Plants and their Diseases Recognition: Multiclass and Multilabel Classification Benchmarks

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Abstract. We introduce a comparison of MobileNetV3Small, EfficientNetB0 and DenseNet121 models pre-trained on ImageNet and fine-tuned on Plant Village and PlantDoc datasets for plants and their diseases multiclass and multilabel classification. As a result of the experiments, it was found that the EfficientNetV2B0 model was the most effective for the plant diseases recognition task with accuracy 0.997 on Plant Village dataset and 0.96 on PlantDoc dataset.

Keywords: Multiclass Classification, Multilabel Classification, Plant Diseases Classification, Convolutional neural network, Computer Vision.

1 Introduction

Timely disease detection in plants remains a challenging task for farmers. The task requires a tremendous amount of labor, expertise within the plant diseases, and takes a considerable amount of time. The development of an automatic classification system for plants and their diseases at different stages of growth can play an important role both in increasing yields and in helping to care for houseplants.

Computer vision and image processing techniques are widely used to address this problem. However, recognizing plants and their diseases at the same time is a difficult task. If a plant has lesions, recognition by color, venation or form will be more difficult, as disease makes these features less pronounced. Moreover, a plant may be afflicted with multiple foliar diseases simultaneously, thereby making recognition even more difficult.

In this work, we evaluate the effectiveness of using computer vision models for solving plants and their diseases classification problems. More precisely, we consider the simultaneous classification of a plant and its disease as a multiclass classification task and evaluate the performance of three pre-trained models on two datasets.

Thus, the contribution of the present research is the development of several benchmarks for the comparison of deep learning models in the task of plant and its disease classification.

The outline of the paper is as follows: section 2 reviews related work on deep learning models and datasets for plant and disease classification. Section 3 describes the methods and materials used in this research Section 4 contains results of our work. The conclusion is presented in the final section of this paper.

2 Related Works

In this section we review existing research in the fields of plant classification and their diseases recognition.

Among the works on plant classification, Heredia [1] used ResNet50 for the classification of large plants based on the whole image and achieved an accuracy of 0.59 on top1 predicted species and 0.74 on top5 respectively. Lee et al. [2] proposed to use a deconvolutional network for visualization to provide insight into how the CNN algorithm perceives a sheet and which features are considered key. Results of research show that venation exceeds traditional solutions with an accuracy of 0.996. Shobana and Perumal [3] classified plants as fresh (live) and faded (dried) with a comparison of SVM and ANN classifiers. SVM outperformed ANN with an accuracy of 0.98 against 0.92. In [4] Giselsson et al. created Plant Seedlings Dataset [5] that consists of some of the most common normal variations of weed species in Danish agriculture at an early stage of growth. In total, 12 species of weeds and cereals common in Danish agriculture were recorded. On the created base authors tested the Naive Bayes algorithm that achieved an f1-score of 0.98-0.99. In [6] Quach et al. presented plant leaves classification using combined hand-crafted features and CNN-based features to improve the performance. Used features: color, shape, vein, Fourier description, texture, and xy-projection histogram. Features are then transformed into a better representation by neural network-based encoders. Then an SVM model classified leaves. The proposed architecture achieved an accuracy of 0.9969 ± 0.0035 on test sets under a random 10-fold cross-validation. All found plant classification approaches are shown in Table 1.

Table 1. Comparison of found plants classification methods.

Reference	Dataset	Features	Task	Model	Accuracy
[1]	observations from iNaturalist [7]	whole image	large plant classification	ResNet50	0.59
[2]	MalayaKew [2]	venation, shape of leaf	classification of plants	MLP	0.99
[3]	collected by author	shading	classification of plants on live and dried	SVM	0.98
[4]	Plant Seedlings Dataset [5]	shape of plant	classification of common weeds in danish agriculture	CNN	f1=0.98-0.99

[6]	Flavia leaf dataset [8]	form, color, leaf venation	plant classification	SVM	0.99

