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ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network

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Abstract

Tomato is the most popular crop in the world and in every kitchen, it is found in different forms irrespective of the cuisine. After potato and sweet potato, it is the crop which is cultivated worldwide. India ranked 2 in the production of tomato. However, the quality and quantity of tomato crop goes down due to the various kinds of diseases. So, to detect the disease a deep learning-based approach is discussed in the article. For the disease detection and classification, a Convolution Neural Network based approach is applied. In this model, there are 3 convolution and 3 max pooling layers followed by 2 fully connected layer. The experimental results shows the efficacy of the proposed model over pre-trained model i.e. VGG16, InceptionV3 and MobileNet. The classification accuracy varies from 76% to 100% with respect to classes and average accuracy of the proposed model is 91.2% for the 9 disease and 1 healthy class.

Keywords: Convolution Neural Network (CNN); supervised learning; hyperparameters; plant leaves dataset

1. Introduction

Tomatoes (biological name: Solanum lycopersicum) grows on mostly any well drained soil [13] and Nine out of 10 farmers grow tomatoes in their field. Many gardeners also grow tomatoes in their garden to use fresh grown tomato in their kitchens and get a good taste of food. However, farmers and gardeners are sometimes unable to get proper progress of the plant growth [12]. The tomatoes may not sometime appear on plant or sometimes the tomatoes may get bad looking and disease-ful black spots at bottom part.

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The identification of tomato plant disease may start from, to diagnose the portion having infection in plant then to note the differences such as brown or black patches and holes on the plant and then to look for the insects also. Tomatoes and similar vegetables like potatoes or brinjal must not be planted on same farm for more than one time in period of three years [11]. To maintain the fertility of soil we should ideally precede tomato planting by any member of grass family e.g. wheat, corn, rice, sugarcane etc.

The tomato problems may be divided into two sections: bacteria or fungi or poor cultivation habits causing 16 diseases while insects causing 5 other type of diseases. Ralstonia solanacearum bacteria causes serious form of Bacterial wilt. This bacterium can survive in soil for long time period and enter roots through natural wounds made during secondary roots emergence or man made during cultivating or transplanting or even insects.

High moisture and high temperature favours disease development. The bacteria fills, water conducting tissue of plant, with slime by multiplying rapidly inside it. This results in affecting the vascular system of plant, while the leaves may stay green. On a cross section view of an infected plant stem, it appears brown with yellowish material coming out of it.

In the research article, we have proposed a novel method to identify the disease in tomato crop after analyzing the images of leaves. The work will solve farmers problems of plant's disease identification without running after plant scientists. It will thus help them cure the plant's disease in timely fashion and will thus increase both quality and quantity of food crops produce and therefore help in increasing farmer's profit. For the experiment purpose we have downloaded tomato leaves dataset from plantvillage [8]. After downloading the dataset, we have developed a Convolution Neural Network model to classify the images. The performance of model has been analysed based on various parameter such as training accuracy, validation accuracy and testing accuracy and number of trainable and number trainable parameters with respect to pre-trained model. The rest of the paper organized as follows: The literature survey about the existing methods is discussed in section 2. Discussion about the dataset is presented in section 3. The experimental setup and result discussion are presented in section 4, followed by the conclusion.

2. Literature Survey

Machine learning algorithms are applied in various fields, but feature engineering remains the main problem. With the emergence of deep neural network, the promising results are available for plant pathology without laborious feature engineering. Deep neural networks significantly increase the image classification accuracy. This section provides a various deep learning technique used by researchers in plant disease identification. Mohanty et al. [10] used AlexNet [9] to train classify plant diseases that were not seen before. Model accuracy was substantially reduced while testing image conditions are different than training image. Sometimes, disease appears on upper sides of the leaves sometime, lower sides of the leaves. Rangarajan et. al., [14] trained both AlexNet and VGG16net with minimum batch size, weight and bias learning rate as hyper-parameters. Accuracy is negatively correlated with minimum batch size in case of VGG16net. Convolution and pooling layers together stacked in a module and applied to GoogleNet architecture as Inception V4 for dimension reduction [16]. Too et al. [19] applied weights that are pre-trained on ImageNet to this architecture average pooling layer of 8×8 for fine tuning. In addition to that DenseNets [6] with 122 layers is also fined tuned for plant disease recognition.

