Proceedings in Adaptation, Learning and Optimization 17

Harish Sharma
Apu Kumar Saha
Mukesh Prasad *Editors*

Proceedings of International Conference on Intelligent Vision and Computing (ICIVC 2022)

Volume 1

MOREMEDIA

Springer

Deep Learning Model for Automated Image Based Plant Disease Classification

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Abstract. India is a rural country where a majority of the population rely on agriculture for their living. Agriculture provides food and raw materials and also acts as a livelihood source for farmers. Farmers are bearing a big loss because of plant diseases that are difficult to be identified. These diseases can be identified by plant pathologists by visual inspection. This is a time-consuming process and needs expertise. With the improvement in digital cameras along with the evolution of machine learning and deep learning, an automated identification of plant disease is in huge demand in precision agriculture. These diseases can be identified by deep learning techniques that enable farmers to take action accordingly beforehand. In this research work, a transfer learning based deep learning model named EfficientNet B0 has been proposed to identify and classify the plant leaf disease for pepper, potato, and tomato plant. Images of these plants have been taken from a popular plant disease dataset named "PlantVillage". These images are trained on the EfficientNet B0 model and performance comparison is done with other CNN based deep learning models. The testing accuracy of the proposed EfficientNet B0 model is 99.79% which justifies the efficacy of the developed model. Therefore, the performance of the proposed model indicates the utility of an automatic plant disease recognition and its ease of application in a farmer's field at a greater scale.

Keywords: Disease Classification · Convolutional Neural Network · Transfer Learning · Deep Learning · EfficientNet B0

1 Introduction

Agriculture is playing a pivotal role in strengthening the Indian economy. It contributes around 14% of GDP. Farmers have to face various issues like climate change, weather forecasting, phenology identification, etc. Crop disease poses a big threat to agriculture as it can spoil the crop yield which creates a problem with food safety. Therefore, the identification of crop disease at an early stage is necessary to ensure a good yield and better quality of the crop. Expert knowledge about various diseases in plants is lacking among villagers. Low inter class and high intra class similarity among disease classes make the disease identification process very challenging for the farmers. This process

H. Sharma et al. (Eds.): ICIVC 2022, PALO 17, pp. 21–32, 2023.
https://doi.org/10.1007/978-3-031-31164-2_3

is time-consuming and may fail as well in a big field. In Kisan Call Centers, sometimes experts cannot see the exact problem that the farmer is facing so a wrong suggestion can also be given sometimes for plant disease identification. Hence, it is required to use modern methods like deep learning and machine learning that can assist the farmer in identifying the disease easily and provide the required solution to deal with these crop diseases.

Machine learning and deep learning are now employed in every sector for classification and prediction purposes due to the advancements in computer vision. Handcrafted and automatically extracted features can be used to detect the leaf diseases. Handcrafted features extraction is fast but generally gives poor results. On the other hand, automatic feature extraction is done by a deep learning approach that give good performances in leaf disease identification. The objective of this research study is to identify and classify the plant disease in pepper, potato, and tomato based on image processing. An automated detection of these diseases can speed up other tasks in agriculture. The images used for the proposed work have been taken from the publicly available popular dataset named "PlantVillage". These images have been trained on convolution neural network (CNN) based model EfficientNet B0 and performances are compared with another deep learning model. Contributions to the proposed research work are as follows:

- To detect disease in pepper, potato, and a tomato plant.
- To classify the disease of pepper, potato, and tomato into 15 disease types.
- To visualize the role of EfficientNet B0 in improved classification accuracy for plant disease.

Following the introduction, Sect. 2 describes the related work done in the field. Section 3 and Sect. 4 cover the proposed methodology and results of the experiment respectively. The conclusion along with future scope is mentioned in Sect. 5.

2 Literature Review

For the purpose of identifying and classifying crops and diseases, various studies have been conducted. Image processing [1] has been used to detect plant disease which assists farmers to identify diseases. Features maps are extracted by image processing [2] and sent to a neural network that classifies these plant disease images. Features are extracted manually using image processing which takes time and is less accurate. Deep Learning models have revolutionized computer vision and are being used in various research areas [3, 4] for object identification and classification. One of the computer vision problems that may be effectively handled by deep learning is the detection of plant diseases.