There are works on plant disease classification as well. Sagar and Dheeba [9] used five pre-trained architectures including VGG16, ResNet50, InceptionV3, Inception-ResNet and DenseNet169 with fine-tuning the last layers of the networks. On top of that, 4 custom convolutional and max pooling layers were added. Two dense layers with 64 neutrons and 2 neurons respectively at the last were used. The best results were achieved using ResNet50 with an accuracy of 0.982, precision of 0.94, recall of 0.94 and F1 score of 0.94. Upadhyay and Kumar [10] proposed a novel convolution neural network approach for rice plant diseases classification based on the size, shape and color of lesions in the leaf image and provided an accuracy of 0.997. In [11] Haruna et al. proposed a CNN-LSTM algorithm for the classification of foliar diseases of apple leaves using the "Plant Pathology 2020 – FGVC7" [12] dataset and achieved 0.98 accuracy. For better performance also different segmentation techniques are used. In [13] Kashyapand & Shrivastava used image segmentation with the Otsu automatic thresholding method. They used ResNet18 pre-trained on the ImageNet dataset, achieving an accuracy of 0.91 and 0.96 for brown spot and frog eye soybean diseases recognition respectively. All found disease recognition approaches are shown in Table 2.

Table 2. Comparison of found disease recognition methods

Reference	Dataset	Task	Classification method	Accuracy
[9]	Plant Village [14]	plant disease detection	ResNet50 pretrained on ImageNet	0.982
[9]	Rice-leaf [15]	plant diseases classification	background removal and classification with CNN	0.997
[11]	Plant Pathology 2020 – FGVC7 [12]	classification of foliar diseases of aples	CNN-LSTM algorithm	0.98
[13]	collected by authors from Google and Plant Village [14]	classification of soybean foliar diseases	Images segmentation with Otsu automatic thresholding method and classification with ResNet18	0.96 on frog eye disease

Finally, multilabel classification can improve the prediction of plant diseases by checking whether the plant species can have this disease. In [16] Ji et al. proposed BR-CNN based on binary relevance (BR) multi-label learning algorithm and deep convolutional neural network (CNN) for automatic recognition of crop species, classification of crop diseases and severity estimation of crop diseases on leaves with Keras TensorFlow. In [17] Yao et al. propose a new model named Generalised Stacking Multi-output

CNN (GSMo-CNN) for plant identification and disease classification on Plant Village [14], PlantDoc [20] and PlantLeaf [21] datasets. Originally, PlantDoc partitioned into a training set of 2, 360 samples and a small test set of 238 samples. This paper refers to this set as PlantDoc-1.0. Original dataset was mixed and split into 70%-10%-20% for training, validation, and testing respectively. This data is referred to as PlantDoc-0.2. In plant identification with the balance weights (BW), GSMo-CNNs achieves the best performance in three cases: Plant Leaves, PlantDoc-0.2, and PlantDoc-1.0. The accuracy and F1-score are as follows, Plant Village: 99.687% & 0.99688); Plant Leaves: 99.646% & 0.99647; PlantDoc-0.2: 49.068%, 0.47960; and PlantDoc-1.0: 46.864% & 0.44804. In diseases classification Plant Village (99.418% & 0.99417), Plant Leaves (97.292% & 0.97201), PlantDoc-0.2 (45.029%,0.41716) and PlantDoc-1.0 (47.542% & 0.46156). In both plant identification and disease classification GSMo-CNN with BW achieves 99.208% accuracy and 0.99245 F1-score on Plant Village; 97.524% accuracy and 0.97746 F1-score on Plant Leaves; 26.175% accuracy and 0.26760 F1-score on PlantDoc-0.2; and 24.153% accuracy and 0.23191 F1-score on PlantDoc-1.0. In [18] Lee et al. propose a new conditional multi-task learning (CMTL) approach which allows the distribution of host species and disease characteristics learned simultaneously with a conditional link between them. In [19] Kabir et al. used pre-trained CNN models with a limit of 100 epochs. All found plants and their diseases classification approaches are shown in Table 3.