Caffe [7] framework is used to develop a CNN with local response normalization for eight class classification [4]. A CNN with local contrast normalization layer is designed for binary classification with ReLu as activation function [8]. AlexNet and GoogleNet are trained and fine-tuned for classification disease regions and symptoms [2]. DeChant et al [3] proposed 3 stage training CNN. In first stage, it learns the presence of lesions while in second stage it produces heat map to identify infection. Finally, features learned from previous stages are classified based on heat maps. Brahimi et al [1] introduced saliency map method for localization of infected regions. This type of visualization improves classification accuracy. Wang et al [20] identified the impact of depth of network on classification accuracy. Even with transfer learning, high classification accuracy is achieved with low number of convolutional layers. Tan et al [18] employed variable momentum rule to CNN for parameter learning from lesions images; that results in quick convergence with comparative good accuracy. Yamamoto et al retrieved detailed images by applying super resolution method over low-resolution method and thus achieved better classification accuracy. Performance of various CNN for plant disease identification depends on various factors: availability of limited number of annotated; poor representation of disease symptoms, image background and capturing conditions; limited variations in disease symptoms [21].

3. Dataset

Images of Tomato disease have been taken from Plant Village dataset [19]. The dataset includes over 50,000 images of 14 crops, such as tomatoes, potatoes, grapes, apples, corn, blueberry, raspberry, soybeans, squash and strawberry. We selected tomato as our target crop.

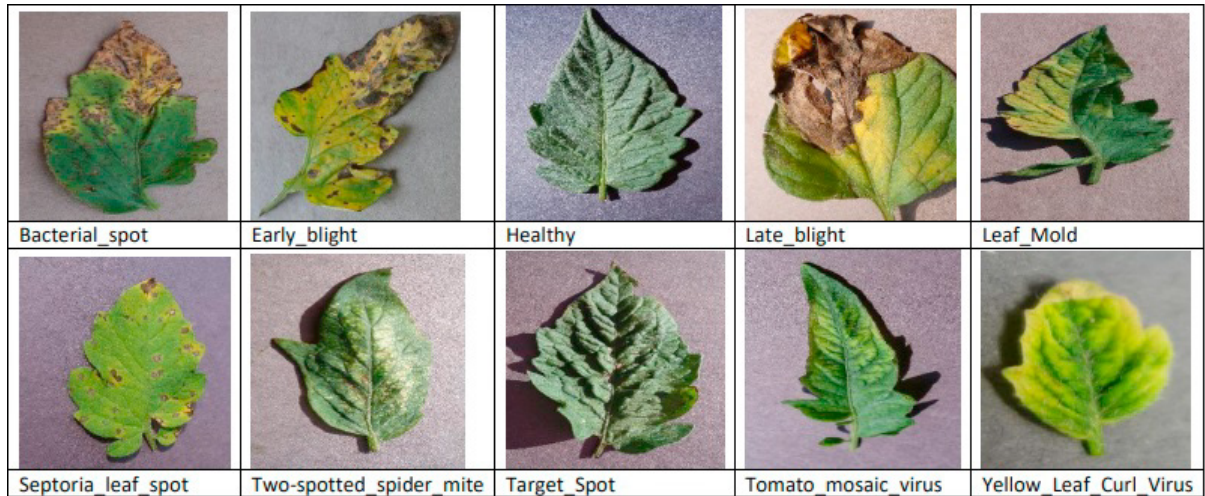The images of various classes of tomato are as follows (refer figure 1).

Fig. 1. Class wise sample image of the dataset.

There are mainly nine types of diseases in tomato: 1) Target Spot, 2) Mosaic virus, 3) Bacterial spot, 4) Late blight, 5) Leaf Mold, 6) Yellow Leaf Curl Virus, 7) Spider mites: Two-spotted spider mite, 8) Early blight and 9) Septoria leaf spot. In proposed work, there are 10000 images in training dataset, 7000 images in validation dataset and 500 images in testing dataset. Out of 10000 training images, 1000 images belong to healthy category and 1000 images belong to each tomato disease category described above. In validation set each class has 700 images and test set has 50 images in each class.

For testing, we randomly picked 50 images from each class from training set and removed them from those folders. From remaining training dataset, we built our project training dataset by putting same number of images (1000) in each class. When the images in any class were less than 1000, we used data augmentation technique to generate some new images. Augmentation was done using Augmentor package of python and it helps to build similar new images by rotating, flipping, cropping and resizing the existing images. When images in any class in training dataset were more than 1000, we picked first 1000 images. We followed same process for validation dataset and made all classes have 700 images each. This process is necessary to prevent bias for any particular class during training of CNN. Size of all the images is 256×256 and format is jpeg.

