataset was extracted from the PlantVillage database and agricultural field photographs. This model achieved 99.55 percent accuracy. The outcome demonstrated that the DCNN model with transfer learning provides superior accuracy. A new framework, proposed by Chen et. al. [16], aimed to address tomato leaf disease recognition. This model achieved impressive effectiveness, which combine Artificial Bee Colony algorithm (ABCK), Binary Wavelet Transform combined with Retinex (BWTR) and Both-channel Residual Attention Network model (B-ARNet) for tomato leaf disease recognition. This model achieved impressive real-time performance, making it suitable for real-world deployment. The application of this model on a dataset comprising 8616 images yields an overall detection accuracy of approximately 89%.

1.3 METHODS AND MATERIALS

Fig. 1.1 describes the working procedure of our model. First, we collect images that are undergone preprocessing steps such as resizing, normalization, and cleaning to prepare them for further analysis. Next, The dataset is augmented by applying various transformations such as rotation, scaling, flipping, and cropping. This helps increase the diversity of the dataset and improve the model's ability to generalize. Thirdly, a Convolutional Neural Network (CNN) model is developed for training and testing. The model consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers, designed to extract meaningful features from the images. Finally, the trained CNN model is used to classify new images. The model analyzes the features of the input images and predicts their

In the following sections, we discuss several steps to detect tomato leaf disease.

1.3.1 Dataset Collection

The dataset used in this paper consists of photographic images. We gathered a substantial number of tomato photographs from Kaggle. While collecting data, we focus on the correct image sizes, resolutions, and quality of both normal and infected images. The dataset contains 6926 PlantVillage images. Using Python TensorFlow Keras, the dataset has been processed. The dataset includes three image types, including Bacterial spot, Tomato yellow leaf curl virus, and Healthy. In the dataset, 1590 images are categorized as healthy, 2127 as bacterial spots, and 3209 as yellow leaf curl virus. Fig. 1.2 (a) represents the leaf of healthy tomato. Fig. 1.2 (b)

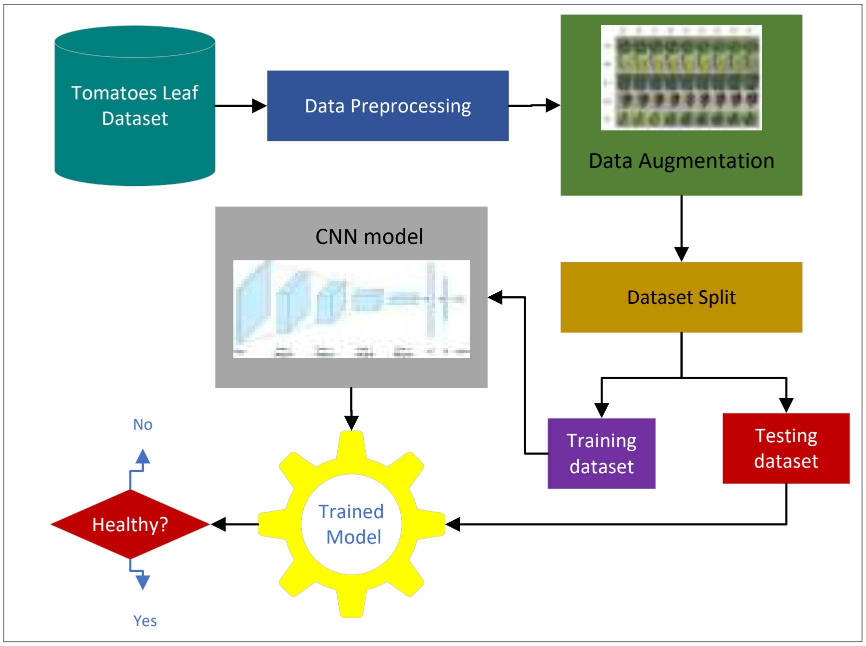

Figure 1.1 Methodology for tomato leaf disease detection.

demonstrates the bacterial affected tomato leaf and Fig. 1.3 shows the tomato leaf has yellow spot of curl virus.