Table 3. Comparison of found plant and their diseases recognition methods

Reference	Task	Classification method	Dataset	Accuracy
[16]	classification of crop diseases and severity estimation of crop diseases on leaves	BR-CNN based on DenseNet121	Plant Village [14]	0.9788
[17]	plant identification and disease classification	GSMo-CNN	Plant Village [14]	0.996
			PlantDoc modified [20]	0.5534
			PlantDoc original [20]	0.5127
			Plant Leaves [21]	0.9823
[18]	plant disease identification	CMTL	Plant Village [14]	0.9452
			Digipathos [22]	0.8638
			IPM [23]	0.6527
			Pl@ntNet [24]	0.6199
			INRAEdi [18]	0.1649

[19]	multi-plant diagnosis	Xception	6 publicly available plant disease datasets from Kaggle	F1-score = 0.9738

At the moment, there are no benchmarks for plants and their diseases recognition tasks.

3 Method

3.1 Datasets

First, we describe the datasets used for creating the benchmarks. We selected publicly available datasets with images of plants and their diseases, containing more than 100 images. The search was carried out on the paperwithcode, google and kaggle databases with the queries: plant diseases, plant diseases dataset, plant disease dataset. Table 4 presents the datasets that were found. Among them, PlantVillage [14] and PlantDoc [20] were selected as they contain the largest number of classes.

Table 4. Datasets

Reference	License	Number of images	Number of classes	Source
[12]	CC BY 4.0	3651	4	https://www.kaggle.com/competitions/plant-pathology-2020-fgvc7/data
[14]	CC0 1.0	54309	38	https://github.com/spMohanty/PlantVillage-Dataset
[20]	Creative common Attribution 4.0 International	2598	28	https://github.com/pratikkayal/PlantDoc-Dataset
[21]	CC BY 4.0	4503	22	https://data.mendeley.com/datasets/hb74ynkjcn/1
[25]	Creative common CC BY	30000 in Bccr-segset dataset; 19600 in can-rad dataset	4	https://academic.oup.com/gigascience/article/9/3/giaa017/5780256#200419497
[26]	Creative common BY SA	9372	9	https://vision.eng.au.dk/leaf-counting-dataset/

[27]	Creative common Attribution 4.0 International	3505	5	https://zenodo.org/records/5557313#.Yxg7yKPP23B

Plant-Village. The dataset contains 54,309 images. The images span 14 crop species and 17 fungal diseases, 4 bacterial diseases, 2 mold (oomycete) diseases, 2 viral diseases, and 1 disease caused by a mite of this species. 12 crop species also have images of healthy leaves that are not visibly affected by a disease. The dataset classes and the number of images in them demonstrated in Table 10 in Appendix. All images of leaves are made on a paper sheet with a gray or black background (see Fig. 1).