In research work [5], the author has used various transfer learning-based deep convolutional neural network models. Authors used pre-trained models like AlexNet [6], VGG [7], GoogleNet [8] and ResNet [9], DenseNet [10] which offer high classification accuracy for plant disease. Research work presented in [11] focuses on the identification of plant disease of 13 different types. The proposed study has an accuracy of 96.3% on the test dataset. A total of 30,880 images have been used for training the model and tested on 2589 images. In [12], the authors presented a deep convolutional neural network for disease identification for 10 commonly found rice diseases and presented model was used on 500 images of infected and healthy rice leaves. The developed model has 95.48% accuracy. In [13], research work focuses on tomato disease identification for 9 commonly occurring tomato diseases. Dataset used in research work has 14828 images of infected tomato leaves and the model offers 99.18% accuracy. CNN-based GoogleNet architecture has been used to identify the diseases. In [14], the author presented a CNN-based VGG16 model for classifying apple disease named apple black rot in four stages based on severity. The author used 1644 images for the research work and achieved an accuracy of 90.4%. In [15], the author used two deep learning frameworks AlexNet and VGG16 for tomato leaf disease classification. Data augmentation has been used to bring the variability and expand the dataset. These two proposed models achieved an accuracy of 97.49 and 96%. In [16], authors provide an overview of various classification techniques used to identify plant diseases. In agriculture, an early detection of plant diseases is very important to improve crop quality and quantity.

Research study was conducted in [17] to use a computer vision enabled Artificial Intelligence techniques for automating the yellow rust disease identification and improving the accuracy of disease identification system. In [18], the authors developed a CNN based model for tomato disease identification and used Conditional Generative Adversarial Network for creation of augmented tomato leaf images. The developed model obtains the classification accuracy of 97.11% on ten classes of tomato leaf disease. In [19], the authors have presented a VGG model combined with Random Forest and Xgboost for disease identification of corn, tomato and potato plants. The experimental results achieve the classification accuracy of 94.47% for corn, 93.91% for tomato plants and 98.74% for potato leaf images.

3 Proposed Methodology

3.1 Data Collection

The dataset used in this research study has been taken from the publicly available "PlantVillage" dataset [20]. The PlantVillage dataset has a total of 39 plant diseases along with some background images. The proposed research work is focused on 12 plant diseases of pepper, potato, and tomato leaf and three classes having healthy leaf images. The used dataset is described in Table 1.

A total of 24313 images of three plants having 12 leaf diseases along with 3 classes with healthy leaves have been used for the research work. Figure 1 displays sample diseased images of the dataset.

3.2 Data Preprocessing

Before these images are fed to CNN models, they are preprocessed and normalized to the same size and remove noises. These images are resized into 224*224 so that they are of the same sizes as the input of the proposed model. Figure 2 represents the workflow of the proposed work.

Table 1. Dataset for plant disease classification

Disease Type	Class Name	Number of Images	Total Training Image	Total Testing Image	Total Validation Image
Pepper_Bacterial spot	Pepper_BS	1000	800	100	100
Pepper_Healthy	Pepper_H	1478	1182	148	148
Potato_Early blight	Potato_EB	1000	800	100	100
Potato_Late blight	Potato_LB	1000	800	100	100
Potato_healthy	Potato_H	1000	800	100	100
Tomato_Early blight	Tomato_EB	1000	800	100	100
Tomato_Bacterial spot	Tomato_BS	2127	1702	213	212
Tomato_Late blight	Tomato_LB	1909	1527	191	191
Tomato_Leaf mold	Tomato_LM	1000	800	100	100
Tomato_mosaic virus	Tomato_MV	1000	800	100	100
Tomato_septoria leaf spot	Tomato_SLS	1771	1417	177	177
Tomato_target spot	Tomato_TS	1404	1123	140	141
Tomato_two spotted spider mite	Tomato_TSSM	1676	1341	168	167
Tomato_Yellow Leaf Curl Virus	Tomato_YLCV	5357	4285	536	536
Tomato_healthy	Tomato_H	1591	1273	159	159
Total Images		24313	19450	2432	2431

