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ORIGINAL PAPER

PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection

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Abstract
Plant diseases and pests cause significant losses in agriculture, with economic, ecological and social implications. Therefore, early detection of plant diseases and pests via automated methods are very important. Recent machine learning-based studies have become popular in the solution of agricultural problems such as plant diseases. In this work, we present two classification models based on deep feature extraction from pre-trained convolutional neural networks. In the proposed models, we fine-tune and combine six state-of-the-art convolutional neural networks and evaluate them on the given problem both individually and as an ensemble. Finally, the performances of different combinations based on the proposed models are calculated using a support vector machine (SVM) classifier. In order to verify the validity of the proposed model, we collected Turkey-PlantDataset, consisting of unconstrained photographs of 15 kinds of disease and pest images observed in Turkey. According to the obtained performance results, the accuracy scores are calculated as 97.56% using the majority voting ensemble model and 96.83% using the early fusion ensemble model. The results demonstrate that the proposed models reach or exceed state-of-the-art results for this problem.

Keywords Plant disease and pest system · Deep features · Support vector machine · CNN · Fusion ensemble

1 Introduction

A large number of diseases occur in plants, depending on adverse environmental and seasonal conditions. Plant diseases cause significant economic, social and ecological losses, and therefore represent a clear need for precautionary measures to be taken in the early detection of plant diseases [1–7]. Today, plant disease detection is mostly conducted by experts manually, which is a both time-consuming and costly process.

Computer vision and deep learning technologies have shown great advances on various object recognition and classification problems in the last 8–10 years. In this context, plant disease detection can be automated, making the entire process easier, less error prone, and with reduced time wastage thanks to advanced image processing techniques [8–13].

Many studies have been conducted for plant disease and pest detection, based on machine learning. In most of the older studies, shape, color and texture feature extraction methods and traditional machine learning classifier methods are used. In more recent studies, CNN-based models have achieved significant successes. While the general aim of systems is the automatic detection of plant diseases and pests in real life, most previous studies used images of diseases obtained within a synthetic or laboratory setting [14–19]. The background of such images therefore consists of a simple, solid-colored background, while the foreground contains only one object. In this context, the methods used in most previous studies are not suited to real-life application systems that use images consisting of different backgrounds obtained from natural environments. On the other hand, the more recent studies of Ramcharan et al. [20], Ferentinos [11], Lu et al. [21] and Picon et al. [22] used images of diseases obtained from natural environments. Detailed information on previous plant disease and pest detection studies is provided in Sect. 2.

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In this paper, we present three ensemble models based on deep learning: (1) simple ensemble averaging; (2) early fusion convolutional neural network ensembles based on SVM classifier; and (3) majority voting convolutional neural networks based on SVM classifier. These approaches are:

(1) Simple ensemble averaging (PlantDiseaseNet-SEA), where we combined the outputs of fine-tuned networks using simple averaging (Sect. 5.1).
(2) Ensemble features applied using the early fusion approach (PlantDiseaseNet-EF). In this case, we concatenated deep features obtained from several deep networks and trained an SVM classifier on these features (Sect. 5.2).
(3) Ensemble class labels applied using the majority voting approach (PlantDiseaseNet-MV). In this case, we concatenated deep features obtained from several deep networks and trained an SVM classifier on these features. Finally, the majority voting was applied for all class labels, with the most predicted class label determined as the overall decision of the system (Sect. 5.3).

The proposed models are trained and evaluated with the pest and plant disease dataset collected in Turkey (Sect. 3.2). The PlantDiseaseNet-MV model was found to be more successful when compared with the state-of-the-art networks and other proposed models.

The contributions of this work are as follows:

- A dataset consisting of 15 classes and 4,447 unconstrained disease and pest images is collected, corresponding to plant diseases and pests most commonly seen in Turkey. The dataset is made publicly available to enable benchmarking research in this area.
- We evaluated 3 common machine learning approaches (ensemble averaging, early fusion and majority voting) for the plant disease and pest detection. The two proposed CNN-SVM combinations (PlantDiseaseNet-EF and PlantDiseaseNet-MV) proved to be more successful compared to the simple averaging of pre-trained networks and achieved results comparable to those in the literature.

2 Related works

In the literature, there are two general approaches: traditional machine learning approaches based on segmentation, handcrafted features and deep learning approaches.

