An Hybrid Deep Learning Based Appraoch For Tomato Disease Classification In Natural Environment

Mamta Gehlot
Research Scholar
Poornima University, Jaipur, India
Rakesh Kumar Saxena
Professor
Poornima University, Jaipur, India

Abstract— Tomatoes are widely cultivated across the globe, boasting a rich array of nutrients like vitamin C and a delicious taste, making them essential for agricultural production and widespread consumption. The threat of plant diseases poses a significant challenge to global agriculture. The early detection and accurate identification of plant diseases are crucial for preventing crop losses and minimizing the use of harmful pesticides. Deep learning models, with their ability to extract complex features from images, have revolutionized the field of computer vision, including plant disease classification. The available CNN architectures like efficientNet, MobileNet etc. proven the remarkable results in various domains, but other than CNN architectures, dataset also plays the vital role for any problem solved using deep learning, similarly for Plant Disease detection. PlantVillage is the most widely used publicly available dataset but prepared in controlled environment, other available dataset is PlantDoc having images near to real-world. But earlier methods not able to provide the good accuracy on PlantDoc dataset, therefore We propose a hybrid technique based on a combination of object detection and classification CNN architectures, which achieved 90.7% accuracy as well as resilient F1 score and recall metrics. The suggested methodology also achieves a high level of accuracy of 85.2% using the lightweight CNN architecture MobileNet, allowing the model to be deployed in mobile/embedded devices.

Keywords— Plant disease classification, Tomato disease, Convolutional Neural Network, Image Processing, Deep Learning, Agriculture

Introduction

The agricultural industry of India, in general, places a significant emphasis on vegetables as one of its most critical parts. The production of vegetables in India is affected by different types of factors. Over the course of the past few decades, India has seen considerable increase in the productivity of its vegetable crops. After China, India is still the world's second largest producer of vegetables. India is responsible for producing 6.0% of the world's total supply of tomatoes [1]. The tomato industry accounts for 8.5% of India's total vegetable production and is ranked third. There are 8.6 million metric tons of tomatoes produced globally. The states of Orissa, Andhra Pradesh, and Karnataka are the most important tomato-growing regions in India. The tomato is a significant crop that is utilised in a wide variety of places. There are relatively few places in the world with better weather for growing tomatoes than Sikkim. In the field, tomato seeds are planted during the rabi season, and the plant can be grown both throughout the summer and during the rainy season.

The production of tomatoes in open fields has suffered as a result of a significant decrease in the fruit yield of tomatoes as well as infections with a variety of pathogens. Additionally, this results in economic loss for the farmers [2]. Therefore, a reliable method that is capable of identifying tomato diseases in a timely manner is necessary.

The presence of bacterial infections, fungal diseases, viral diseases, and insect diseases in tomato plants are the primary obstacles to the creation of a decent yield. There has been an increase in the number of illnesses caused by diseases such as late blight, early blight (Alternaria solani), and leaf curl virus, which are particularly damaging to the outdoor production of tomatoes in the Gangetic plains of eastern India.

As reported by both India and Canada, early blight disease can result in a loss in output of up to 79 percent. The loss of seedlings brought on by collar rot ranges from 30–40% when it occurs in the field [3]. The late blight disease is responsible for significant losses in regions that have weather that is chilly and wet. There have been reports of the tomato leaf spot known as target leaf spot in a number of different countries on both greenhouse and field tomatoes. In the Gangetic plains of West Bengal, India, there has been an increase in the level of concern due to the spread of disease, which is further encouraged by high humidity and moist leaf conditions. The illness known as collar rot, which is caused by a fungal infection, is responsible for a thirty percent reduction in production in tomato fruit.

Globally, tomatoes are one of the most important crops, providing essential nutrients and vitamins to people worldwide. However, tomato plants are prone to various diseases caused by fungi, bacteria, and viruses, which can lead to significant yield losses and quality reduction. Effective disease management depends on the early identification and detection of tomato diseases and prevention of further spread, which can be accomplished using advanced technology such as deep learning.

