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Recognizing Plants and Their Diseases: Benchmarks for Multiclass and Multilabel Classification

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Abstract—The development of an automatic system for classifying plants and their diseases at different stages of growth could play an important role in both increasing crop yields and assisting in the care of indoor plants. However, existing studies on plant and disease recognition are not systematic enough and use different datasets, making it difficult to identify the best models. In this paper, we consider the problem of constructing benchmarks for the problem of simultaneous classification of plants and their diseases and evaluate the performance of three models, MobileNetV3Small, EfficientNetB0, and DenseNet121, pretrained on the ImageNet and further trained on the PlantVillage and PlantDoc datasets. As a result of the experiments, it was found that the EfficientNetV2B0 model was the most effective for the task of plant disease recognition with an accuracy of 0.997 on the PlantVillage dataset and 0.96 on the PlantDoc dataset.

Keywords: multiclass classification, multilabel classification, plant disease classification, convolutional neural networks, computer vision

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1. INTRODUCTION

Early detection of plant diseases is a challenge for farmers. It requires a huge amount of work and expertise in plant diseases. The development of an automatic system for classifying plants and their diseases at different stages of growth could play an important role in both increasing crop yields and assisting in the care of indoor plants.

Computer vision and image processing methods are widely used to solve this problem. However, simultaneously recognizing plants and their diseases is a difficult task. If a plant is affected, recognition by color, venation, or shape will be difficult because the disease makes these characteristics less pronounced. Moreover, a plant can be affected by several leaf diseases at the same time, which further complicates the task of recognition. The situation is made worse by the fact that existing studies on plant and disease recognition rarely use the same datasets, making it difficult to identify the best models.

In this paper, we compile benchmarks of the effectiveness of computer vision models for solving problems of plant and disease classification. More specifically, we consider the simultaneous classification of a plant and its disease as a multiclass and multilabel classification problem and evaluate the performance of three pretrained models on two datasets.

Thus, the contribution of this study is to develop several benchmarks to compare deep learning models in the task of plant and disease classification.

The structure of the paper is organized as follows: Section 2 provides an overview of the work on deep learning models and datasets for plant and disease classification. Section 3 describes the methods and materials used in this study. Section 4 presents the results of our work. The conclusion is presented in the last section of this paper.

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Table 1. Comparison of the found methods of plant classification

Reference	Features	Task	Model	Dataset	Accuracy
[6]	Whole image	Classification of large plants	ResNet50	Observations with iNaturalist	0.59
[16]	Venation, leaf shape	Classification of plants	MLP	MalayaKew	0.99
[4]	Plant shape	Classification of common weeds in Danish agriculture	CNN	Plant Seedlings	F1 = 0.98–0.99
[19]	Shape, color, venation	Classification of plants	SVM	Flavia leaf	0.99

2. SIMILAR WORKS

In this section, we review existing research in the field of plant classification and disease recognition.

Among the works on plant classification, Heredia [6] used ResNet50 to classify large plants from the whole image using observations from iNaturalist [10] and achieved an accuracy of 0.59 for the top-1 predicted species and 0.74 for the top-5, respectively. Lee et al. [16] proposed to use a deconvolutional network for visualization to understand how the CNN (convolutional neural network) algorithm perceives a leaf and which features are considered key, using the MalayaKew dataset they created. The results of the study showed that venation outperforms traditional solutions with an accuracy of 0.996. In [4], Giselsson et al. created the Plant Seedlings Dataset, which consists of some of the most common early-stage normal weed variations in Danish agriculture. A total of 12 species of weeds and cereals common in Danish agriculture were recorded. On the database created, the authors tested a naive Bayes classifier, which achieved an F1-score of 0.98–0.99. In [19], Quach et al. presented a plant leaf classification on the Flavia leaf dataset [27] using a combination of hand-crafted features and CNN-based features to improve the performance. The features used were color, shape, veins, Fourier description, texture, and histogram of projection onto axes x and y (xy-projection histogram). The features are then transformed into a more precise representation using neural-network-based encoders. Then the SVM (support vector machine) model classifies the leaves. The proposed architecture achieved an accuracy of 0.9969 ± 0.0035 on the test sets under random 10-fold cross-validation. All found approaches to plant classification are presented in Table 1.