The traditional approaches and corresponding datasets and performance results are summarized in Table 1. These studies generally consist of three basic steps:

- Segmentation of disease and pest images using methods such as color conversion, thresholding and mathematical morphology;
- Representative feature extraction from obtained segmented images using shape-, texture- and color-based feature extraction methods;
- Plant disease and pest detection using traditional machine learning methods.

Typically, these older systems have used small datasets and aimed at distinguishing only a few species apart.

Table 1 Plant disease and pest studies based on traditional methods

Researchers	Feature extraction methods	Classification methods	Disease/pest kind	Accuracy score
Kurniawati et al. [23]	Color and shape features	–	Paddy	94.70%
Pujari et al. [17]	GLCM method and color features	SVM	Fungal disease	83.83%
Dandawate and Kokare [24]	Scale- invariant feature transform (SIFT)	SVM	Soybean	93.79%
Yun et al. [25]	Color, texture and shape features	Probabilistic neural network (PNN)	Cucumber	91.08%
Ramakrishnan [26]	Color and texture features	BPNN	Groundnut	97.41%
Dubey and Jalal [15]	LBP method and Zernike moments	SVM	Apple	95.94%
Padol and Yadav [16]	GLCM method and color features	SVM	Grape	88.89%
Sabrol and Satish [27]	Color, texture and shape features	Classification tree	Tomato	97.30%
Athanikar and Badar [14]	GLCM method and color features	PNN	Potato	92.00%
Waghmare et al. [19]	LBP method	SVM	Grape	96.60%
Prasad et al. [18]	Gabor wavelet transform and GLCM methods	KNN	–	93%
Singh and Misra [9]	GLCM method	SVM	Five leaf disease	95.70%
Kaur et al. [28]	Color and texture features	SVM	Soybean	90.00%
Hossain et al. [29]	Texture features	SVM	Tea	93.33%

Researchers typically use their private datasets, consisting of various plant types such as apple, tomato, tea and corn. Reported accuracies range from 84% to more than 97%.

Recently, many deep learning-based studies have been conducted for the detection of plant-based diseases. Table 2 provides general information related to these systems, along with the used datasets and obtained results. In most of these studies, fine-tuning and feature extraction approaches based on pre-trained deep networks have been used. The largest dataset is that of Arsenovic et al. [30] with 42 disease/pest kind and almost 80,000 images. The reported accuracy for this system is almost 94%.

The systems in the literature often cannot be compared directly, as they use different datasets and more importantly, some classify only 2 plant species, while others classify about 40 species.

3 Background

In this section, we describe the dataset and the deep learning approaches used in the proposed systems.

3.1 Deep networks

In the last years, convolutional neural networks have achieved very successful results in the field of object recognition. In the current study, CNN-based pre-trained networks are used based on the deep feature extraction approach. The characteristics of these networks are presented in Table 3.

The pre-trained deep networks detailed in Table 3 each have unique architectures. While the AlexNet model is based on sequential convolution layers and three fully connected layers, the GoogleNet model was developed using the Inception module based on different sized filtering operations. The ResNet18, ResNet50 and ResNet101 networks includes skip connections that feed residual values to the next layer. The