Deep learning is a subfield of machine learning that involves training artificial neural networks with multiple layers to extract and learn relevant features from large and complex datasets. This method has demonstrated promising results in the identification of plant diseases and has been effectively utilised in several fields, including picture classification and object detection.

The goal of employing deep learning in disease detection in tomato leaves is to increase disease diagnosis accuracy, speed, and efficiency. Traditional disease detection methods include skilled visual inspection of leaves, which can be time-consuming, labor-intensive, and subjective, resulting in misdiagnosis and false positives.

By using deep learning algorithms, accurate and automated detection/classification of tomato diseases can be achieved in real-time, enabling farmers to take immediate action to prevent further spread and reduce crop losses. Moreover, deep learning can help in identifying disease patterns and predicting outbreaks, which can aid in the development of effective disease management strategies.

CNN is also able to extract more different useful features [4] and CNN can work in any illumination, brightness, shape distortion and environment condition. CNN can detect more robust and discriminative features required for classification. Different architecture of CNN is AlexNet, GoogeNet, VGGNet, ResNet, DenseNets, SqueezNet [5].

The primary objective of the provided work is to categorise disease in tomato plants using Convolution neural network and ensure minimal resource utilization and good results compared to other methods. For this purpose, various CNN architectures with different layers will be examined. These models with different layers will be examined and evaluated for the best result. In this study, disease which affect tomato plant will be examined using PlantVillage and PlantDoc dataset [5]. This dataset will cover Bacterial spot, early blight, leaf mould, Septoria leaf spot, spider mites, mosaic virus [6] diseases.

The remaining parts of the paper are organized as follows: The relevant work is presented in Section II, the proposed methodologies are presented in Section III, the results and discussion of them are shown in Section IV, and our conclusions are presented in Section V.

Literature Survey

The papers examined concern disease detection in plants. Back Propagation Neural Network, ANN, Deep Residual Neural Network, Bayesian Network, CNN model, YOLO, SSD R-FCNN, and other methods were employed by the authors.

The author of the article [7] built a model to categorise healthy and diseased classes of tomato based on photographs of the tomatoes. For the purpose of achieving this goal, the two-deep learning AlexNet and VGG16Net models were constructed. The first stage of the research consisted of providing the pre-trained neural networks AlexNet and VGG16Net with augmented photos to use as input. Using a trained model, the objects in 1000 different categories from the ImageNet dataset were classified. The topmost layer was changed into an output layer with the same number of rows as the number of classes. AlexNet and VGG16 Net both achieved an accuracy of classification of 97.49%, with VGG16 Net coming in slightly ahead at 97.23%. The second portion of the discussion focused on the evaluation of model performance, which involved calculating the effects of modifying hyper parameters and the number of hypermeters. The Weight, Minibatch size, and Learning Rate hypermeters were utilised for performance evaluation. The time required to carry out the operation was ten epochs. In terms of the computational burden while maintaining the minimum number of executions, VGG16 Net was less efficient than AlexNet. AlexNet was similarly good in accuracy compared to VGG16 Net.

According to the research that was done [8], the purpose of the suggested study was to cut down on the total number of assessments and determine when the early blight disease in tomato plants should be evaluated. The effectiveness of ANN is going to be investigated through the use of a statistic known as the area under the disease progress curve (AUDPC). The Levemberg-Marquardt optimization and the ANN Multi-Layer-Perceptron with back propagation technique were both developed with the assistance of the neural network MATLAB software toolbox. The required output answer was compared to the one that was obtained by this approach, which generated the output response with the help of sample input (AUDPC). If any discrepancies between the predicted and observed value (AUDPC) were discovered, the connection weights were modified accordingly. In total, 120,00 MLP networks were trained using the system under consideration. There was a total of 120 networks chosen based on having the lowest mean square error. The ANN method allows the proposed method to not only produce positive results but also increase operational efficacy.

