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Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models

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Abstract

It is important to identify a high-performance model that can classify all leaves and even differentiate according to regional variations of the same leaf type. In this study, a leaf classification model was created using 5 different datasets with different number of images and compared with models. For this purpose, 4 different pre-trained models called VGG16, InceptionV3, MobileNet and DenseNet are used. In addition, a new model was proposed and model training was carried out using these datasets . Using the all models, inputs are transformed into feature vectors by parameter transfer method and used for classification with the nearest neighbor algorithm and support vector machine. The performance of the classifications were compared with similar studies in the literature.

Keywords:

Artificial intelligence, machine learning, deep learning, parameter transfer, pre-trained model, feature transformation

Article history:

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Introduction

Useful plants that are frequently used in daily life to raise our living standards such as pharmacy, alternative medicine, medicine. However, there are harmful plants as well as useful plants. Moreover, expert knowledge is required for its use. Misuse of plants based on hearsay information or the use of plants that are thought to be medicinal by the public even though they are poisonous cause serious problems. Moreover, it could cause people to die. It is known that many plants are used in alternative medicine in Turkey as well as all over the world. When leaf similarities are

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taken into account, if people do not have expertise, they cannot be expected to have detailed knowledge about these plants. There is a known fact that leaf characteristics provide many useful clues for taxonomy of the leaf (Jiang et al., 2013). With technological developments, it is possible to produce solutions or improve such problems. For this reason, it is aimed to develop a recognition system based on artificial intelligence applied to leaf images for this problem that requires expertise such as recognizing plants and using them correctly.

Artificial intelligence is developing gradually. Compute Unified Device Architecture (CUDA) was developed by Nvidia. Therefore, researchers started using GPU as it allowed easy processing of big data in Artificial intelligence algorithm. CUDA enables simultaneous parallel processing of neural networks using thousands of cores in GPUs (Ilievski et al., 2018). It is frequently used in different areas such as social media, e-commerce, suggestion systems, autonomous system etc. in our daily life. As a result of its use in such different areas, customized methods have been developed for different processes. One of these methods is specially trained convolutional neural network models. These models are also called feature learning because they directly calculate the parameters using input data. However, due to this feature, a large dataset is needed for the training of the convolutional neural network model. On the other hand, working with a large amount of datasets can be extremely costly due to the need for hardware. For this reason, feature transformation is performed using pre-trained models and classification is evaluated with the obtained feature set.

This method is defined as parameter transfer or transfer learning. It is a convolutional neural network (CNN), which is one of the sub-branches of deep learning and is frequently used in many areas where high performance is required (Kutlu et al., 2017). In this method, there are parameters such as multiple functions, layers and filters that may vary according to the work done. While developing a new convolutional neural network model, it is necessary to examine appropriate parameters by considering many parameters such as pooling layer parameter (Camgözlü & Kutlu, 2019), filter size, image size (Camgözlü & Kutlu, 2020), number of layers.

In literature there are many studies for leaf classification such as convolutional neural network models (Wu et al., 2007; Kadir et al., 2013; Kulkarni et al., 2013; Atabay, 2016; Barre et al., 2017), support vector machine (Hewitt and Mahmoud, 2018; Zhang et al., 2020; Tsolakidis et al., 2014; Shah et al., 2017; Tomar and Agarwal, 2016; Wang et al., 2014, 2020), nearest neighbor algorithm (Tomar & Agarwal, 2016; Wang et al., 2014). In addition, There are studies in which classification is made with different methods using feature vectors extracted from the trained convolutional neural network called pre-trained models (Lee et al., 2017; Beikmohammadi & Faez, 2018; Wang et al., 2018; Raj & Va jravelu, 2019). Different classification methods such as logistic regression (LR) , support vector machine (SVM), Naive Bayesian, linear discriminant analysis (LDA), radial fundamental probabilistic neural network (RF-PNN), multilayer perceptron (MP), AdaBoost, probabilistic neural network have been used (Silva et al., 2013; Jiang et al 2013; Padao & Maravillas, 2015; Mostafa et al., 2020; Sujith & Neethu, 2021).