Table 2 Plant disease and pest studies based on deep learning

Researchers	Feature extraction and classification methods	Disease/pest kind	Accuracy score
Mohanty et al. [31]	AlexNet, GoogleNet (fine-tuning)	Leaf disease	99.35%
Fujita et al. [32]	Modified VGGNet	Cucumber	82.30%
Sladojevic et al. [33]	CaffeNet (fine-tuning)	Leaf disease	96.30%
Liu et al. [34]	Modified AlexNet	Apple	97.92%
Amara et al. [35]	LeNet (fine-tuning)	Banana	99.72%
Ramcharan et al. [20]	Inceptionv3 + SVM	Cassava	93.00%
Wang et al. [36]	VGG16, VGG19, Inceptionv3, ResNet50 (fine-tuning)	Apple	90.40%
Brahimi et al. [37]	AlexNet, GoogleNet (fine-tuning)	Tomato	99.18%
Lu et al. [21]	7-layer CNN architecture	Rice	95.48%
Ferentinos [11]	AlexNet, VGGNet, AlexNetOWTBn, Overfeat, GoogleNet (fine-tuning)	Leaf disease	99.53%
Sapkal and Kulkarni [38]	AlexNet/GLCM + BPNN	Leaf disease	93.85%
Wallelign et al. [39]	13-layer CNN architecture	Soybean	99.32%
Barbedo [40]	GoogleNet (fine-tuning)	Corn	76%
Picon et al. [22]	Modified ResNet50	Wheat	98%
Altuntaş et al. [41]	AlexNet, VGGNet, GoogleNet and ResNet (fine-tuning)	Corn	94.22%
Özgüven and Adem [42]	Faster R-CNN model	Sugar beet	95.48%
Geetharamani and Pandian [12]	9-layer CNN architecture	Leaf disease	96.46%
Too et al. [4]	VGG16, Inceptionv4, ResNet50, ResNet101, ResNet152 and DenseNet121 (fine-tuning)	Leaf disease	99.75%
Hu et al. [43]	VGG16 (fine-tuning)	Tea	90%
Zhang et al. [44]	15-layer CNN architecture	Tomato	91.50%
Arsenovic et al. [30]	AlexNet, VGG19, Inceptionv3, DenseNet201 and ResNet152 (fine-tuning)	Leaf disease	93.67%
Wang et al. [45]	CNN model based on Inception module and dilated convolution	14 different crops	99.37%
Chen et al. [46]	Enhanced VGGNet-based Inception module	Maize	91.83%
Zhong and Zhao [47]	DenseNet-121 (fine-tuning)	Apple	92.29%
Li et al. [48]	GoogLeNet (fine-tuning)	Crop pest	98%
Jiang et al. [49]	7-layer CNN architecture and SVM classifier	Rice	96.8%

Table 3 Characteristics of deep networks used in this work

Models	Depth	Size (MB)	Parameters (Millions)	Image input size
AlexNet [50]	8	227	61	227 × 227
GoogleNet [51]	22	27	7	224 × 224
ResNet18 [52]	18	44	11.7	224 × 224
ResNet50 [52]	50	96	25.6	224 × 224
ResNet101 [52]	101	167	44.6	224 × 224
DenseNet201 [53]	201	77	20.0	224 × 224

DenseNet and ResNet models are similar networks; however, while the ResNet architecture receives information from the previous module (layer), each layer in the DenseNet architecture receives information from all the previous layers. This difference in the DenseNet architecture intensively connects each subsequent layer in a feedforward manner [54–58]. In the current study, transfer learning is performed to adapt pre-trained networks to the problem of plant disease and pest classification.

In addition to end-to-end training deep networks, the pre-trained CNNs can also be used as feature extractors, due to their powerful representation ability. In this work, we evaluated the use of extracted deep features using the fully connected layers of the fine-tuned CNNs; fc6 layer for AlexNet model, loss3-classifier layer for GoogleNet model; and fc1000 layer of the ResNet18, ResNet50, ResNet101 and DenseNet201 models. Indeed, we show that this latter approach results in higher accuracies, due to the higher performance of the SVM classifier instead of the output layer.

3.2 Turkey plant diseases and pests dataset

In the scope of the proposed study, we constructed a dataset to include common images of plant diseases and pests to be found in Turkey. The Turkey-PlantDataset called as Turkey Plant Diseases and Pests Dataset (https://github.com/mturkoglu23/PlantDiseaseNet) was obtained from academics working in the field of plant protection at the Agricultural Faculty of Bingol and Inonu Universities in Turkey. This dataset consists of a total of 4,447 images in 15 classes. The images in the dataset were obtained from experimental field studies of the Faculty of Agriculture at Inonu and Bingol Universities. The three-channel (RGB) color images were obtained using a Nikon 7200d camera, with an image resolution of 4000 × 6000 pixels. In addition, the dataset contains unconstrained images including different scenarios such as soil, trees, leaves and sky. Figure 1 provides sample images for each diseased plant or pest specie.

4 Proposed system

In this paper, we apply transfer learning to six state-of-the-art networks for the plant disease and pest classification problem. After evaluating the classifiers individually, using the separate test data, we compare three ensemble methods: simple averaging (4.1), early fusion (4.2) and majority