In the research publication [9], the authors proposed the use of transfer learning in conjunction with a deep convolutional neural network to diagnose tomato leaf disease. Classification was accomplished with the help of the CNN models AlexNet, GoogleNet, and ResNet. These models have been given prior training. To analyse ResNet's performance, the Number of Iteration batch size [5] was changed in a few different ways. Iteration number 4992 was employed throughout this system, and the batch size was 16. The performance of the system is unaffected by either the huge batch size or the vast number of iterations that are performed. Both the number of iterations and the batch size were decided upon after considering the dataset and the type of network. There was some fine tuning done with the finest possible combination structure. When it comes to identifying tomato leaf disease, fine-tuning ResNet layers results in the highest accuracy (97.28%) possible. The author believes that the method will be useful in other visual identification methods and has the potential to be developed to cover additional crops.

The author of this study [10] devised a method based on artificial neural networks (ANN) to forecast the late blight illness that would appear on tomatoes. In this model, spectral data was utilised in the process of disease diagnosis. The artificial neural network (ANN) was designed with the use of a backpropagation (BP) neural network and a gradient-descent learning method. The findings exhibit discrete data showing various degrees of illness infection. The correlation coefficients of prediction values and observed data were 0.99 and 0.82, respectively, for field data and remote sensing image data. According to the findings of the study, spectral analysis might benefit from the combination of an ANN and back-propagation training.

According to the relevant research [11], the objective of the suggested work was to identify the easiest solution to the challenge of disease detection in tomato leaf. Method based on convolutional neural networks. The system that was used to classify tomato leaf diseases utilised a version of LeNet that had a minimal number of levels. The dataset that was utilised was the one that was made available to the public. The classification model received as its input the standard size of the photos after they had been resized. After making some minor adjustments, the classification model LeNet was applied to the task of performing classification on the input photos. The general layers of the classic convolution model LeNet include fully connected, convolutional, and activation layers. Other general layers include pooling layers. The proposed model had an accuracy of between 94 and 95% on average, which meant that it might work even under unfavourable conditions. In the future, it may be possible to make use of a variety of learning rates and optimizers.

In literature [12] describe a method for detection and identification of diseases that cause infection in tomato plant. In this study Gabor Wavelet Transform [4]was used for the feature extraction. For classification Support vector Machine was used with different kernel functions including Invmult Kernel, Cauchy kernel and Laplacian Kernel [12]. The proposed method detected and identified early blight disease or Powdery mildew in tomato leaf. The test dataset used had 200 images. The experimental results show that the proposed approach achieves excellent results with accuracy of 99.5 %.

In the study [13] tomato diseases were classified i.e. Septoria spot, tomato late blight, bacterial spot, bacterial canker healthy tomato plant leaf and tomato leaf curl and stem images. The classification was done by using features like color, shape and texture features which were extracted tomato plant image from dataset. The classification accuracy achieved was 97.3%. For future work other techniques like Neural Networks, Adaptive neurofuzzy, Genetic algorithm. Support vector machines etc. for image classification can be used.

In literature [14] new approach to extract Scale Invariant Feature Transform (SIFT) [15] texture features using Johnson SB distribution [14] was given. It uses statistical texture information in the form of matrix to represent an image. To calculate parameters of Johnson SB distribution Momentum method was used. SIFT feature was very complex to be used in classification of image. So, to simplify this, a new statistical feature was introduced with a smaller number of dimensions. The statistical color information was extracted to find the color feature of RGB color channel image. The combination of mean, moments, and standard deviation from each RGB color channel was used to represent statistical color features. The combination of color features and statistical texture features classifies tomato plant disease. The diseases were classified using multiclass Support Vector Machine (Multi-Class SVM) [14]. These classifiers solve the multiclass problem in single optimization processing. Quadratic SVM Classifier with proposed features give more average compared to other SVM Classifiers. The proposed classification Quadratic SVM classifier gives 85.1% accuracy.