Different dataset was used in these studies. Therefore, five different leaf datasets (which are Mendeley, Swedish Leaf, Flavia, UCL, Leafsnap) were used in this study. Silva et al. (2013), Padao & Maravillas (2015), Tomar & Agarwal (2016) have been used UCL dataset to classify leaf using LDA, Naive Bayesian and SVM respectively.

Barre et al. (2017), Beikmohammadi & Faez (2018), Shah et al. (2017), Hewitt & Mahmoud (2018), Kumar et al. (2012) have been used leafsnap dataset to develop classification model. Barre et al. (2017) used CNN models. Beikmohammadi & Faez (2018) used pretrained CNN models. Hewitt & Mahmoud (2018) used SVM models. Shah et al. (2017) used SVM and CNN models. Kumar et al. (2012) used KNN models.

Swedish Leaf dataset has been used by Hewitt & Mahmoud (2018), Zhang et al. (2020), Tsolakidis et al. (2014), Sujith & Neethu (2021), Atabay (2016), Anubha Pearline et al. (2019) to develop classification model. SVM has been used by Hewitt & Mahmoud (2018), Zhang et al. (2020), Tsolakidis et al. (2014). Sujith & Neethu (2021), Atabay (2016), Anubha Pearline et al. (2019) have used MLP, CNN and pre-trained model respectively.

The Flavia dataset was used by Wu et al. (2007), Kumar et al. (2012), Kulkarni et al. (2013), Kadir et al. (2013), Tsolakidis et al. (2014), Lavania & Matey (2014), Wang et al. (2014), Atabay (2016), Shah et al. (2017), Barre et al. (2017), Lee et al. (2017), Anubha Pearline et al. (2019), Hewitt and Mahmoud (2018), Beikmohammadi & Faez (2018), Raj & Vajravelu (2019), Wang et al. (2020), Zhang et al. (2020), Mostafa et al. (2020) Sujith & Neethu (2021), with different classification models such as KNN PNN SVM CNN etc.

It is important to identify a high-performance model that can classify all leaves and even differentiate according to regional variations of the same leaf type. In this study, 5 different datasets consisting of leaf images were determined in order to create a good model and compare. Four different convolutional neural network modelswhich are trained previously, were used. These pre-trained models are VGGNet (Simonyan & Zisserman, 2015), InceptionV3 (Szegedy et al., 2001), MobileNet (Howard et al. 2017), DenseNet (Huange et al, 2017). In addition, a new convolutional neural network training was carried out with the existing datasets . It is used on classification with nearest neighbor algorithm (KNN) and support vector machine (SVM) after feature transfer. All results are compared in detailed with the similar studies in literature.

Material and Methods

Datasets and Data Augmentation

As a result of the literature review, Many different types sc of gray or black images with different color spaces were found in the images. images with many different species and with different color space were found. In addition, these data sets will be combined into a new data set to create a more general model.

- Mendeley Data Set (Chouhan et al., 2019): Mendeley dataset consists of diseased and healthy leaves. In this data set, which includes 12 species and 4404 images, those unsuitable for use were excluded from diseased leaf images.
- Swedish Leaf Dataset (Soderkvist, 2001): 1125 leaf images of 15 species in the Swedish Leaf dataset have white backgrounds.
- Flavia Dataset (Wu et al., 2007) : Leaf images in the Flavia dataset , which includes 32 species and 1907 images, have white backgrounds.
- UCL Data Set (Silva et al., 2013): In the UCL dataset , which includes 40 species and 443 images, the background colors of the leaf images differ.
- Leafsnap Data Set (Kumar et al., 2012): Images in the section called lab in the Leafsnap data set, which consists of 2 parts, were used. This dataset consists of 185 species and 23147 images.
- Combined Data Set: While all data sets were combined, similar species were reduced to a single species, thus reducing the total number of species from 283 to 270.