1.3.2 Convolutional Neural Network (CNN)

In the field of image classification, deep learning has made significant advancements, and one popular technique used is Convolutional Neural Networks (CNNs) [17, 18]. To further improve the performance of CNNs, various architectural modifications can be applied. These modifications include introducing dropout layers between layers, altering the number of layers and filters in the convolutional models, adjusting the stride window size, filter size, and utilizing max pooling.

We have proposed a specific CNN architecture for the detection of tomato leaf diseases, as shown in Figure 1.4. This architecture has been designed to effectively classify and identify different diseases affecting tomato plants.

1.3.3 Dataset Preprocessing

We used a large amount of image data in our proposed system. Due to the different sizes of the images, this contains redundant information that impacts the classification of tomato leaf diseases negatively. We did not need to manually remove noise from the acquired dataset since most of the images have minimal noise. The images in the dataset were resized to 256 $\times$ 256 resolution to speed up the training process and make the model training computationally feasible.

(a) Healthy Tomato leaf images of the dataset. (b) Bacterial Spot affected Tomato leaf images of the dataset.

Figure 1.2 Tomatoes leaf: Healthy vs Bacterial Infected

1.3.4 Data Augmentation

To achieve improved results with CNN models, a large amount of training data is typically required. However, in scenarios where training data is limited, this becomes necessary to employ techniques such as image augmentation to enhance the model's performance. Image augmentation involves generating additional images in the dataset by applying various distortions and transformations. This helps in reducing overfitting and improving the model's ability to generalize.

In our model, we utilized two common image augmentation techniques: random flipping and random rotation. These techniques introduce variations in the training data by horizontally flipping images and applying random rotations. By incorporating image augmentation into the training pipeline, we aimed to enhance the performance of our CNN model despite the limited amount of training data available.

1.3.5 Features Extraction

Feature extraction in image processing refers to the process of extracting meaningful information or features from an image, such as edges, corners, textures, shapes, or colors. These features can be used to represent the image in a more compact and meaningful way, making it easier to analyze, classify, or recognize [19, 20, 21, 22].

We used Convolutional Neural Networks (CNNs) to extract features. The model consists of two part. In the first part of the model, this consist of 5 Convolutional layers with Relu activation function, each followed by Max Pooling layer. In the second part, the flatten layer contains two dense layers. The summary of the model is presented in Table 1.1.

Figure 1.3 Yellow Leaf Curl virus affected tomato leaf images of the dataset.

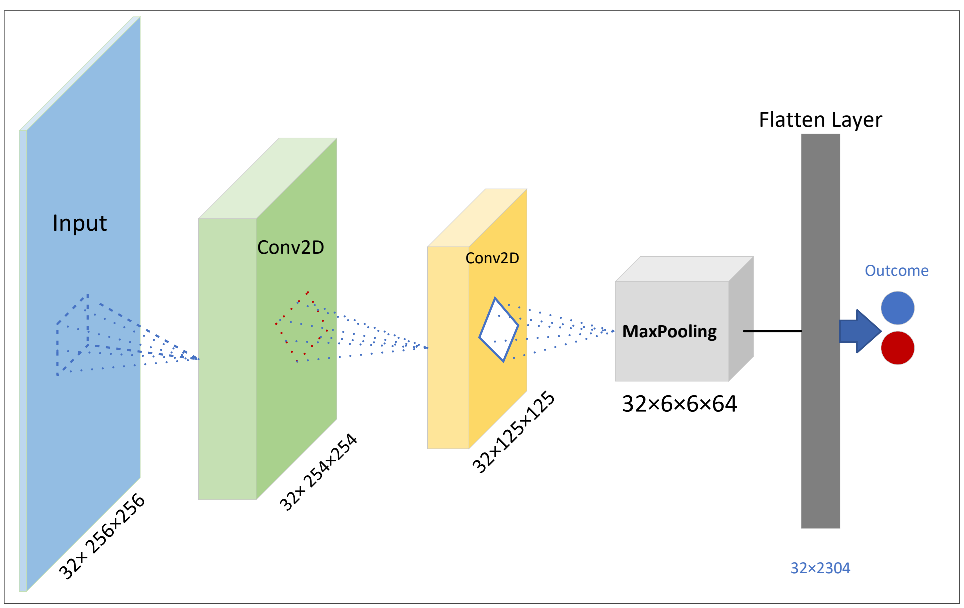

Figure 1.4 CNN architecture to detect tomato disease.