In literature [16] proposed a method for detection of disease using tomato leaf images. The author constructed the convolution neural network model VGG16 to detect disease in tomato using transfer learning. The Keras/TensorFlow deep learning framework was used for training of deep learning model. The first algorithm VGG16 works as feature extractor from image and then disease was classified using SVM. In the second part of algorithm VGG16 model with fine tuning was constructed. VGG16 is a model which has 3 fully connected layers. But in this proposed method VGG16 with 2 fully connected layers was used. For the model best accuracies were recorded ranged between 84% ~100%. The model achieves an average classification accuracy of 89%. Performance of fine tuning was better than VGG16 and SVM model.

Proposed Method

The threat of plant diseases poses a significant challenge to global agriculture. The early detection and accurate identification of plant diseases are crucial for preventing crop losses and minimizing the use of harmful pesticides. Deep learning models, with their ability to extract complex features from images, have revolutionized the field of computer vision, including plant disease classification. The available CNN architetures like efficientNet, MobileNet etc. proven the remarkable results in various different domains, But other than CNN architetcures , dataset also plays the vital role for any problem solved using deep leraning, similary for Plant Disease detection.

The PlantVillage dataset the most popular and largest dataset available publicly, but this dataset prepared in the lab environment /controlled environment, i.e infected or healthy disease are plucked from the farms and then single-single leaf captures using cameras and these images have one leaf per images and the same background and lightening conditions, which do not depict the real-world or natural farms environment. In real-world or natural environment, the one image may have multiple leaves and different background and lightening conditions.

The next publicly available dataset is PlantDoc, in which real world images are captured using web scrapping and the dataset was prepared. We have experimented with various CNN architectures and Deep learning approaches to improve the accuracy of PlantDoc dataset while model trained on

PlantVillage, not succeeded to improve accuracy on PlantDoc dataset and proposed a hybrid approach to improve the classification accuracy, which is detailed in this section.

A. Dataset

The dataset, which is available for public use is the Plant Village [17], [18] website and PlantDoc dataset[19], serves as the basis for the data that is collected. The PlantVillage dataset includes more than 540000 different images of leaves. The images are all saved in the JPEG file format. The photos are saved as RGB files that are 256 pixels wide and 256 pixels height. The classes of the datasets and number of images of each class that were used in the model development are presented in Table 1.

Table-1 No. of Tomato disease leaf Images in PlantVillage and Plantoc dataset

Tomato related datasets	**Category**	**No. of Images**
D1-PlantVillage (Segmented/Normal)	Bacterial_spot	2127
	Early_blight	1000
	Healthy	1591
	Late_blight	1909
	Leaf_Mold	952
	Septoria_leaf_spot	1771
	Spider_mites Two-spotted_spider_mite	1676
	Target_Spot	1404
	Tomato_mosaic_virus	373
	Tomato_Yellow_Leaf_Curl_Virus	5357
D2-PlantDoc	Bacterial_spot	110
	Early_blight	88
	Healthy	63
	Late_blight	111
	Leaf_Mold	91
	Septoria_leaf_spot	151
	Spider_mites Two-spotted_spider_mite	3
	Tomato_mosaic_virus	54
	Tomato_Yellow_Leaf_Curl_Virus	76

B. State of art experiments carried out to improve accuracy on PlantDoc dataset

As shown in Table-2 it clearly indicates that the CNN architectures/Models trained on PlantVillage Dataset are performing well on test dataset of PlantVillage but when same model predicting on PlantDoc dataset, classification accuracy is very low.