4. Experimental result and Discussion

The proposed CNN model has been executed on NVIDIA DGX v100 machine. The machine is equipped with 40600 CUDA cores, 5120 tensor cores, 128 GB RAM and 1000 TFLOPS speed. As in the data set images per class are different, so make the class balance data augmentation technique has been applied. In proposed CNN architecture there are three convolution and max pooling layer are used. In each layer various number of filters has been applied. The architecture of proposed CNN model is depicted in following figure, figure 2.

To get the better accuracy, Panda approach has been applied and the hyper parameters for the model is described in table 1. The activation after each convolution layer is represented in figure 3.
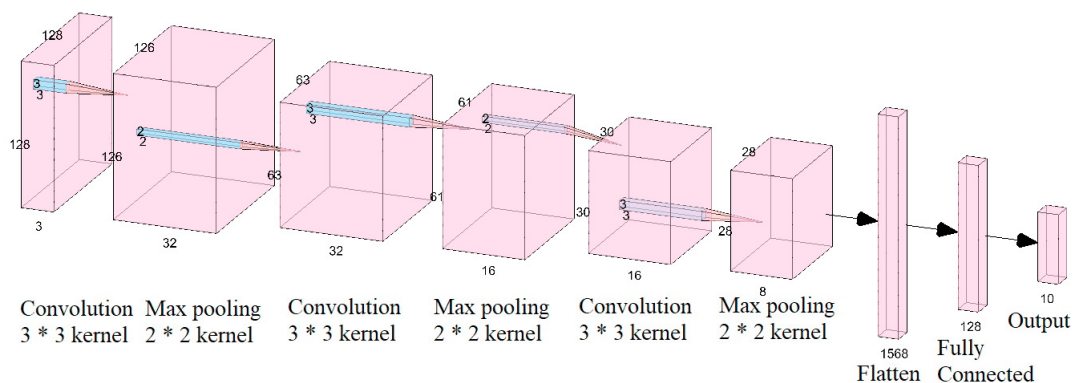
Fig. 2. Pictorial representation of the proposed convolution network.

Table 1. Hyper parameters for convolution neural network.

Hyperparameter	Description
No. of convolution layer	3
No. of max polling layer	3
Drop out rate	.5
Network weight initialization	Glorot uniform
Activation function	Relu
Learning rate	0.001
Momentum	0.999
Number of epoch	1000
Batch size	64

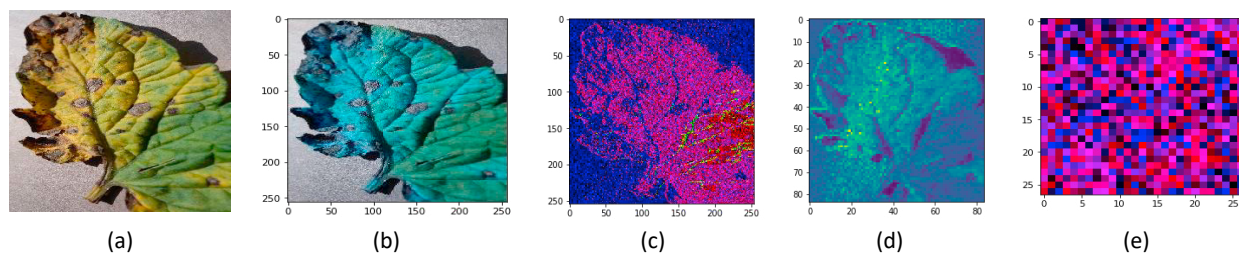(a)   (b)   (c)   (d)   (e)

Fig. 3. (a) Image passed in the CNN model (b) extracted features at first convolution layer (c) extracted features at second hidden layer (d) extracted feature at third hidden layer and (e) extracted features at fourth layer hidden layer.

Moreover, we ran the proposed model for 1000 epochs and validation and training accuracy is presented in figure 4. For the calculation of loss, the categorical cross entropy method has been applied. The formula for calculating it represented in following equation 1.

$$loss = -\sum_{c=1}^{M} log(p_{o,c}) \tag{1}$$

where M - number of classes, y - binary indicator (0 or 1) if class label c is the correct classification for observation o and predicted probability observation o is of class c.