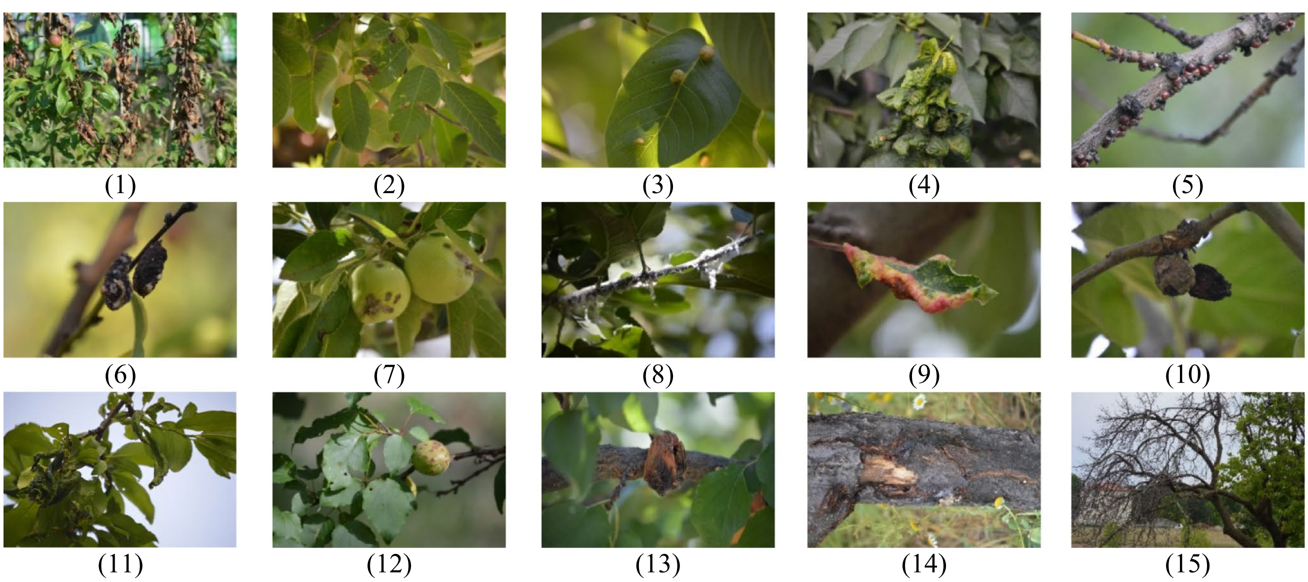

Fig. 1 Sample plant disease and pest images from the Turkey-Plant-Dataset dataset collected in this work. (Legend: 1) Erwinia amylovora, 2) Gnomonia leptostyla, 3) Eriophyes erineus, 4) Aphis spp., 5) Parthenolecanium corni, 6) Monillia laxa, 7) Venturia inaequalis, 8) Eriosoma lanigerum, 9) Aphis spp., 10) Monillia laxa, 11) Aphis spp., 12) Coryneum beijerinckii, 13) Monillia laxa, 14) cancer symptom, 15) drying symptom

voting (4.3). The SVM classifier is selected as an alternative to a shallow network block for accomplishing the fusion in the case of the PlantDiseaseNet-EF model and the last layers of the deep networks in the case of the PlantDiseaseNet-MV model.

4.1 PlantDiseaseNet-SEA

In this approach, we tried an approach for *sample ensemble averaging* with late fusion. Firstly, we applied transfer learning to AlexNet, GoogleNet, ResNet18, ResNet50, ResNet101 and DenseNet201 architectures. In this case, we have added a fully connected layer, a softmax layer and a classification layer, instead of the last 3 layers of these deep architectures. Following the fine-tuning process, the performance of each deep architecture was evaluated using the test data. Finally, we took the ensemble average of the fine-tuned networks.

4.2 PlantDiseaseNet-EF

In this approach, we concatenated using the *early fusion* approach for deep features obtained from fully connected layers of several deep networks and trained an SVM classifier on these features. A general flowchart of this model is illustrated in Fig. 2.

As shown in Fig. 2, deep features obtained from multiple pre-trained deep networks are combined and then trained using the SVM classifier. In this approach, we used different combinations of the AlexNet, GoogleNet, ResNet18, ResNet50, ResNet10 and DenseNet201 networks to determine the class label using the proposed PlantDiseaseNet-EF model.

4.3 PlantDiseaseNet-MV

In this approach, we first extracted deep features from the fully connected layer of pre-trained deep architectures described in Sect. 3.1. We then replaced the last 3 layer with an SVM of pre-trained deep architectures, as done in [7, 20, 41]. The deep features obtained from each architecture were used in training the SVM classifiers. Finally, the majority voting method was applied for all class labels, with the most predicted class label determined as the overall decision of the system. The general flow diagram of the proposed PlantDiseaseNet-MV model is presented in Fig. 3.