In the eperiment-1 to 5 , CNN architetcures EfficientNetB0, MobileNetV3Small, MobileNetV3Large, NASNetMobile, and EfficientNetB7 are being deployed respectively, which was trained on Train subset of PlantVillage-Tomato dataset and when the tested on test subset able to achieve the accuracy of 99.45%, 99.34% , 99.14%, 97.42% and 98.79% respectively for experiment 1 to 5, similarly when trained model tested on PlantDoc-Tomato dataset accuracy was 28%, 25%, 23%, 22% and 20% respectively. All the CNN architecture uses pre-trained weights on ImageNet dataset for transfer learning purposes.

In experiment-6, an ensemble-based approach with weighted average or poll based techniques are followed in which the results i.e prediction probabilities of different CNN architectures like MobileNet, EfficientNet etc. are combined and results are predicted on PlantDoc-Tomato dataset and achieved the accuracy of 30%.

In experiment 7, the model was trained overall PlantVillage dataset including the disease other than Tomato. The accuracy on PlantVillage dataset was 95.50% and on PlantDoc-Tomato dataset the accuracy was 15%. Furthermore, in experiment-8 the weights trained in experiment-7 on Full PlantVillage dataset was used as pre-trained weights. The classification accuracy was 99.78% and 25% for Plantvillage and PlantDoc dataset respectively.

For experiment 9 and 10, no pretrained weights were used and the models were trained from scratch, in both EfficientNetBo architecture used, however differs in no of epochs for the training, which was 70 and 250 epochs respectively for experiment-9 and 10. The classification accuracy on PlantVillage was 83.83% and 87.62% respectively for experiment-9 and 10, similarly the classification accuracy on PlantDoc was 17% and 13% respectively for experiment -9 and 10.

In continuation to experiment-1, further online augmentation like RandomFlip, RandomRotation, RandomZoom, RandomBrightness, RandomContrast was used during the training to improve the generalization of dataset for experiment-11. However, we have not seen any improvement for this case, the classification accuracy was 96.60% and 26% for PlantVillage and PlantDoc respectively. Further in experiment-12, the base model was marked as frozen and only a few upper layers were going to change weights during the training. The classification accuracy was 97.97% and 20% for PlantVillage and PlantDoc respectively.

In the experiment-13 the notion of unsupervised learning was used by implementing Autoencoder techniques, in which there was one encoder and decoder and Full PlantVillage dataset images without labels are feed to the encoder and decoder will try to generate same image in the output and with this process weights trained are saved and then applied as pre-trained weights while applying the classification CNN like EfficientNetBo. The classification accuracy was 28% on PlantDoc dataset.

Table-2 Various state of art experiments carried out to improve model trained on PlantVillage to predict results on PlantDoc

Experiment	CNN architecture	Model/architecture trained on	Pre-trained Weights	Additional Details	Accuracy on PlantVillage-Tomato	Accuracy on PlantDoc-Tomato
Exp-1	EfficientNetB0	PlantVillage-Tomato (Train-80)	ImageNet		99.45%	28.00%
Exp-2	MobileNetV3Small	PlantVillage-Tomato (Train-80)	ImageNet		99.34%	25.00%
Exp-3	MobileNetV3Large	PlantVillage-Tomato (Train-80)	ImageNet		99.14%	23.00%
Exp-4	NASNetMobile	PlantVillage-Tomato (Train-80)	ImageNet		97.42%	22.00%
Exp-5	EfficientNetB7	PlantVillage-Tomato (Train-80)	ImageNet		98.79%	20.00%
Exp-6	Ensemble Approach	PlantVillage-Tomato (Train-80)	ImageNet	Combine results of Various CNN architectures like MobileNet, EfficientNet etc.	NA	30.00%
Exp-7	EfficientNetb0	Full PlantVillage (Train-80)	ImageNet		95.50%	15.00%
Exp-8	EfficientNetb0	PlantVillage-Tomato (Train-80)	Weights saved in		99.78%	25.00%