There are also works on the classification of plant diseases. Sagar and Dhiba [21] used five pretrained architectures, including VGG16, ResNet50, InceptionV3, Inception-ResNet, and DenseNet169, with retraining of the last layers of the networks on the Plant Village dataset [9]. Additionally, four new convolution and pooling layers with max pooling function were added. The last layers were two linear layers with 64 and 2 neurons, respectively. The best results were achieved using ResNet50: accuracy of 0.982, precision of 0.94, recall of 0.94, and F1-score of 0.94. Upadhyay and Kumar [26] proposed an approach for classification of rice plant diseases using Rice-leaf dataset [20] based on convolutional neural networks and obtained an accuracy of 0.997. The size, shape and color of damage on the leaf image are used as features. In [5], Haruna et al. proposed a CNN-LSTM (convolutional neural networks and long short-term memory) algorithm to classify foliar diseases of apple leaves using the Plant Pathology 2020—FGVC7 dataset [25] and obtained an accuracy of 0.98. Various segmentation techniques were also used to improve performance. In [14], Kashyap and Shrivastava used Otsu's method to segment images collected from Google and Plant Village. They used ResNet18 pretrained on the ImageNet dataset and achieved an accuracy of 0.91 and 0.96 for recognizing soybean brown spot and frog's eye spot diseases, respectively. All found approaches to plant disease recognition are presented in Table 2.

Finally, multilabel classification can improve plant disease prediction by testing whether a given plant species is likely to have the disease. In [12], Ji et al. proposed BR-CNN (binary relevance and convolutional neural networks) on the basis of the binary relevance multilabel learning algorithm and deep convolutional neural network for automatic crop species recognition, crop disease classification, and crop disease severity assessment on leaves using Keras TensorFlow. In [28], Yao et al. propose a novel model called Generalized Stacking Multi-output CNN (GSMo-CNN) for plant identification and disease classification on the Plant Village [9], PlantDoc [22], and PlantLeaf [2] datasets. PlantDoc was initially split into a training set of 2360 samples and a small test set of 238 samples. In this paper, this set is called PlantDoc-1.0. The original dataset was shuffled and split into three samples, 70%/10%/20% for training, validation, and testing respectively. These data are referred to as PlantDoc-0.2. GSMo-CNN achieves the best performance when using balance weights (BW) and transfer learning (TF). The accuracy and F1-score are as follows: Plant Village: 99.6% and 0.99625; Plant Leaves: 98.231% and 0.98225; PlantDoc-0.2: 55.34% and 0.54967; and PlantDoc-0.2: 51.271% and 0.50652. In [17], Lee et al. propose a novel conditional multitask learning (CMTL) approach on the Plant Village [9], Digipathos [1], IPM [11], Pl@ntNet [18], and

Table 2. Comparison of the found methods of plant disease recognition

Reference	Task	Classification method	Dataset	Accuracy
[21]	Classification of plant diseases	ResNet50 pretrained on ImageNet	Plant Village	0.982
[26]	Classification of plant diseases	Background removal and classification with CNN	Rice-leaf	0.997
[5]	Classification of foliar diseases of apples	CNN-LSTM algorithm	Plant Pathology 2020—FGVC7	0.98
[14]	Classification of foliar diseases of soybean	Image segmentation with Otsu's method and classification with ResNet18	Collected by authors from Google and Plant Village	0.96 on frog eye spot

Table 3. Comparison of the found methods of classification of plants and their diseases

Reference	Task	Classification method	Dataset	Accuracy
[12]	Classification of agricultural crop diseases and assessment of severity of agricultural crop diseases on leaves	BR-CNN based on DenseNet121	Plant Village	0.9788
[28]	Plant identification and disease classification	GSMo-CNN + BW + TF	Plant Village	0.996
			PlantDoc 0.2	0.5534
			PlantDoc	0.5127
			Plant Leaves	0.9823
[17]	Plant disease identification	CMTL	Plant Village	0.9452
			Digipathos	0.8638
			IPM	0.6527
			Pl@ntNet	0.6199
			INRAEdi	0.1649
[13]	Diagnosis of several plant diseases	Xception	Six open source plant disease datasets from Kaggle	F1-score = 0.9738

INRAEdi [17] datasets, which enables simultaneous learning of host species distribution and disease characteristics with conditional association between them. In [13], Kabir et al. used pretrained CNN models with a limit of 100 epochs. All found approaches to the classification of plants and their diseases are presented in Table 3.