Six networks that were pre-trained, namely AlexNet, GoogleNet, ResNet18, ResNet50, ResNet10 and DenseNet201, were used in this ensemble.

5 Experimental studies

In this paper, we present an ensemble models of SVM classifiers based on deep features and an ensemble averaging model of CNN. We evaluate three different approaches for fusing pre-trained deep networks: late fusion, early fusion and majority voting. These deep networks are: AlexNet, GoogleNet, ResNet18, ResNet50, ResNet10 and DenseNet201.

In our experimental studies, a Turkey-PlantDataset was used that we constructed containing plant disease and pest images obtained from the natural environment to test the performance of the proposed models. Class information about this dataset and the number of images for training and test used in experimental studies are given in Table 4. MATLAB software was used for these studies, together with a computer which

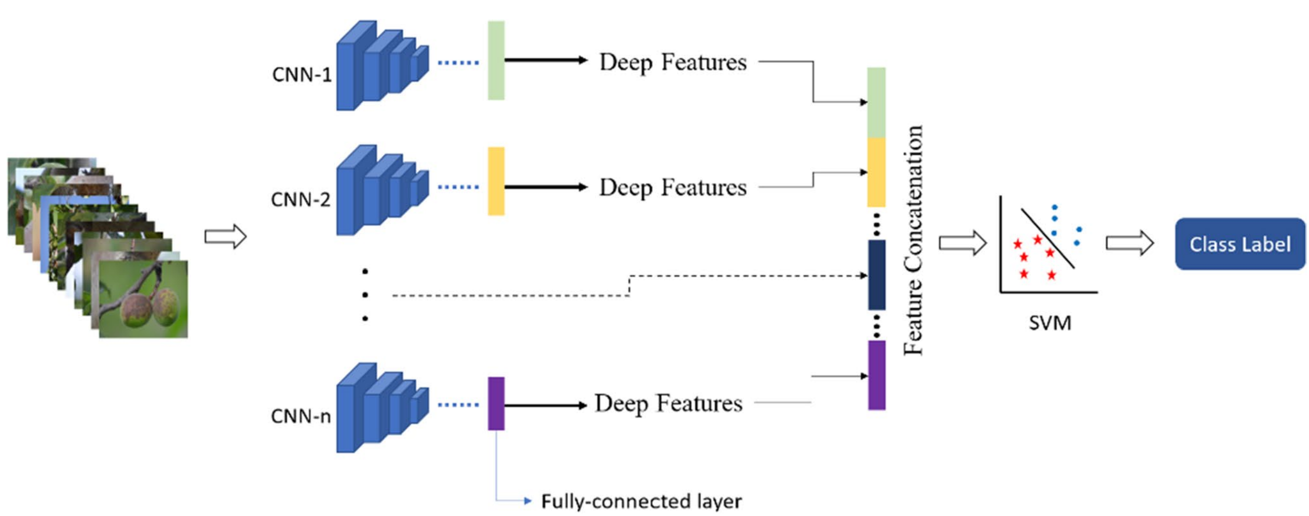

Fig. 2 General flowchart of PlantDiseaseNet-EF model

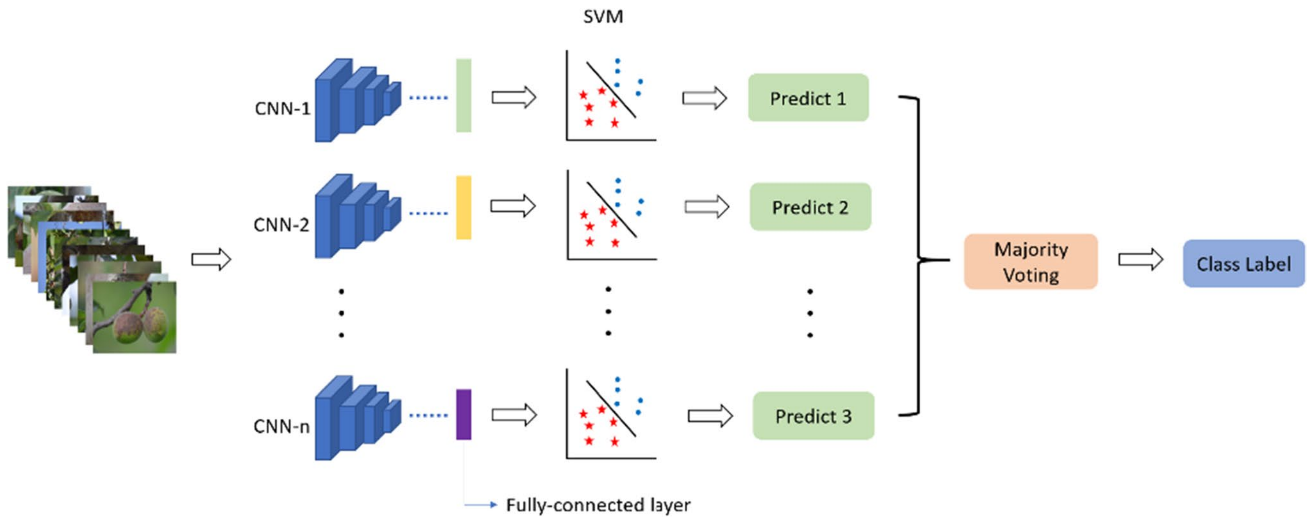

Fig. 3 General flowchart of PlantDiseaseNet-MV model

Table 4 Turkey-PlantDataset

Plant type	Disease or pest type	Train	Test	Total image count
Pear	Erwinia amylovora	194	21	215
Walnut	Gnomonia leptostyla	162	18	180
Walnut	Eriophyes erineus	62	7	69
Cherry	Aphis spp.	320	36	356
Peach	Parthenolecanium corni	384	43	427
Peach	Monillia laxa	283	31	314
Apple	Venturia inaequalis	570	63	633
Apple	Eriosoma lanigerum	329	37	366
Apple	Aphis spp.	146	16	162
Apple	Monillia laxa	230	25	255
Plum	Aphis spp.	63	7	70
Apricot	Coryneum beijerinckii	1000	110	1100
Apricot	Monillia laxa	76	9	85
Fruit trees	Cancer symptom	68	8	76
Fruit trees	Drying symptom	125	14	139
Total		4002	445	4447

has an 2xCore Intel Xeon E5 with 64 GB memory, NVIDIA Quadro P4000 and 8 GB memory.

In the following subsections, we detail the experimental results and performance comparisons.

5.1 Performance results of deep networks

In the current study, we fine-tuned for pre-trained CNN models based on the transfer learning approach. The fine-tuning process is based upon transferring new layers (a fully connected layer, a softmax layer and a classification output layer) instead of the last three layers of the pre-trained networks to our classification task. To observe the effects of transfer learning on system performance, we evaluated