After analyzing the performance of proposed model, we undergo for the testing. For the testing purpose, total 500 sample has been used and for the various classes testing accuracy is different and it is ranging from 76% to 100% and the average accuracy of the proposed model is 91.2%.
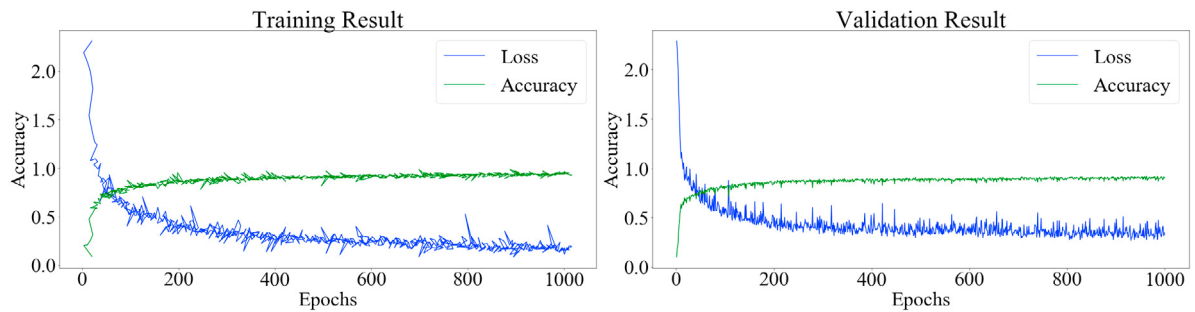
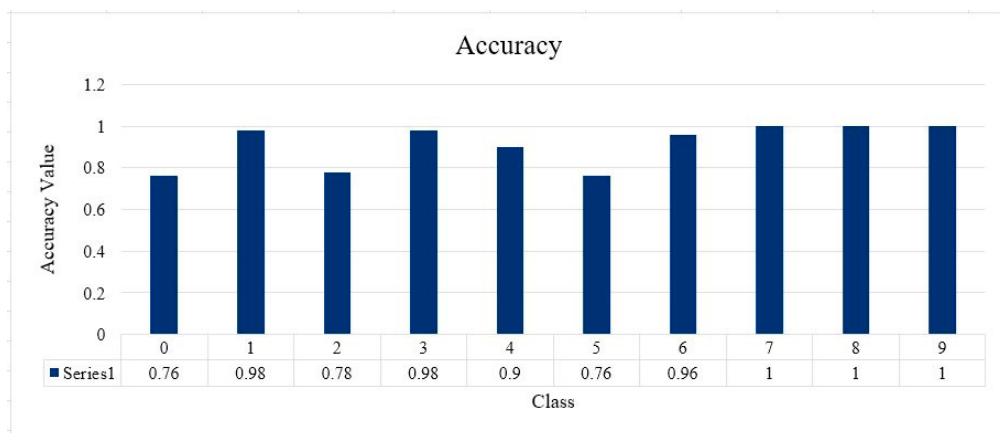Fig. 4. (a) Training loss (b) Validation loss of proposed model.

Fig. 5. Testing accuracy for the 10 classes.

In proposed work, we also ran some pre-trained model for the performance comparison purpose. Brief discussion about these pre-trined model is given as follows:

VGG 16 [15] is the CNN architecture created by VGG (Visual Geometry Group, University of Oxford) for the ILSVRC-2014 (ImageNet Large Scale Visual Recognition Challenge). In brief its architecture has input image size of 224×224. Filters size is 3×3 and padding is done to keep the resolution of intermediate outputs same. It has 13 convolution layers and 3 Dense layers. Activation function used is relu in all layers. 2 penultimate layers have 4096 hidden nodes each and final layer has 1000 output nodes equal to number of classes in the ILSVRC. We tried to load the VGG 16 pre trained weights and added a output layer of 10 dimension corresponding to 10 classes of tomato. We found that transfer learning using VGG16 was not very encouraging in our modelled dataset of tomato leaves from PlantVillage dataset folders. We obtained final accuracy of 77.2% when we trained our code for 1000 epochs on NVIDIA supercomputer.