3.3 Convolutional Neural Network

A convolution Neural Network (CNN), one of the types of deep learning frameworks, is used for object detection and classification in vision tasks. It consists of a number of layers which are densely connected that extracts the features automatically. In these layers, different size filters are used for extraction of features like color, edge, curve, etc. After each layer, there is a pooling layer that is used to reduce the dimension of feature space so that computation is decreased. At last, this feature vector is fed to a fully connected layer that is connected with the output layer. This whole process is automated where features are extracted automatically unlike machine learning where feature engineering is done manually which is time-consuming. With a large dataset, machine learning generally does not give good results. Deep Learning models outperform machine learning models so we have used this approach in the proposed research. Transfer learning is an application of a model trained on different tasks to a similar task like object classification.

A well-known CNN-based Deep Learning architecture named EfficientNet B0 [21] has been used in the proposed work. This model has been selected based on its great results on ImageNet Large Scale Visual Recognition Challenge ILSVRC [22].

EfficientNet B0 Architecture

EfficientNet was proposed by Google and has eight models ranging from B0 to B7. The accuracy of these models increases gradually while the number of parameters increases slowly. The objective of EfficientNet architecture is to provide good accuracy results with appropriate scaling of width, depth of the deep network, and improvement in resolution of an image. This architecture uses compound scaling by incorporating scaling of depth, width, and image resolution so that their appropriate dimensions are determined. These dimensions can be calculated by the following formulas.

$$\begin{gathered} d = \alpha^{\phi}(depth) \\ w = \beta^{\phi}(width) \\ r = \gamma^{\phi}(resolution) \\ \text{Such that } \alpha.\beta^2.\gamma^2 \approx 2 \text{ and } \alpha \geq 1,\ \beta \geq 1,\ \gamma \geq 1 \end{gathered} \tag{1}$$

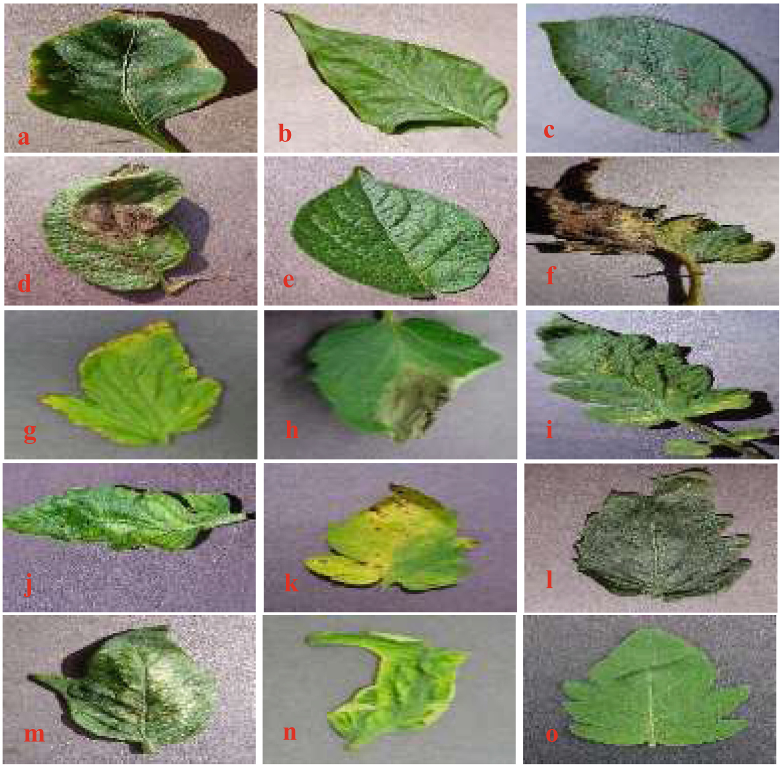

Fig. 1. a) Pepper_BS, b) Pepper_H, c) Potato_EB, d) Potato_LB, e) Potato_H, f) Tomato_EB, g) Tomato_BS, h) Tomato_LB, i) Tomato_LM, j) Tomato_MV, k) Tomato_SLS, l) Tomato_TS, m) Tomato_TSSM, n) Tomato_YLCV, o) Tomato_H