			Experiment-7			
Exp-9	EfficientNetb0	PlantVillage-Tomato (Train-80)	From Scratch		83.83%	17.00%
Exp-10	EfficientNetb0	PlantVillage-Tomato (Train-80)	From Scratch	with Higher epochs (250)	87.62%	13.00%
Exp-11	EfficientNetb0	PlantVillage-Tomato (Train-80)	ImageNet	with online Augmentations	96.60%	26.00%
Exp-12	EfficientNetb0	PlantVillage-Tomato (Train-80)	ImageNet	Baseline model false	97.97%	20%
Exp-13	Autoencoder	Full PlantVillage(Train-80)	ImageNet and then save weights from Autoencoder and use in CNN classification	Autoencoder architecture based on MobileNetV3Small and use unsupervised learning and then apply efficientNet	NA	28.00%
Exp-14	EfficientNetb0	PlantDoc-Tomato (Train-80)	ImageNet		NA	41.43%
Exp-15	MobileNetV3Small	PlantDoc-Tomato (Train-80)	ImageNet	with online Augmentations	NA	54.00%
Exp-16	MobileNetV3Small	PlantDoc-Tomato (Train-80)	Full Plandoc weights		NA	51.00%

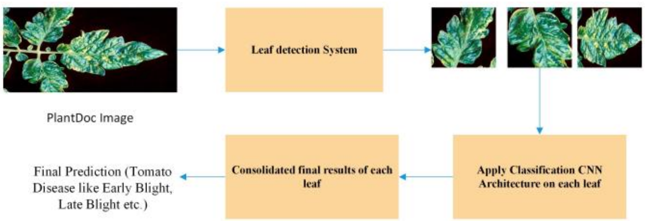
Further in experiment 14,15 and 16 CNN architectures were trained directly on PlantDoc-Tomato dataset rather than PlantVillage. The classification accuracy was 41.43%, 54% and 51% respectively for experiment 14,15 and 16. These experiments confirm that dataset of real-world environment i.e., PlantDoc are difficult for classification predictions in comparison to dataset of controlled environment images i.e., PlantVillage.

C. Proposed Model

After analysis the various experiments, it was found models trained on PlantVillage not performing well due to large differences in dataset, as PlantVillage contains one leaf per images, whereas in PlantDoc dataset the image may have multiple images and may contain different background and lightening conditions.

To overcome these challenges, we propose a hybrid approach based on deep learning to improve the classification accuracy on PlantDoc dataset. The approach depicted in Fig.1

Fig. 1 Proposed Hybrid approach for Tomato Disease detection



The Hybrid approach for Tomato disease classification system is shown in Fig.1. The whole system has three phases: Leaf detection to extract individual leaves from images, apply CNN Classification on each leaf, Consolidate the results of each leaf and generate final prediction of Tomato disease.

For Leaf detection, object detection techniques like Yolo7 and Yolo8 were deployed, initially the model was trained with leaf detection dataset available on Kaggle i.e "Kaggle Leaf detection" dataset[20], containing 1130 images, which was further randomly split into the train and validation subsets contains 1017 and 113 images respectively. After the training the trained model was used in the proposed approach to detect the leaves in PlantDoc dataset images. The Object detection algorithms trained for leaf detection are detailed in Table-3.

Further once leaves are detected using object detection techniques, the areas of leaf extracted and different CNN architectures like efficientNet, MobileNet etc. were applied on each leaf to predict the tomato disease, afterwards the results of individual leaves were consolidated, and final tomato disease predicted by the system.

Table-3 Various state of art Object detection algorithms for leaf detection

Model Name	Model Parameters	Model GFLOPs	Model size (MB)	Validation Accuracy	
				mAP 50	mAP (50-95)
YOLO8-n	3M	8.1	6	0.66	0.43
YOLO8-s	11M	28.4	23	0.69	0.45
YOLO8-m	25M	78.7	52	0.68	0.45
YOLO7	36M	103.2	71	0.63	0.41
YOLO7-Tiny	6M	13	12	0.65	0.39

Results And Discussion

In this section, we've outlined the metrics for assessing models and CNN architectures as well as the proposed model's outcomes.