When the data sets used were examined, data duplication was applied using image processing techniques in order to reduce the number of images per species in each data set and to increase the training performance. After pre-processing, 5 different datasets Mendeley Swedish Leaf, Flavia, UCL , Leafsnap which have different types and amount were shown in Table 1. The samples of images from each datasets is shown in Figure 1. UCL and Mendeley datasets have colored backgrounds, while the others have white backgrounds. While the UCL dataset, which has fewer images than the others, was first subjected to mirroring and then to rotation, other datasets were only rotated. In the rotation process performed on all 4 datasets, 11 different angles of rotation were applied from 30 degrees to 330 degrees with an increase of 30 degrees, and a total of 12 different angles were obtained by including the original images as shown in Figure 2. Leafsnap dataset, which is out of these 4 datasets, was created from images that were rotated 90, 180 and 270 degrees in addition to the original images. Since the images in the datasets are in different rotations, data augmentation made limited to avoid over-learning. It was applied at different scales according to the change in the number of images for the species with many images. All datasets were converted to images with the same background by applying background color correction to non-white backgrounds in 5 different datasets..This process ensured that the combined data set had similar properties. While all data sets were combined, similar species were reduced to a single species, thus reducing the total number of species from 283 to 270. Total amount of images are 62.424.

Table 1. The database information according to species, images, data and augmentation.

Dataset	Number of species	Number of images	Number of images after data augmentation
Mendeley	12	4.149	52.624
Swedish Leaf	15	1.125	13.500
Flavia	32	1.907	22.877
UCL	40	443	10.632
Leafsnap	184	11.234	57.966

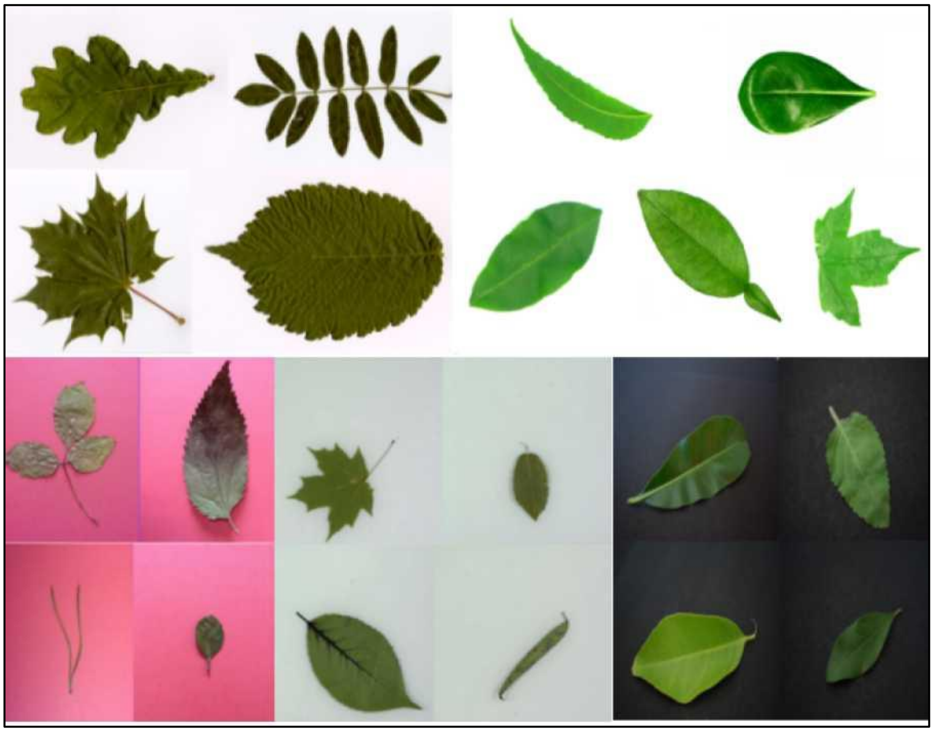

Figure 1. The samples of images from each datasets.

Figure 2. An image sample with different angles in the rotation process.