Inception V3 [17] is a 42-layer deep learning network with fewer parameters. The reduction in parameters is done with help of factorizing convolutions. For example, a 5×5 filter convolution can be done by two 3×3 filter convolutions. The parameters in this process reduces from $5 \times 5 = 25$ to $3 \times 3 + 3 \times 3 = 18$. Thus, it brings 28% reduction in number of parameters. With a smaller number of parameters, the model will less overfit and thus increase the accuracy. This model became 1st runner up in ILSVRC-2015. We used the Inception V3 pretrained model to perform transfer learning on our 10-class tomato disease problem. We found the accuracy is even less than VGG16 and comes to 63.4 % when we trained for 1000 epochs on NVIDIA. The model we felt will work well on a greater number of classes as 42-layer deep architecture makes it overfit for small number of classes when the distinction features are not obvious or big.

Mobilenet [5] was proposed in 2017 and comes with keras package of python. It is 32 times smaller than VGG 16 and still has similar accuracy. The smaller the network the faster it runs and uses less battery power. The compression of convolution layers is done by sorting the weights and throwing smallest weights. Mobile net also uses depth wise
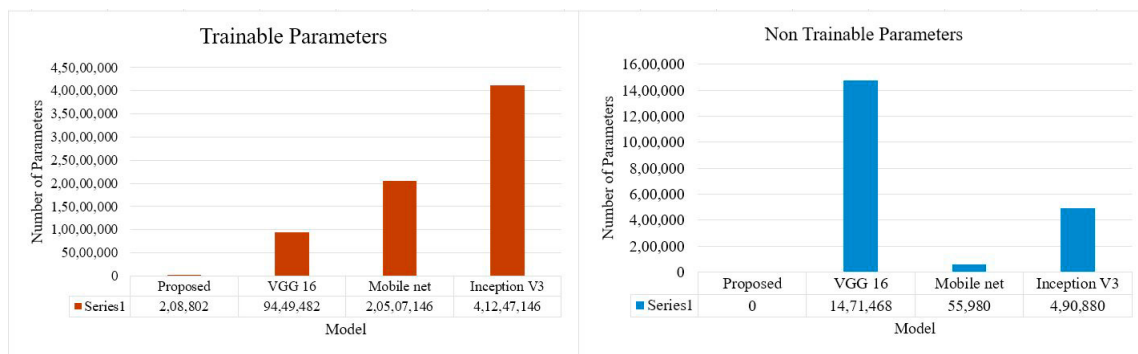
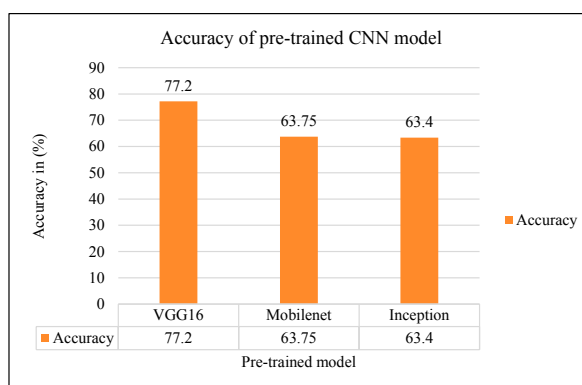Fig. 6. Comparison of number of parameters in various Models.

Fig. 7. Test accuracy using different pre-trained models i.e. VGG16, MobileNet and InceptionV3.

separable convolutions which makes its work 9 times faster as comparable to similar neural networks with similar accuracy. Relu and Batch normalization are used in this building blocks of separable convolutions. Mobile net has 17 such blocks (28 layers if we count depth wise and point wise convolution as separate layers) followed by global average pooling and a classification layer. We tried to use transfer learning with mobilenet also and found with 1000 epochs it gave 63.7% accuracy on our 10-class tomato disease problem. This may be due to still deep network causing overfitting in a smaller number of classes.

The proposed algorithm is also compared with pre-trained model in terms of number of trainable and non-trainable parameters and it is observed that the proposed model is far better than the pre-trained models i.e.VGG16, MobileNet and InceptionV3. The comparative bar charts are depicted in following figure 4. The comparison is also described in table 2. As seen the storage space needed by proposed model is much less than pretrained models and is thus more suited to mobile devices with limited storage space. The performance of proposed algorithm is also better than pre-trained models in terms of accuracy (refer figure 7). Performance of proposed model in terms of Precision, Recall and F1-score is given in Fig 8. Moreover, the RoC-AUC curve for all 10 classes with respect to proposed model is presented in figure 9.