C. Exeperimental Setup

The experiments in this study were performed on a Tesla P100 GPU with 16 GB of RAM while using the TensorFlow 2 and Python 3.7 environments. The PlantVillage dataset and PlantDoc dataset were used. The input images are 256x256x3 pixels in size, and there are 32 images in the batch.

D. Evalution Metrices

The model's performance is assessed using accuracy, precision, recall, and the F1 score [21], [22]. Additionally, the test dataset's confusion matrix is used to assess performance parameters. The confusion matrix's diagonal members show the proper categorization, whereas its nondiagonal elements show misclassification. The expected accurate or incorrect results for binary classification are shown in the confusion matrix. True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are its four subcomponents. The definitions of Accuracy, Precision, Precision, and F1 Score are as follows:

Accuracy = TP+ TN/ TP + TN + FP + FN (1)

Precision = TP/ TP + FP (2)

Recall = TP/ TP + FN (3)

F1 score = 2 × Recall × Precision/ Recall + Precision (4)

Further, for the object detection techniques IOU (intersection over union), mAP50(Mean Average Precision), mAP50-95 were used performance evaluation metrics.

E. Results

In the proposed hybrid approach, first step is to detect the leaves and afterwards each extracted leaf went to classification CNN architetcure to classify the leaf to tomato diseases. The CNN architetcures appilied in proposed approach are depicted in Table-4.

Table-4 Various state of art CNN classification architecture results

CNN Architecture	CNN architecture trained on dataset	Results on PlantDoc-Tomato Dataset		
		Accuracy	F1 Score	Recall
EfficientNetb0	PlantVillage-Tomato	49.2	48.1	48.2
MobileNetV3Small	PlantVillage-Tomato	44.2	44.1	44
EfficientNetb0	PlantDoc-Tomato (offline cropped leaves)	90.7	90.4	90.1
MobileNetV3Small	PlantDoc-Tomato (offline cropped leaves)	85.2	85.1	85.1

The hyperparameters epoch was set to a value of 70, and the Adam optimizer was used to carry out the optimization. A modified learning rate of 10e-6 was used. The loss function categorical cross entropy was used.

As seen earlier in the experiments depicted in Table-2, when the model trained on PlantVillage dataset and tested on PlantDoc dataset the maximum accuracy was about 30% only, but after implementing leaf detection additionally it improves to 49% with efficientNet architecture. Further in offline manner we have created a “PlantDoc-Tomato-Single-Leaf” dataset by extracting the leaves from PlantDoc images and saving these images individually. The CNN architectures were trained on this “PlantDoc-Tomato-Single-Leaf” dataset and deployed with object detection in proposed approach, able to achieve classification accuracy of 90.7%, which much higher than the author provided in original paper also.

Conclusion

Plant diseases pose a significant challenge to global agriculture, requiring early detection and accurate identification to prevent crop losses and minimize pesticide use. Deep learning models, such as efficientNet and MobileNet, have revolutionized computer vision, but datasets also play a crucial role in solving problems. PlantVillage is the most widely used openly available dataset but does not have real-world images. The PlantDoc dataset images have real-world tomato disease images, but earlier method not able to achieve the good accuracy on this dataset.

We propose a hybrid technique based on a combination of object detection and classification CNN architectures, which achieved 90.7% accuracy as well as resilient F1 score and recall metrics. The suggested methodology also achieves a high level of accuracy of 85.2% using the lightweight CNN architecture MobileNet, allowing the model to be deployed in mobile/embedded devices.

The proposed method may have limitations when applying to real world farms, with disease not covered in trained dataset. As the PlantDoc dataset prepared with web scrapping, some images may have unnatural backgrounds or object which may be not relevant to actual farm. In future a dataset with images from actual farms, greenhouses with more Tomato diseases may be created, also rather than creating classification dataset, object detection dataset will be more effective.

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