As can be seen, different datasets are currently used in different studies and there are no unified benchmarks for plant and disease recognition tasks.

3. METHODS

3.1. Datasets

We first describe the datasets used to create the benchmarks. We selected from publicly available sets of images of plants and their diseases, containing more than 100 images. The search was carried out in the PaperswithCode, Google, and Kaggle databases using the following queries: plant diseases, plant diseases dataset, plant disease dataset. The search yielded the following datasets: Plant Pathology 2020—FGVC7 [25], Plant Village [9], PlantDoc [22], PlantLeaf [2], Bccr-segset and can-rad [15], Leaf counting [24], and DiaMOS [3]. The description of the found datasets is presented in Table 4. Among them, PlantVillage [9] and PlantDoc [22] were chosen because they contain the largest number of classes.

Plant Village. The dataset contains 54309 images. The images cover 14 crop species and 17 fungal diseases, 4 bacterial, 2 mold (oomycete), and 2 viral diseases, and 1 disease caused by a mite of this species. For 12 types of agricultural crops, there are also images of healthy leaves not affected by the disease. The classes of datasets and the number of images in them are presented in Table 5.

All images of leaves are made on a sheet of paper with a gray or black background (see Fig. 1).

Table 4. Datasets

Reference	License	Number of images	Number of classes	Resource
[25]	CC BY 4.0	3651	4	https://www.kaggle.com/competitions/plant-pathology-2020-fgvc7/data
[9]	CC0 1.0	54309	38	https://github.com/spMohanty/PlantVillage-Dataset
[22]	Creative Commons Attribution 4.0 International	2598	28	https://github.com/pratikkayal/PlantDoc-Dataset
[2]	CC BY 4.0	4503	22	https://data.mendeley.com/datasets/hb74ynk-jcn/1
[15]	Creative Commons CC BY	30000 in Bccr-segset dataset; 19600 in can-rad dataset	4	https://academic.oup.com/gigascience/article/9/3/giaa017/5780256#200419497
[24]	Creative Commons BY SA	9372	9	https://vision.eng.au.dk/leaf-counting-dataset/
[3]	Creative Commons Attribution 4.0 International	3505	5	https://zenodo.org/records/5557313#.Yxg7yKPP23B

PlantDoc. This dataset was created by Singh et al. [22]. It consists of 9216 RGB images of healthy and unhealthy plant leaves and has 28 classes, of which we selected 27 for evaluation of models. The tomato two spotted spider mites leaf class was not used because it is not in the test set and only has two images in the