Table 1.1 Model Summary

Layer(type)	Output Shape	Param#
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1(Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(32, 6, 6, 64)	0
flatten (Flatten)	(32, 2304)	0
dense (Dense)	(32, 64)	147520
dense_1 (Dense)	(32, 3)	195

1.3.6 Compiling the Model

Adam is utilized as the optimizer in this study. Adam is an effective optimization algorithm that allows for dynamic adjustment of the learning rate during the training process. The 'categorical' cross-entropy loss function is employed to train the model, which is suitable for multi-class classification tasks.

$$\mathrm{CCE}(\mathbf{y}, \mathbf{t}) = -\sum_{i} \left(t_i \log(y_i) + (1 - t_i) \log(1 - y_i)\right)$$

1.3.7 Training and Testing

The dataset is first used to validate the model and then to test it. The model is trained using the fit function, which iteratively measures the system's performance over a specific number of epochs. Once the training process is completed, the model is configured for the testing procedure. This ensures that the trained CNN model is fully optimized and ready to demonstrate its potential.

1.4 EXPERIMENTAL RESULT AND ANALYSIS

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1.4.1 Experimental Setup

We used 80% of the data to train the model and 10% of the data to test the model. In addition, the data set aside for training was split again, this time by 10% for validation. The total number of epoch count is 50. The Python Keras library were used to implement the model. The experiment was run utilizing the Google-provided graphics processing unit (GPU) Colab.

1.4.2 Performance Evaluation Metric

We analyze the performance of the proposed CNN model in terms of accuracy and loss. The accuracy is calculated from the confusion matrix. We require the followings to compute accuracy.

- TP (True Positive) indicates a correct prediction of Tomato Leaf diseases.
- FP (False Positive) indicates healthy cases of tomato leaf.
- TN (True Negative) is the correctly classified Tomato Leaf disease.
- FN (False Negative) is the disease cases that are misclassified as normal or leaf disease.

an 'accuracy' metric is incorporated to measure the model's performance on the validation set, providing insights into how well the model is able to correctly classify the data. The accuracy of the proposed CNN model is computed as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100$$

In addition, Figure of the suggested system's evaluation metrics Fig. 1.5 (a) graph for accuracy Fig. 1.5 (b) graph for Loss. The accuracy and loss in the learning and validation stages of the CNN classifier are visually evaluated at epoch 50, with training and validation accuracy of 98.93% and 98.39%, respectively. We can notice that as the number of epochs increases, the loss decreases and the accuracy improves. Additionally, the validation loss and validation accuracy also show similar trends, indicating that the model is performing well on unseen data.

Table 1.2 shows the training, testing accuracy and loss of the CNN model at different epochs.

Table 1.2 Result of CNN model at different epochs

No. of epochs	**Loss**	**Accuracy**	**Validation loss**	**Validation accuracy**
10	0.0932	0.9672	0.0898	0.9643
20	0.0503	0.9822	0.0460	0.9851
30	0.0408	0.9830	0.0266	0.9896
40	0.0559	0.9808	0.0596	0.9807
50	0.0495	0.9839	0.0434	0.9807

Loss, accuracy, validation loss and validation accuracy for each instance of the system is summarized in Table. The proposed CNN network achieved for the first 10 epoch 0.0932 loss, 96.72% accuracy, 0.0898 validation loss, 0.9643 validation accuracy and for the 50 epoch we got 0.0495 loss, accuracy 98.39% accuracy, 0.0434 validation and 0.9807 validation accuracy.