5. Conclusion

In the proposed work, we have developed a CNN based model to detect the disease in tomato crop. In the proposed CNN based architecture there are 3 convolution and max pooling layers with varying number of filters in each layer. For the experiment purpose, we have taken the tomato leaf data from PlantVillage dataset. In the dataset there are 9 disease classes and class which is having the healthy images. As the images inside class is not balanced, so that data

Table 2. Comparison of time and space complexity with Pretrained models.

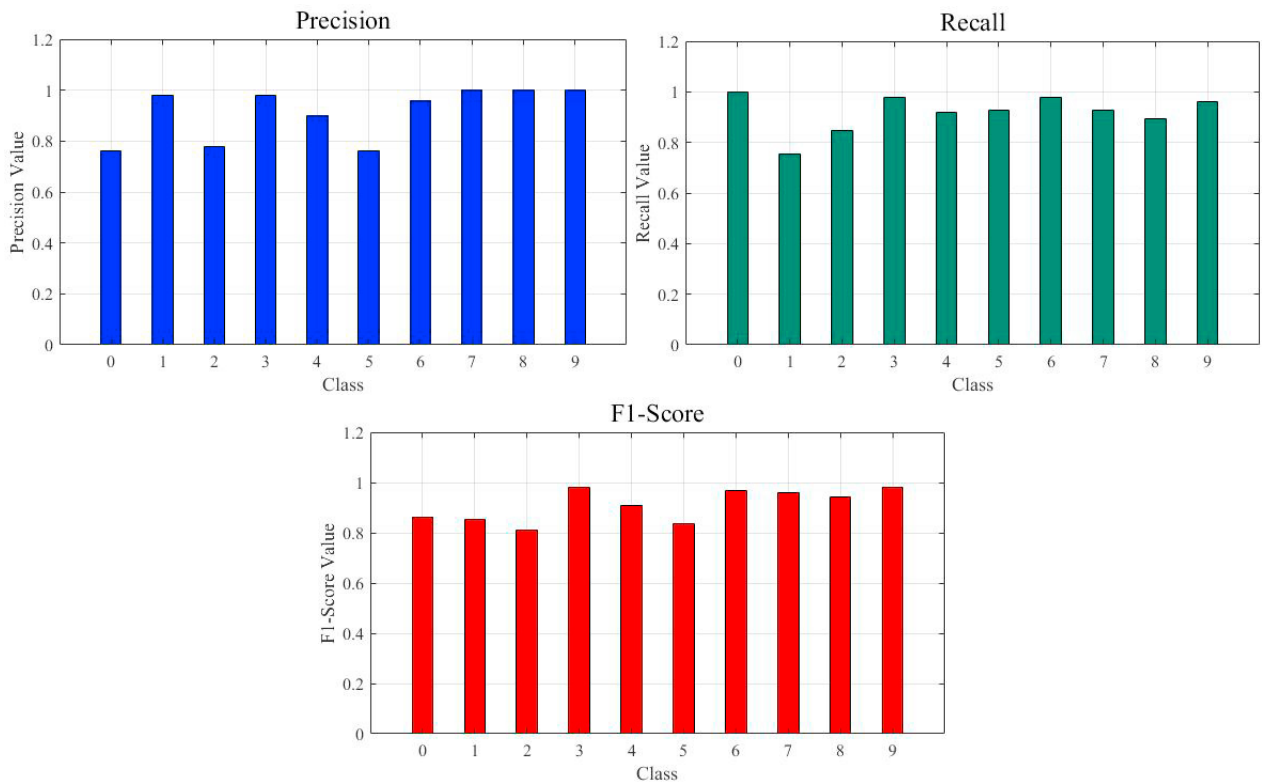| S.No.	Model	Accuracy	Storage Space	Trainable Params	Non trainable Params
1	Mobilenet	63.75%	82,498 KB	20,507,146	559,808
2	VGG 16	77.2%	94,452 KB	9,449,482	14,714,688
3	InceptionV3	63.4%	1,63,734 KB	41,247,146	490,880
4	**Proposed Model**	**91.2%**	**1,696 KB**	**208,802**	**0**

Fig. 8. Various performance evaluation metrics for proposed algorithm (a) Precision (b) Recall (c) F1-Score .

augmentation techniques have been applied to balance the images inside the class. Experimentally, it is observed the testing accuracy of the model is ranging from 76% to 100% for the classes. Moreover, the average testing accuracy of the model is 91.2%. The storage space needed by proposed model is of order of 1.5 MB whereas pretrained models have storage space needs of around 100 MB thus showing the benefit of the proposed model over pretrained models.