where α, β, *and* γ are the constants. Among all these parameters, the value of ϕ can be used to determine the optimum dimension of width, depth and resolution. Research work proposed in [21] found the optimum value of α, β, and γ as 1.2, 1.1, and 1.15 respectively for EfficientNet B0 architecture. Inverted bottleneck MBConv is the basic building block of this architecture that was presented in MobileNetV2 [23]. In this layer, channels are expanded and compressed. Parameters of EfficientNet B0 have been shown in Table 2. EfficientNet B0 architecture is shown in Fig. 3.

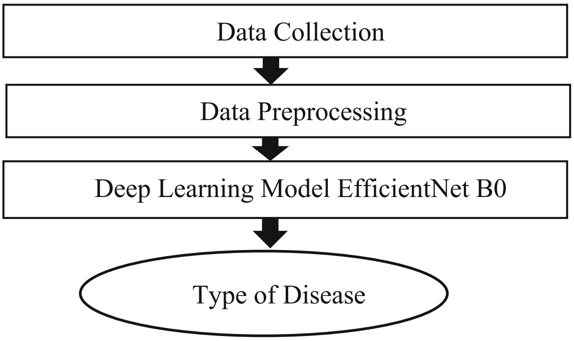

Fig. 2. Proposed methodology of research work

Table 2. Parameter of EfficientNet B0 architecture

Stage i	Operator $\hat{F}_i$	Resolution $\widehat{H} \times \widehat{W}$	#Channels $\widehat{C}_i$	#Layers $\widehat{L}_i$
1	Conv3 × 3	224 × 224	32	1
2	MBConv1, k3 × 3	112 × 112	16	1
3	MBConv6, k3 × 3	112 × 112	24	2
4	MBConv6, k5 × 5	56 × 56	40	2
5	MBConv6, k3 × 3	28 × 28	80	3
6	MBConv6, k5 × 5	28 × 28	112	3
7	MBConv6, k5 × 5	14 × 14	192	4
8	MBConv6, k3 × 3	7 × 7	320	1
9	Conv1 × 1&Pooling&FC	7 × 7	1280	1

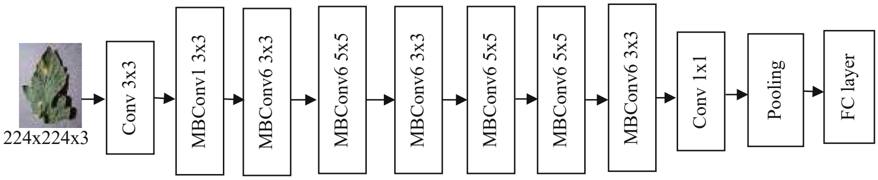

Fig. 3. EfficientNet B0 architecture for Plant Disease Classification

4 Results and Discussions

One popular deep learning model EfficientNet B0 has been proposed in research work to detect and classify the 12 diseases of pepper, potato, and tomato plants along with the healthy images of these plants. We have used the transfer learning approach in the EfficientNet B0 model, trained on ImageNet data and now are trained on a new dataset for our research work. This model has been trained with the learning rate of 0.001 and batch size of 32. Adam optimizer has been used with a momentum of 0.9 and 30% dropout has been used along with L1 regularizer in the model. Rectified linear unit (ReLU) function has been used as an activation function in the architecture. Adam is a combination of Stochastic Gradient Descent and RMSprop with momentum. It scales the learning rate using squared gradients and uses the momentum to move the average of gradients rather than gradients.

The proposed work has been implemented using Google Colaboratory Pro which offers GPU & TPU support. A total of 80%, 10%, and 10% data were used for training, validation, and test data respectively. We have used the early stopping with 3 as a patience value and defined the maximum epoch as 50. Table 3 summarizes the various hyperparameters used in the proposed research work.