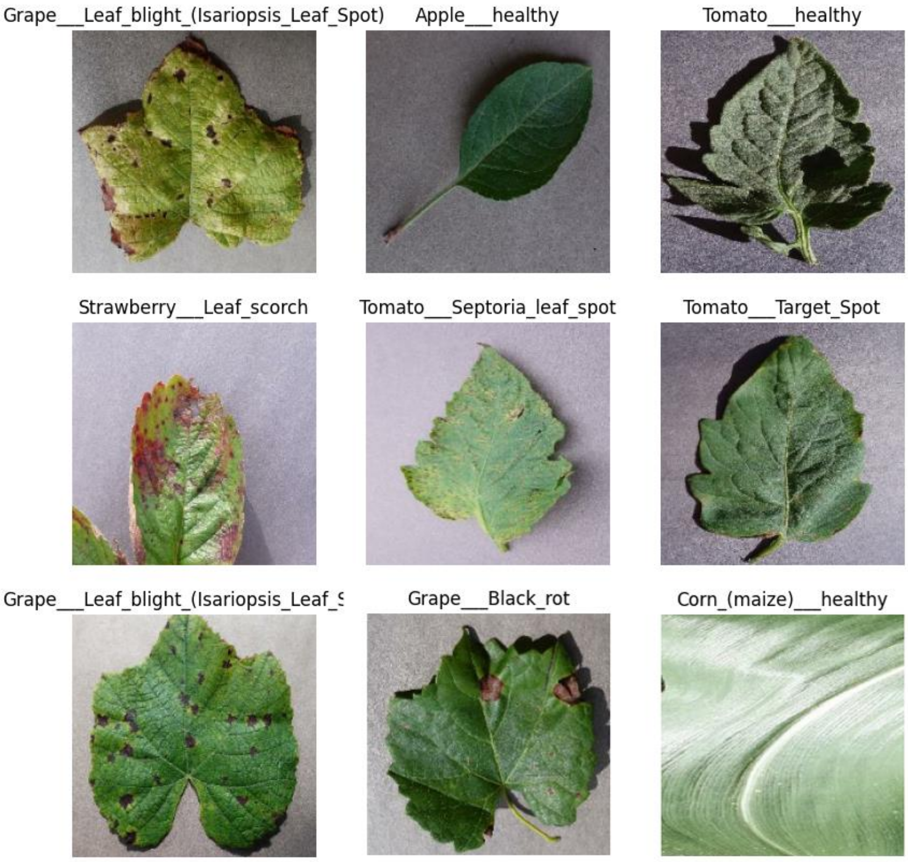

Fig. 1. Sample images in the Plant Village dataset.

PlantDoc. The dataset was created by Singh et al. [20]. It consists of 9216 RGB images of healthy and unhealthy plant leaves having 28 classes out of which we have selected 27 for evaluation of the models. These classes are shown in Table 11 in Appendix.

3.2 Data pre-processing

The images of both datasets were resized to 224x224 pixels. We used data augmentation such as 70° rotation to increase the number of images for all classes of the PlantDoc dataset to 200 (see Fig. 2).

Fig. 2. Sample of augmented images in the PlantDoc dataset.

1.1 Deep Learning Models

Since the recognition of plants and their diseases may be relevant in the field, i.e. without an access to the Internet and from mobile devices, the performance and resource consumption of the models were important to us. Thus, the MobileNetV3Small [28], EfficientNetB0 [29] and DenseNet121 [30], pre-trained on the ImageNet dataset, were selected based on their size, number of parameters and time taken for classification. For multiclass classification, the keras library was chosen, containing deep learning models with pre-trained weights. As a result, six different models were trained based on the selected models for the 2 datasets. The models are available in the Github repository[1].

In this approach plants and their diseases form one class that looks like name_of_the_plant_name_of_the_disease. For all models, softmax activation function and adam optimizer are used. The number of learning epochs is 5. For models trained on the Plant Village dataset, the batch size and learning rate are set to 8 and 0.01 respectively. For models trained on the PlantDoc dataset, the batch size and learning rate are 32 and 0.001.

For multilabel classification we used pytorch, here plant and disease are independent labels. BCEWithLogitsLoss is selected as an activation function for all models. For optimizer, AdamW is chosen. The number of learning epochs is 10. For all models the batch size and learning rate are set to 50 and 0.001. The multilabel classification models are also available in the GitHub repository.[2]

4 Results

All our multiclass classification experiments were performed in Google Colaboratory on GPU, which provides 15 GB of RAM. Additionally, we used psutil, the cross-platform library for system monitoring to collect information on memory consumption during the training of classification models. Table 5 shows the accuracy for each model on the Plant Village dataset, the time and memory consumption for model training. Table 6 shows the accuracy for each model on the PlantDoc dataset. Finally, table 7 shows the accuracy for each model on the extended PlantDoc.

Table 5. Models Accuracy on Plant Village dataset for multiclass.

Model	Memory consumption	Time (seconds)	Accuracy
MobileNetV3Small	5261246464	86.12	0.946
EfficientNetV2B0	3929538560	273.96	0.947
DenseNet121	4321898496	194.71	0.791

Table 6. Models Accuracy on PlantDoc dataset for multiclass.

Model	Memory consumption	Time (seconds)	Accuracy
MobileNetV3Small	2457079808	54.91	0.478
EfficientNetV2B0	2547220480	81.17	0.607

[1] https://github.com/shiyanna/PlantDoc-and-PlantVillage-recognition

[2] https://github.com/shiyanna/Plant-foliar-diseases-recognition

DenseNet121	3024367616	145.61	0.339

Table 7. Models Accuracy on Extended PlantDoc dataset for multiclass.