Convolutional Neural Network

Convolutional neural networks use local receptive fields, shared weights, and subsampling to extract local features and then combine them in an invariant manner (Kwolek, 2005). It performs these operations effectively with the model created as a result of the combination of different layers. In the convolutional neural network model, which consists of different numbers of convolution and pooling layers, different results can be obtained by changing the parameters such as function and filter size in these layers. The multidimensional matrix with the features obtained through the filters used transforms it into a one-dimensional vector through the plane layer and transmits it to the fully connected layer for classification. In this layer, classification is done by making predictions according to the labels. The convolutional neural network structure is shown in Figure 3 in detail, classification is made using the feature vector obtained as a result of feature learning from the leaf images taken as input data.

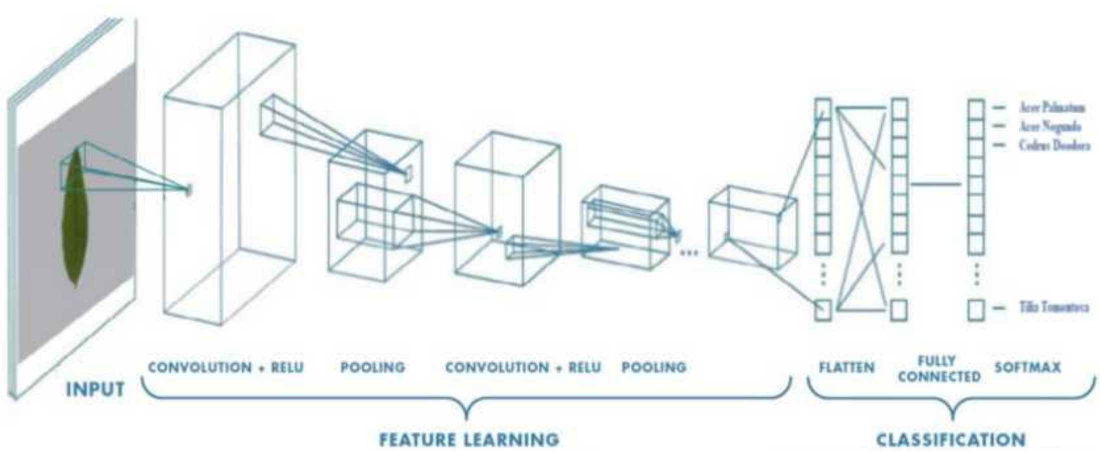

Figure 3. The CNN structure Model.

Pre-trained Models

There are many pre-trained models that are trained with high image size, number of images and processing power. The model structure is shown in Figure 4. In these examinations, 4 pre-trained models with 2 different plane layer sizes were determined. The image sizes to be used for these models are limited due to the pre- training. 128x128 color images were used, taking into account the processing power and time required for the operations to be performed after feature extraction.

In this study, VGGNet developed by Simonyan and Zisserman (2015), InceptionV3 developed by Szegedy et al. (2015), MobileNet developed by Howard et al. (2017), and finally DenseNet created by Huang et al. (2018) were preferred as pre-trained models. 128x128 was chosen as the input image size for all transfer model. The VGGNet pre-trained model is trained with a subset of ImageNet with 1000 classes and 1000 images for each class. This cluster contains 1.2 million training data, 50 000 validation data and 150 000 test data. The InceptionV3 pre-trained model was trained using the dataset in the large-scale visual recognition competition ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC2012). The MobileNet pre-trained model is trained using ImageNet. MobileNet is based on a modern architecture that uses deeply separable convolutions to create lightweight, deep neural networks. In the DenseNet pre-trained model, each layer is connected with other layers in a feed-forward manner. The large-scale image recognition competition was trained using the dataset set in ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC2012).

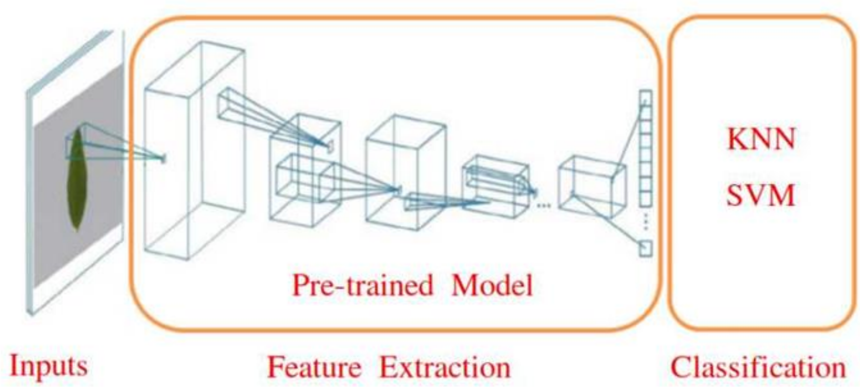

Figure 4. The classification structure using Pre-trained CNN Model.