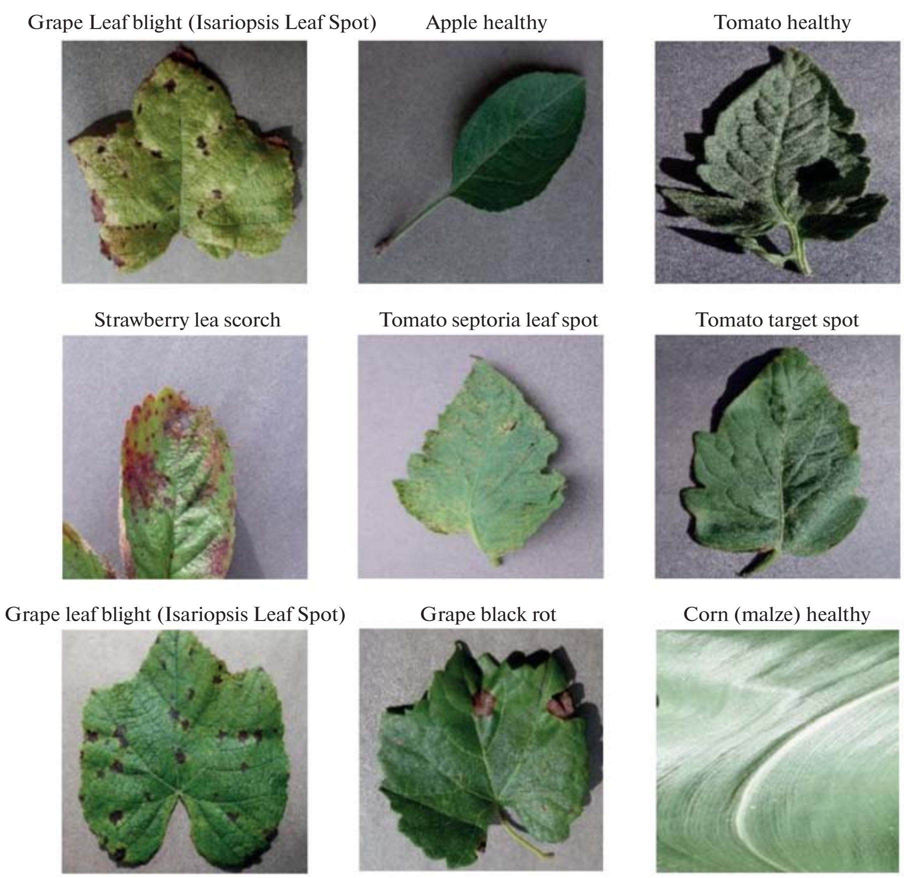

Fig. 1. Samples of images of the Plant Village dataset.

Table 5. Classes of the Plant Village dataset

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 6. Classes of the PlantDoc dataset

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

Table 7. Accuracy of models on the Plant Village dataset for multiclass classification

Model	Memory consumption, MB	Time, s	Accuracy
MobileNetV3Small	5017.5	86.12	0.946
EfficientNetV2B0	3747.5	273.96	0.947
DenseNet121	4121.7	194.71	0.791

Table 8. Accuracy of models on the PlantDoc dataset for multiclass classification

Model	Memory consumption, MB	Time, s	Accuracy
MobileNetV3Small	2343.2	54.91	0.478
EfficientNetV2B0	2429.2	81.17	0.607
DenseNet121	2884.2	145.61	0.339

training set. The selected classes are presented in Table 6.

3.2. Data Preprocessing

Images of both datasets were resized to 224 × 224 pixels. We used data augmentation, specifically a 70° rotation, to increase the number of images for all classes in the PlantDoc dataset to 200 (see Fig. 2).

3.3. Deep Learning Models

Since the recognition of plants and their diseases can be relevant in field conditions, that is, without access to the Internet and from mobile devices, the performance and resource intensity of the models were important to us. Thus, the MobileNetV3Small [7], EfficientNetB0 [23], and DenseNet121 [8] models pretrained on the ImageNet dataset were chosen on the basis of their size, number of parameters, and classification time. For multiclass classification, the Keras library was chosen, which contains deep learning models with pretrained weights. As a result, six different models were trained on the two datasets. The models are available in the GitHub repository.[1]

In our approach, plants and their diseases form one class, which appears as plant_name_disease_name. All models use the softmax activation function and the adam optimizer. The number of training 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, where plant and disease are independent labels. BCEWithLogitsLoss is selected as the activation function for all models. AdamW was chosen as the optimizer. The number of training epochs is 10. For all models, the batch size and learning rate are set to 50 and 0.001. Multilabel classification models are also available in the GitHub repository.[2]

4. RESULTS

All multiclass classification experiments were performed in Google Colaboratory on a GPU that provides 15 GB of RAM. Additionally, we used psutil, a cross-platform system monitoring library, to collect memory consumption information during training of classification models. Table 7 shows the accuracy of each model on the Plant Village dataset and the time and memory consumption for training the model. Table 8 shows the accuracy for each model on the

[1] https://github.com/shiyanna/PlantDoc-and-PlantVillage-recognition
[2] https://github.com/shiyanna/Plant-foliar-diseases-recognition