Model	Memory consumption	Time (seconds)	Accuracy
MobileNetV3Small	5378113536	116.43	0.700
EfficientNetV2B0	5227995136	220.18	0.844
DenseNet121	6079160320	280.32	0.587

For multilabel classification, all experiments were performed on NVIDIA GeForce GTX 1070 with 8192MiB of RAM. Table 8 shows the validation accuracy and weighted f1-score for our method for each model and for comparison method from related works on the PlantDoc dataset, the time and memory consumption during model training. Table 9 shows the validation accuracy and weighted f1-score for our method for each model and for comparison method from related works on the Plant Village dataset.

Table 8. Models Accuracy on PlantDoc Dataset for multilabel.

Approaches	Model	Memory consumption	Time (minutes)	Accuracy	F1-score
Our method	MobileNetV3Small	**348.2**	**8.2**	0.952	0.945
	EfficientNetV2B0	1191.2	10.7	**0.96**	**0.957**
	InceptionV3	2241.8	11.2	0.952	0.944
	ResNet50	1027.6	9.8	0.958	0.954
	DenseNet121	1054.9	9.5	0.956	0.95
GSMo-CNN [16]	InceptionV3	-	-	0.512	-

Table 9. Models Accuracy on Plant Village Dataset for multilabel.

Approaches	Model	Memory consumption	Time (minutes)	Accuracy	F1-score
Our method	MobileNetV3Small	**350.2**	**17.2**	0.995	0.995
	EfficientNetV2B0	1191.2	27.8	**0.997**	**0.997**
	InceptionV3	2065.7	66.6	0.99	0.991
	ResNet50	696.3	41.7	0.994	0.995
	DenseNet121	1189.1	42.7	0.996	0.996
BR-CNNs [15]	InceptionV3	-	-	0.976	-
	ResNet50	-	-	0.974	-

	DenseNet121	-	-	0.978	
GSMo-CNN [16]	InceptionV3	-	-	0.996	-

For evaluation and system metrics visualization and comparison we used MLflow and matplotlib, see fig. 3 and fig. 4.