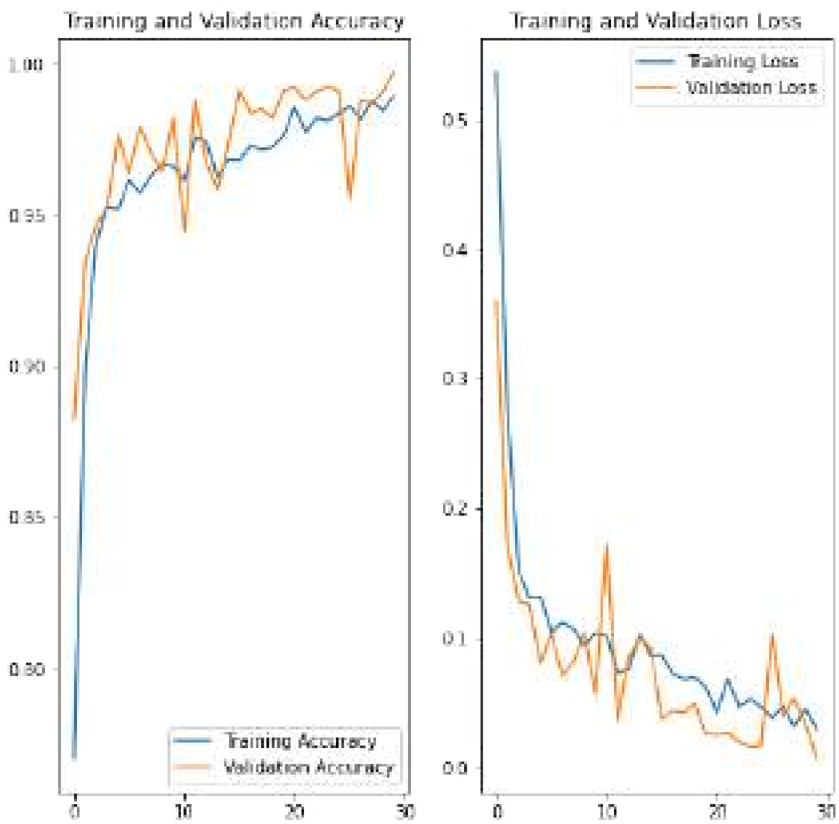

Figure 1.5 Evaluation metrics of the proposed system (a) Graph for Accuracy (b) Graph for Loss.

Figure 1.6 Results of the prediction and confidence level.

The prediction and confidence for tomato leaf diseases is shown in Fig. 1.6.

Fig. 1.7 presents the comparison of accuracy between the proposed CNN and other state-of-the-art works. Overall, the proposed CNN model performed well and achieved a competitive accuracy of 98.39%. It is comparable to the accuracy obtained by other state-of-the-art models, such as Mohanty et al.[23] (99.35%) and Zhao et al.[24] (99.24%). The results indicate the effectiveness of the proposed CNN model for the given task.

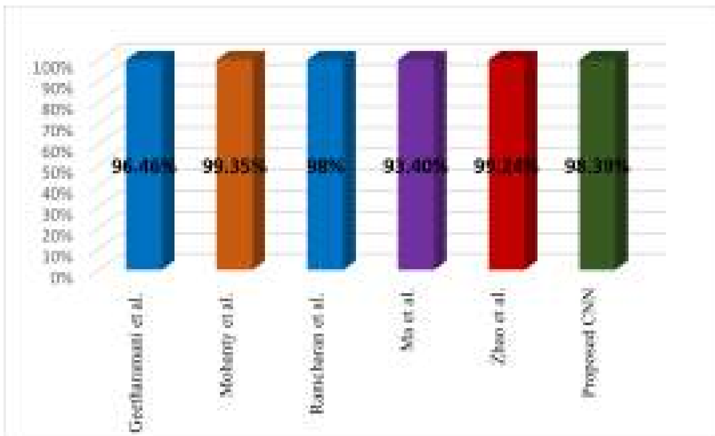

Figure 1.7 Accuracy comparison with the existing works

1.5 CONCLUSION

This study focuses on the classification of tomato leaf images, where a deep Convolutional Neural Network (CNN) system was developed to detect diseases in tomato leaves. The CNN architecture was employed to identify patterns and features, successfully distinguishing healthy leaves. The proposed architecture achieved impressive results, including a loss of 0.0495, an accuracy of 98.39%, a validation loss of 0.0434, and a validation accuracy of 0.9807. However, one major constraint is the lack of specialized equipment and instruments. Therefore, future work aims to conduct tests using relevant tools and establish collaborations with radiologists to further enhance the applicability of our model. Overall, this research presents a robust CNN-based system for the classification of tomato leaf diseases, showcasing its superior performance compared to some existing approaches.

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