The convolutional neural network model created in this study and the pre-trained models used in the plane layer size, initial image dimensions and the final state of the feature extraction data before the plane layer are shown in Table 2. Looking at these data, it is seen that the high image size and flattening layer size of the pre-trained models are higher than the model created. In addition, high image size and multi-layer structure are among the main reasons for the high leveling layer size.

Table 2. Parameters of models.

Model Names	Flatten Layer Sizes	Image Size	Before Flatten Layer
VGGNet (Simonyan ve Zisserman, 2015)	8 192	128 x 128 x	4 x 4 x 512
InceptionV3 (Szegedy et al., 2001)	8 192	128 x 128 x	2 x 2 x 2048
MobileNet (Howard et al. 2017)	16 384	128 x 128 x	4 x 4 x 1024
DenseNet (Huange et al, 2017)	16 384	128 x 128 x	4 x 4 x 1024
New CNN Model	1 536	90 x 75 x 1	3 x 2 x 256

Creating New CNN Model

There are many parameters in convolutional neural networks. There is no specific method for determining these parameters. For this reason, the parameters is determined experimentally. In this study, the parameters obtained in the previous studies of Camgözlü & Kutlu (2019; 2020) were used . For this purpose, appropriate parameters were used in studies where the effects of parameters such as mean pooling, filter size, image background color, image size were also examined. The model to be used in this study consists of 6 convolution layers and 3 pooling layers. As a result of the studies, the pooling layer size was determined as 3 and the pooling type was determined as average pooling, while the convolution filter size was determined as 3.

Feature Extraction

In this study, an image entered pre-trained models as inputs was transferred into an feature vector after operations such as convolution, pooling, which were done before the classification layer. Therefore, an image is converted to a new input vector depending on the model’s parameters by using pre-trained models. The feature map is obtained with the transformation approach in the middle layers of the CNN models and is given as an input to the last layer called classification layer. In this study, KNN and SVM algorithms are preferred as classifiers in the classification layer.

K-Nearest Neighbors

There are many machine learning classification algorithms in the literature. One of these algorithms is the nearest neighbor algorithm (KNN). In addition to the use of different types of distance calculation functions in the KNN algorithm, which is based on the distance between two points, the parameters such as how many nearest neighbors will be made during the calculation vary. There are different methods to measure the performance of this algorithm. This feature selection method allows the removal of features that do not add new information, with which some other features highly interact with them, which might otherwise lead to redundancy and poor predictive ability (Soucy & Mineau, 2001a).

Support Vector Machine

Support Vector Machines is one of the supervised learning algorithms that can be applied to both classification and regression problems. It has an algorithm that finds a decision boundary between the two classes that are furthest from a point using training inputs. An SVM classifier creates a maximum-margin hyperplane located in a transformed input space and maximizes the distance to the nearest clean-split instances when generating instance classes.

It has the ability to classify nonlinear data by expanding the input data area, thanks to different kernel functions such as linear, polynomial, radial basis, sigmoid. The task of learning a support vector machine is typically treated as a constrained quadratic programming problem. However, in its natural state it is in fact an unconstrained empirical loss minimization, with a penalty term for the norm of the classifier being learned (Soucy & Mineau, 2001b).

Cross Validation and Performance Criteria

In classification problems, the performance of the model when new data other than the training data comes in is called generalization performance. The generalization performance of classification models in applications is measured with examples not used in training. For this purpose, cross validation is used to ensure that all examples are used both in training and in generalization performance as a test. The 10- fold cross validation visualization is given in the Figure 5.