the accuracy scores of fine-tuning for the AlexNet, GoogleNet, DenseNet201, ResNet18, ResNet50 and ResNet101 models. In this specific task, by trial and error, the mini-batch size was chosen as 20, the maximum epoch number was set to 10, the weight decay factor was adjusted to 0.0001, and the initial learning rate was searched between 0.001 and 0.01. In addition, the optimization method used for the deep networks was used the SGDM (stochastic gradient descent with momentum) learning. The training procedure ended after 2000 iterations. Accuracy scores obtained for this experimental study are given in Table 5.

As given in Table 5, the highest accuracy between deep networks based on transfer learning was achieved using the DenseNet201 architecture with 93.47%, while the lowest performance was achieved using the AlexNet architecture with 86.94%. We thus observe that increased network complexities result in higher accuracies. In addition to the performances of the fine-tuned models, we then replaced the final layer with an SVM. Thus, deep features obtained from pre-trained CNN networks were fed into an SVM, with results presented in Table 6. The parameters of SVM classifier used in this study

Table 5 Accuracy scores of fine-tuned deep networks (%)

AlexNet	GoogleNet	ResNet18	ResNet50	ResNet101	DenseNet201
86.94	87.61	91.44	93.02	93.24	93.47

were determined as tenfold cross-validation method, cubic and quadratic kernel functions and one-vs.-all approach.

As given in Table 6, the highest accuracy for plant disease and pest detection was achieved using the DenseNet201 architecture with 94.85%. More importantly, we observe that all the results in Table 6 are higher than those in Table 5, showing that using an SVM at the last layer is beneficial. Hence, in the remainder of the work, we use SVM with pre-trained deep features.

5.2 Performance results of PlantDiseaseNet-SEA model

As a baseline, we combined the aforementioned pre-trained models using simple averaging where the scores obtained from deep networks for each class are averaged [59]. The accuracy score based on score-based fusion method of the combined deep networks (ResNet18, ResNet50, ResNet101 and DenseNet201) with the highest performance was calculated and obtained a weighted average accuracy of 93.6% based on the class distribution, as shown in the last column of Table 7.