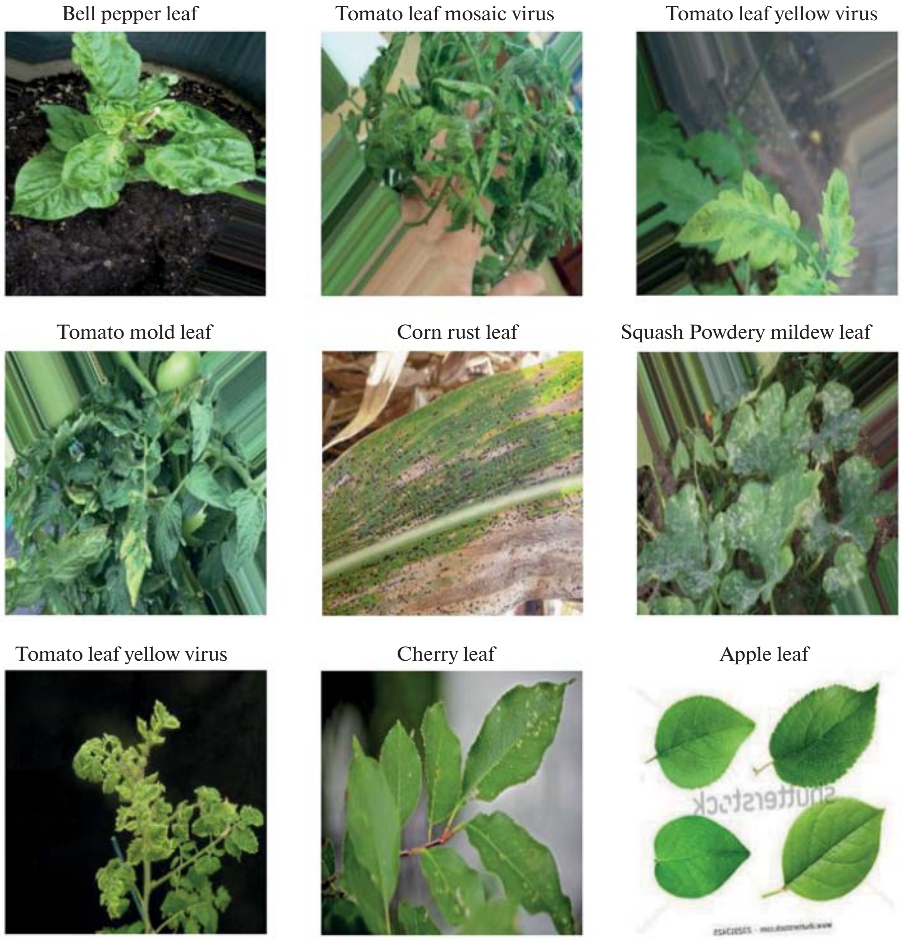

Fig. 2. Example of generated images in the PlantDoc dataset.

PlantDoc dataset. Finally, Table 9 shows the accuracy for each model on the extended PlantDoc dataset.

For multilabel classification, all experiments were performed on NVIDIA GeForce GTX 1070 with 8 GB of RAM. Table 10 shows the validation accuracy, weighted F1-score, training time, and memory consumption for each of the models we used and, for comparison, the method from [28], which also uses PlantDoc. Table 11 shows the validation accuracy and weighted F1-score on the Plant Village dataset for each model from our method and for the comparison of models from [12, 28].

Table 9. Accuracy of models on the extended PlantDoc dataset for multiclass classification

Model	Memory consumption, MB	Time, s	Accuracy
MobileNetV3Small	5128.9	116.43	0.700
EfficientNetV2B0	4985.8	220.18	0.844
DenseNet121	5797.5	280.32	0.587

To evaluate and visualize system metrics and compare them, we used MLflow and matplotlib; see Figs. 3 and 4.

Comparing the performance of our methods on the Plant Village and PlanDoc datasets shows that models trained on Plant Village perform better. However, the images of the Plant Village dataset were taken in the lab on a paper sheet with a gray or black background, so in real-world scenarios, a model trained on this dataset should perform worse than a model trained on the PlantDoc dataset, whose images were taken in the wild.