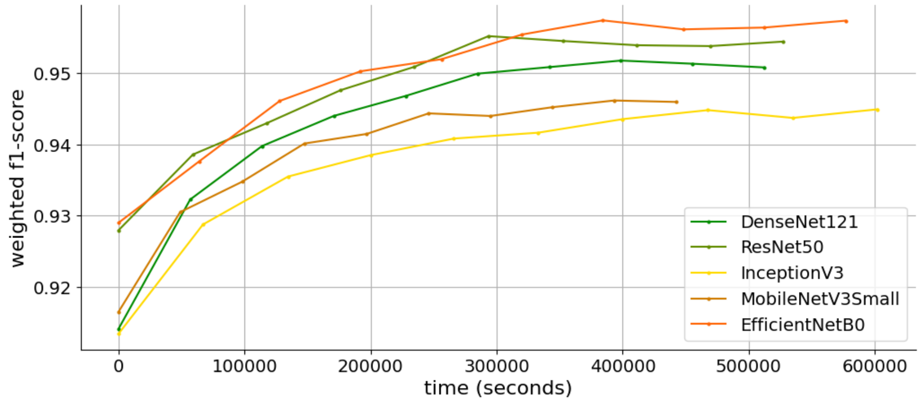

Fig. 3. PlantDoc F1-score comparison

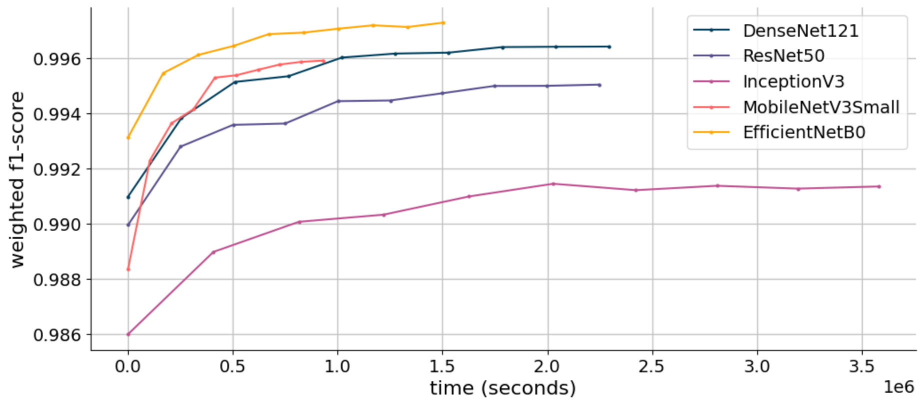

Fig. 4. Plant Village F1-score comparison

The comparison of the performance of our methods on the Plant Village and PlanDoc datasets shows that models trained on Plant Village exhibit higher metrics. The Plant Village dataset images were taken in the laboratory on a paper sheet with a gray or black background. Consequently, in real-world scenarios, the model trained on this dataset is expected to perform worse than the model trained on the PlantDoc dataset, which images were taken under natural conditions.

5 Conclusion

In this study models of image classification MobileNetV3Small, EfficientNetB0 and DenseNet121, pre-trained on the dataset ImageNet, were evaluated on Plant Village and PlantDoc datasets for multiclass and multilabel classification. As a result of the experiments, it was found that the EfficientNetV2B0 model, achieving f1-scores of 95.7% and 99.7% for the PlantDoc and Plant Village datasets, respectively, was the most accurate for the plant disease recognition tasks. In our future research, we intend to seek out datasets featuring instances of multiple diseases present on a single leaf to apply our benchmarks on it. Additionally, we will search for plants ontologies that encompass information about their diseases, with the goal of accuracy improvement by identifying the dependence between the type of disease and the kind of plant that may be affected by the disease.

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Appendix

Table 10. Plant Village dataset classes.

Plant	Disease	Number of images
Apple	Gymnosporangium juniperi-virginianae	276
	Venturia inaequalis	630
	Botryosphaeria obtusa	621
	Healthy	1645
Blueberry	Healthy	1502
Cherry	Podosphaera spp	1052
	Healthy	854
Corn	Cercospora zeae-maydis	513
	Puccinia sorghi	1192
	Exserohilum turcicum	985
	Healthy	1162
Grape	Guignardia bidwellii	1180
	Phaeoacremonium spp.	1384
	Pseudocercospora vitis	1076
	Healthy	423
Orange	Candidatus Liberibacter	5507
Peach	Xanthomonas campestris	2292
	Healthy	360
Bell Pepper	Xanthomonas campestris	997

	Healthy	1478
Potato	Alternaria solani	1000
	Phytophthora infestans	1000
	Healthy	116
Raspberry	Healthy	371
Soybean	Healthy	5090
Squash	Erysiphe cichoracearum / Sphaerotheca fuliginea	1835
Strawberry	Diplocarpon earlianum	1109
	Healthy	456
Tomato	Alternaria solani	1000
	Septoria lycopersici	1771
	Corynespora cassiicola	1404
	Fulvia fulva	952
	Xanthomonas vesicatoria	2127
	Phytophthora infestans	1910
	Tomato yellow leaf curl virus	5357
	Tomato mosaic virus	373
	Tetranychus urticae	1676
	Healthy	1592

Table 11. PlantDoc dataset classes

Plant	Disease	Number of images
Tomato	Leaf yellow virus	76
	Leaf late blight	111
	Early blight leaf	88
	Leaf bacterial spot	110
	Mold leaf	91
	Leaf mosaic virus	54
	Healthy	63
	Septoria leaf spot	151
Potato	Leaf early blight	117
	Leaf late blight	105
Squash	Powdery mildew leaf	130
Corn	Leaf blight	192
	Gray leaf spot	68
	Rust leaf	116
Strawberry	Healthy	96

Apple	Rust leaf	89
	Healthy	91
	Scab leaf	93
Soyabean	Healthy	65
Cherry	Healthy	57
Grape	Healthy	69
	Leaf black rot	64
Peach	Healthy	112
Bell pepper	Healthy	61
	Leaf spot	71
Blueberry	Healthy	117
Raspberry	Healthy	119

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