As a future work, we are trying to modify the model with a greater number of images with some other crop. Moreover, we are also in process to improve the same model on same dataset as testing accuracy is less.

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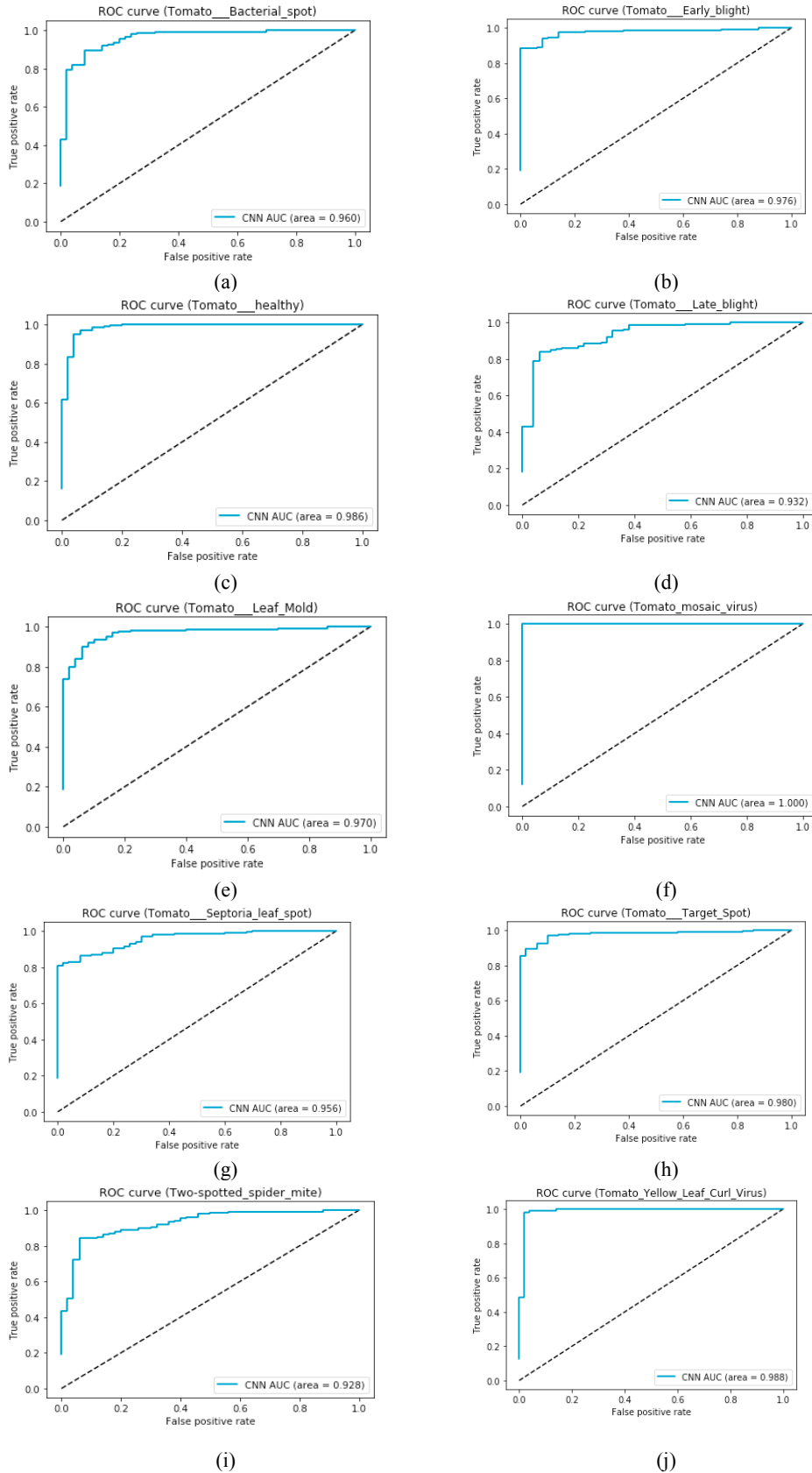
Fig. 9. RoC-AUC curve with respect to different classes.