5. CONCLUSIONS

In this study, we evaluated the performance of image classification models in two tasks, multiclass and multilabel classification, on two datasets, Plant Village and PlantDoc, thereby obtaining four benchmarks. We used three models, MobileNetV3Small, EfficientNetB0, and DenseNet121, pretrained on the

Table 10. Accuracy of models on the PlantDoc dataset for multilabel classification

Approach	Model	Memory consumption, MB	Time, min	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 [28]	InceptionV3	–	–	0.512	–

Table 11. Accuracy of models on the Plant Village Dataset for multilabel classification

Approach	Model	Memory consumption, MB	Time, min	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 [12]	InceptionV3	–	–	0.976	–
	ResNet50	–	–	0.974	–
	DenseNet121	–	–	0.978	
GSMo-CNN [28]	InceptionV3	–	–	0.996	–

ImageNet dataset and compared them with existing solutions using the same datasets. As a result of experiments, it was found that the EfficientNetV2B0 model, which achieved an F1-score of 95.7 and 99.7% on PlantDoc and Plant Village, respectively, is the most accurate for plant disease recognition tasks. In our future research, we intend to consider datasets that reflect more complex tasks, such as recognizing multiple diseases present on a single leaf. In addition, we plan to introduce plant ontologies containing information about plant diseases into the recognition process in order to improve accuracy by taking into account the

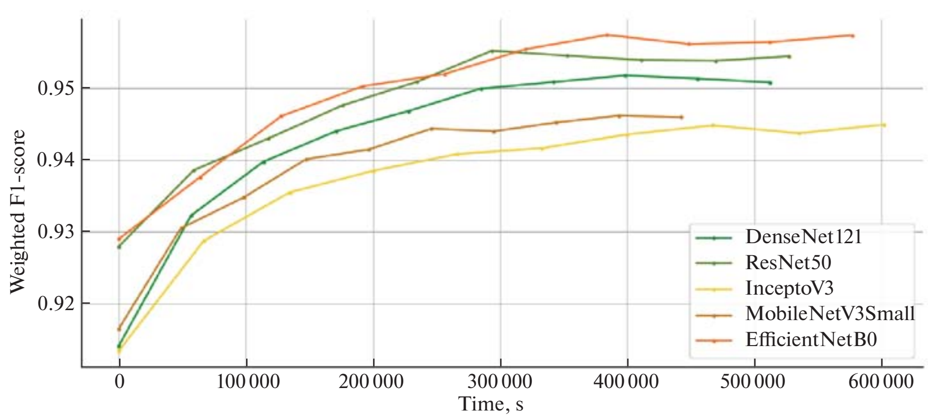

Fig. 3. Comparison of PlantDoc F1-score.

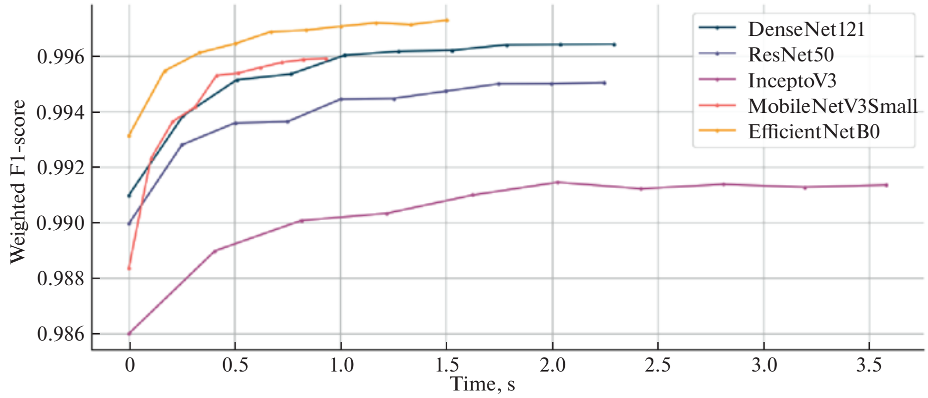

Fig. 4. Comparison of Plant Village F1-score.

relationship between the type of disease and the type of plant that may be affected by this disease.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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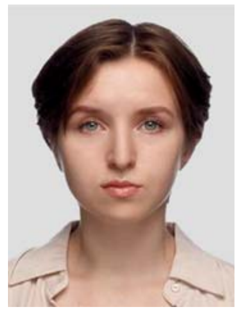

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