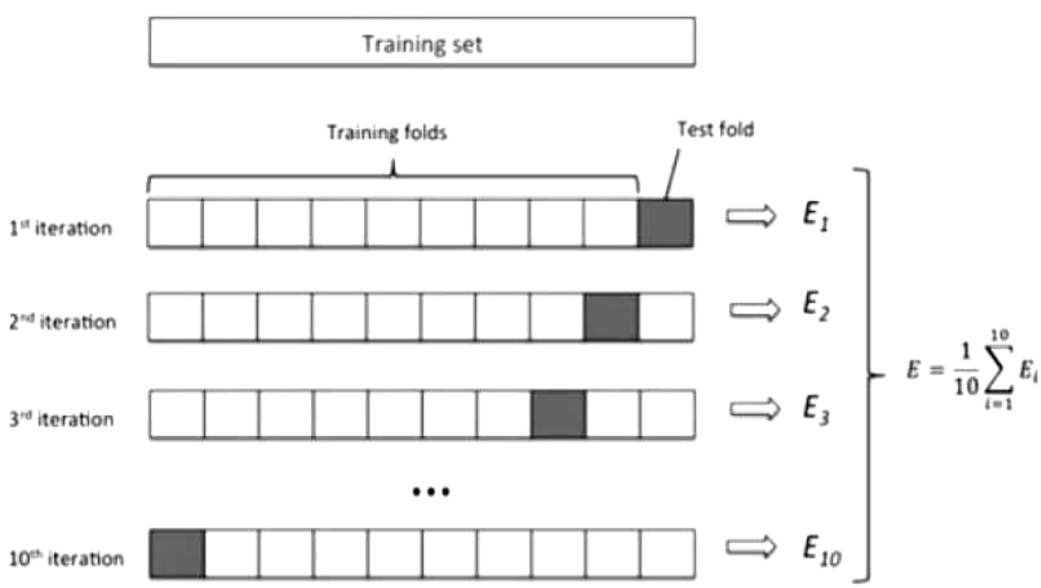

Figure 5. The 10-fold cross validation visualization (Petkov, 2018).

In K-Fold cross validation method, all dataset is separated into k subsets. While k-1 subset of these is used as train set, one of them is used as test set. Since the test dataset do not used during training, performance is obtained with test dataset. This process is repeated until the all subset is used for testing. The performance of classifier is evaluated as test performance by taking the averages separately for training and testing results.

Experimental Study

In this study, the open source tensorflow library used for CNN training was used. A computer with AMD Ryzen 5 3600x processor, Nvidia GTX 1080 graphics card and 32 gigabytes of system memory was used in these processes. In the CNN training, python was chosen from programming languages such as C++, python, and java, and the tensorflow library, which is an open-source library, was used.

In this study, five different datasets were used to determine suitable models for leaf classification. It was carried out to develop a new CNN model for leaf classification and to determine the appropriate parameters. In addition, four pre-trained models were used. The pre-trained models, which includes new trained CNN, were utilized as feature extraction (feature transformation). After feature extraction the feature vectors were used for classification in KNN and SVM. The results were evaluated together according to the number of images in the datasets, the number of species, the number of iterations and the obtained success rates. In addition, the results are compared each other's and with similar studies in literature.

While developing the new CNN model, the datasets used for training and testing were separated at a rate of 80% and 20%. The results of the new model, which includes the number of species in the datasets, the number of images, the number of iterations and accuracy rates, are given in Table 3. According to these results, it can be said that a good performance was achieved with low iteration.

Table 3. The accuracy rates of the new CNN model in classification with different datasets.

Dataset	**Number of species**	**Number of images**	**Number of iterations**	**Train accuracy**	**Test accuracy**
Mendeley	12	52 624	5 000	97,35	92,08
Swedish Leaf	15	13 500	10 000	98,94	90,87
Flavia	32	22 877	10 000	97,60	91,89
UCL	40	10 632	20 000	98,58	88,00
Leafsnap	184	57 966	10 000	95,50	86,78

The feature vectors obtained from the new CNN model and pre-trained models were classified with KNN, and the results are shown in Table 4. As the results, pre-trained models performed close results when the number of species were low, performed poorly in the Leafsnap dataset with high species counts. But using high amount of images in new CNN model, it made the performance increased.