5.3 Performance results of PlantDiseaseNet-EF model

The proposed early fusion CNN-SVM model was based on the early fusion combination of the features obtained from deep networks (see Fig. 2). We have used different combinations of the six different deep networks and obtained the results presented in the second column of Table 8. In addition, the accuracy scores given in Table 8 were dedicated according to the calculated average accuracy score across the folds and their standard deviation.

According to the performance results shown in Table 8, the highest accuracy score achieved for the proposed PlantDiseaseNet-EF model was 96.83% using the combination of AlexNet, GoogleNet, DenseNet201, ResNet50 and ResNet101 networks. Hence, we see that the best results are obtained with almost all the networks; we presume that ResNet18 is not useful in the presence of ResNet50 and ResNet101.

5.4 Performance results of PlantDiseaseNet-MV model

The results obtained with PlantDiseaseNet-MV model (see Fig. 3) which is based on the majority voting of predicted labels obtained from the SVM with deep features are evaluated with different combinations of the six pre-trained

Table 6 Accuracy scores of deep networks (%) when the last layer is replaced with an SVM

AlexNet	GoogleNet	ResNet18	ResNet50	ResNet101	DenseNet201
90.42	90.89	91.84	94	94.63	94.85

Table 7 Accuracy scores (%) of late fusion-based fine-tuned deep networks (numbering is given in Fig. 1)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Overall
92.85	83.3	90.1	89	99.32	85.95	86.15	100	85.7	96.88	98.6	100	99.1	100	80.65	**93.6**

Table 8 Results to PlantDiseaseNet-EF model and PlantDiseaseNet-MV model

Combination process	PlantDiseaseNet-EF model			PlantDiseaseNet-MV model		
	Accuracy score	F1-Score	Standard deviation	Accuracy score	F1-score	Standard deviation
DenseNet201 + ResNet50 + ResNet101	96.42	95.02	0.1062	96.45	95.75	0.1383
AlexNet + GoogleNet + ResNet50 + ResNet101	96.45	95.75	0.2089	96.42	95.72	0.1654
AlexNet + GoogleNet + DenseNet201 + ResNet50	96.56	95.52	0.1013	96.58	95.95	0.1071
AlexNet + GoogleNet + DenseNet201 + ResNet101	96.58	95.67	0.1305	96.65	96.02	0.1293
GoogleNet + DenseNet201 + ResNet18 + ResNet50 + ResNet101	96.67	95.96	0.1614	96.90	96.29	0.1289
AlexNet + DenseNet201 + ResNet18 + ResNet50 + ResNet101	96.78	95.77	0.1537	96.99	96.61	0.0828
AlexNet + GoogleNet + DenseNet201 + ResNet18 + ResNet50 + ResNet101	96.83	95.81	0.1175	97.21	96.81	0.1203
AlexNet + GoogleNet + DenseNet201 + ResNet50 + ResNet101	96.94	96.15	0.1569	97.56	97.07	0.2431

networks. The results are shown in the third column of Table 8.

According to these results, the highest accuracy score achieved using the PlantDiseaseNet-MV model was 97.56%, using a combination of the AlexNet, GoogleNet, DenseNet201, ResNet50 and ResNet101 networks. These results parallel those obtained in Table 8 where the best results were also obtained with all the networks except ResNet18.

5.5 Summary and conclusions

In this paper, we compared different methods for obtaining ensembles of deep convolutional networks trained for plant disease and pest classification. State-of-the-art pre-trained deep networks (AlexNet, GoogleNet, ResNet18, ResNet50, ResNet101 and DenseNet201) were used with transfer learning to classify a given image; as well as feature extractors used in combination with an SVM classifier. The performances of different combinations based on these deep networks were calculated and reported.

In order to verify the validity of the proposed models, we collected Turkey-PlantDataset consisting of 4447 unconstrained photographs of disease and pest images. According to the comprehensive evaluations, we noted that the 97.56% accuracy was obtained using the proposed PlantDiseaseNet-MV model and 96.83% using the proposed PlantDiseaseNet-EF model. These results reveal the efficiency of the proposed models compared to the state-of-the-art algorithms.

In future studies, we plan to develop models based on a combination of different machine learning classifiers and deep learning networks. In addition, feature reduction methods will also be investigated as a means to elicit the most efficient features from the obtained deep features.

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