Table 3. Hyperparameters used for the proposed model

Model	Input Size	Optimizer	Epoch	Learning Rate	Batch Size	Momentum	Dropout	Activation function
EfficientNet B0	224 × 224	Adam	50	0.001	32	0.9	0.30	ReLU

Table 4 summarizes the performance comparison of different models with EfficientNet B0 on the dataset. As seen from the results, the EfficientNet B0 model has both training and testing accuracy of 99.92% and 99.79% which are higher than that of other models.

Figure 4 displays the accuracy and loss curve of the EfficientNet B0 model for validation and training data. It is evident from the figures that EfficientNet B0 gives approx. 99.92 and 99.81 percent accuracy on training and validation data respectively for 15 disease types. Initially, both training loss and validation loss were large but these losses decreased with an increase in the epoch. The minimum validation loss occurs at epoch = 30. The result of the proposed model has been analyzed using a confusion matrix

Table 4. Performance comparison of different models

Model	Input size	Total parameter	Avg. Training Accuracy (%)	Avg. Validation Accuracy (%)	Avg. Testing Accuracy (%)
DenseNet121	224 × 224	8.1M	99.70	99.75	99.59
DenseNet169	224 × 224	14.3M	99.82	99.67	99.63
DenseNet201	224 × 224	20.2M	99.84	99.83	99.75
EfficientNet B0 (Proposed Model)	224 × 224	5.3M	99.92	99.81	99.79

and shown in Fig. 5. One image in Pepper_H, one in Tomato_EB, one in Tomato_SLS, and two images in Tomato_TS have been misclassified as Pepper_BS, Tomato_SLS, Tomato_MV, and Tomato_TSSM respectively. Out of 15 classes, four classes have a total of 5 samples that have been misclassified. For the remaining classes, the model classifies all images correctly.

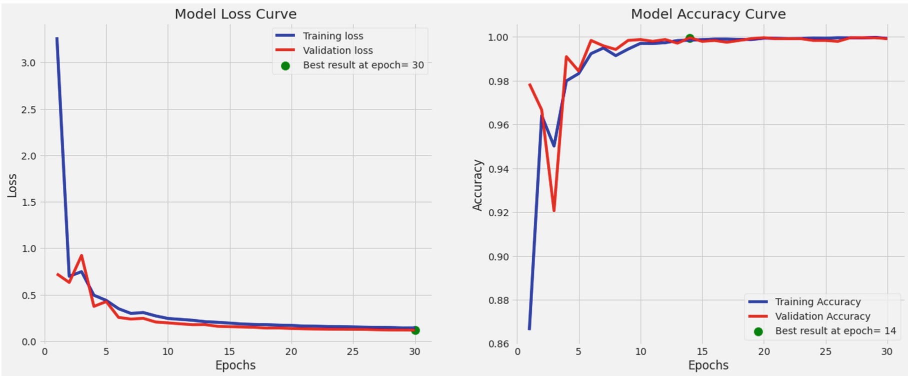

Fig. 4. Model loss and accuracy curve for EfficientNet B0 model

For object detection and classification tasks, many performance metrics are used. Some of them are precision, recall, F_1 score, and classification accuracy and calculated using Eqs. (2–5). Four important terminologies like true positive (TP), false positive (FP), true negative (TN), and false negative (FN) are used for the calculation of these performance metrics.

A true positive gives the number of correctly classified positive examples. True negative counts the total number of correctly classified negative samples. False positive refers to the total number of misclassified positive examples. False negative gives the total number of misclassified negative examples.

Precision gives the ratio of correctly classified positive examples to total positive examples. The recall is the measure of actual positives that have been correctly classified.

F_1 score is the function of precision and recall. It is the harmonic mean of precision and recall. A confusion matrix is a NxN matrix that summarises the all predicted results for a classification model where total number of classes is denoted by N. The confusion matrix for the presented model has been displayed in Fig. 5. Table 5 summarizes the recall, precision and F_1 score of the proposed model.

$$\text{Precision(i)} = \frac{\#TP(i)}{\#TP(i) + \#FP(i)} \tag{2}$$

$$\text{Recall(i)} = \frac{\#TP(i)}{\#TP(i) + \#FN(i)} \tag{3}$$

$$\text{F1 score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

$$\text{Classification accuracy} = \frac{\#TP(i) + TN(i)}{\#TP(i) + \#FP(i) + TN(i) + FN(i)} \tag{5}$$

where i is the number of classes.

From Table 5, it can be observed that EfficientNet B0 has a precision value of 0.99 for Pepper_BS, Tomato_MV, Tomato_SLS, and Tomato_TSSM. Similarly, a recall value of 0.99 is there for Pepper_H, Tomato_EB, Tomato_SLS, and Tomato_TS. As seen in Table 4, through comparative analysis with DenseNet121, DenseNet169, and DenseNet201, it is observed that EfficientNet B0 has better classification accuracy for these 15 disease types which proves the utility of the EfficientNet B0 model.

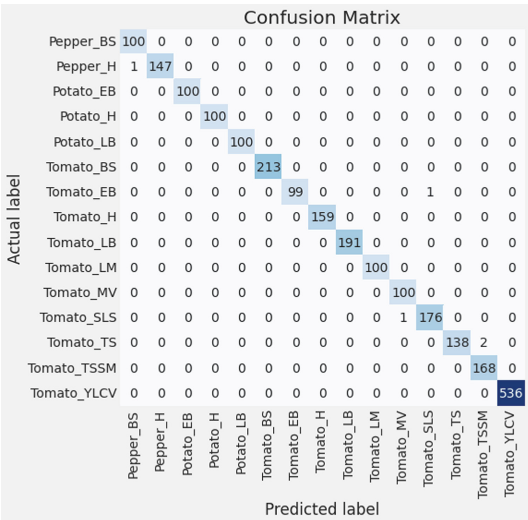

Fig. 5. Confusion matrix for EfficientNet B0 model

Performance comparison of the presented model has been done with different CNN based models and shown in Table 6. With more classes, the proposed model has better testing accuracy than these CNN based models.

Table 5. Precision, recall, and F_1 score of EfficientNet B0 for 15 disease types.

	Disease Type	EfficientNet B0		
		Precision	Recall	F_1 score
1	Pepper_BS	0.99	1.00	1.00
2	Pepper_H	1.00	0.99	1.00
3	Potato_EB	1.00	1.00	1.00
4	Potato_H	1.00	1.00	1.00
5	Potato_LB	1.00	1.00	1.00
6	Tomato_BS	1.00	1.00	1.00
7	Tomato_EB	1.00	0.99	0.99
8	Tomato_H	1.00	1.00	1.00
9	Tomato_LB	1.00	1.00	1.00
10	Tomato_LM	1.00	1.00	1.00
11	Tomato_MV	0.99	1.00	1.00
12	Tomato_SLS	0.99	0.99	0.99
13	Tomato_TS	1.00	0.99	0.99
14	Tomato_TSSM	0.99	1.00	0.99
15	Tomato_YLCV	1.00	1.00	1.00
Accuracy		1.00		
Macro Avg.		1.00	1.00	1.00
Weighted Avg.		1.00	1.00	1.00

Table 6. Performance comparison of proposed model with other CNN based models

Model	Dataset	Number of Classes	Avg. Testing Accuracy (%)
Custom Model [16]	Own Dataset	2	97.30
DenseNet121 [18]	PlantVillage	10	97.11
VGG with Xgboost [19]	PlantVillage & Corn Dataset	11	95.71
DenseNet121	PlantVillage	15	99.59
DenseNet169	PlantVillage	15	
DenseNet201	PlantVillage	15	
EfficientNet B0 (Proposed Model)	PlantVillage	15	99.79

5 Conclusions

The study incorporates the novel deep learning architecture for automated early diagnosis and an accurate image-based classification approach. The proposed work has been carried out for identification and classification of 12 diseases of pepper, potato, and tomato plants along with healthy images of these plants, and these images used have been taken from the PlantVillage dataset. The proposed EfficientNetB0 models were implemented using the transfer learning approach and achieved an accuracy of 99.79% without data augmentation. The authors believe that the proposed EfficientNet B0 model can be utilized as a tool for identifying plant diseases and assisting farmers in the field. In the future, presented research work can be extended to enhance the robustness of the model by incorporating more disease-infected images for various plants at different disease severity levels.

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