Table 4. Accuracy rates of pre-trained models using KNN classifier.

Methods	Mendeley	Swedish Leaf	Flavia	UCL	Leafsnap
New CNN + KNN	**95,65**	97,32	97,21	89,48	**87,46**
InceptionV3 + KNN	82,19	92,47	93,15	90,17	54,33
MobileNet + KNN	89,09	**98,67**	**98,87**	**95,81**	62,53
VGGNet + KNN	86,91	97,56	96,98	93,52	56,18
DenseNet + KNN	89,00	97,15	96,77	95,80	61,22

The feature vectors obtained from the new CNN model and pre-trained models were classified with SVM as well, and the results of 5 different datasets and 5 model are shown in Table 5. According to these results, it was seen that better results were obtained in the pre-trained models in the datasets that do not have a high number of species. Using high amount of images in new CNN model, it made the performance increased when using SVM as well.

Table 5. Accuracy rates of pre-trained models using SVM classifier.

Methods	Mendeley	Swedish	Flavia	UCL	Leafsna
New CNN + SVM	97,27	98,47	97,47	94,35	**91,71**
InceptionV3 + SVM	91,17	97,22	96,26	94,59	68,33
MobileNet + SVM	**97,74**	**99,82**	**99,56**	**98,78**	80,51
VGGNet + SVM	96,52	99,45	98,63	98,25	78,21
DenseNet + SVM	96,57	99,29	98,53	97,89	80,39

Finally, all data sets were combined and used as a single data set and the results were obtained. Since some species are similar in these datasets, a dataset containing a total of 270 different species was created. After data reproduction, 62424 images were created and used in classification. The feature transformation was performed with combining all data sets and classification was carried out with KNN and SVM models. The classification results are given in Table 6.

Table 6. Accuracy rates of all models using KNN and SVM classifier for Combined Dataset.

Methods	Accuracy
New CNN + KNN	**81,18**
InceptionV3 + KNN	68,57
MobileNet + KNN	75,31
VGGNet + KNN	70,45
DenseNet + KNN	75,55
New CNN + SVM	**86,00**
InceptionV3 + SVM	72,77
MobileNet + SVM	84,36
VGGNet + SVM	82,79
DenseNet + SVM	83,56

Comparison of the Classification Performances

Comparing the proposed models with other studies in the literature is a bit difficult because of the reasons such as preprocessing, methods, datasets, and the number of images in the datasets. In this respect, a comparison was made with studies using similar datasets in terms of making the comparison a little more meaningful and the consistency of the method.

Mendeley dataset is a kind of leaf disease. Therefore, there is no study in the literature that has been classified leaf images using Mendeley dataset. There are 12 different leaf species in dataset. When the results among the models are considered, it is seen that the MobileNET + SVM approach provides the best performance among the methods in the dataset. The classification performance of the Mendeley dataset is shown in Table 7.

Table 7. Comparison of classification performances for Mendeley dataset.

Methods	**Mendeley Dataset**		**Classification Accuracy**	
for Feature Transformation	**Number of species**	**Number of images**	**with KNN**	**with SVM**
new CNN			**95,65**	**97,27**
InceptionV3			82,19	91,17
MobileNet	**12**	**52.624**	89,09	**97,74**
VGGNet			86,91	96,52
DenseNet			89,00	96,57

The UCL dataset has been used less than other datasets due to its high number of species and low number of images. The comparison of the results of methods, which used the UCL dataset, are shown in Table 8. The best performance was obtained from MobileNET + SVM models which achieved a much higher performance.

Table 8. Comparison of classification performances of the UCL dataset with different classification methods.

Published by	Method	Number of species	Number of images	Accuracy
Padao, 2015	Naive Bayesian	30	340	74,10
Tomar, 2016	SVM	40	443	84,70
Silva, 2013	LDA	15	171	87,00
In this study	**MobileNet + SVM**	**40**	**10 632**	**98,78**

The Leafsnap dataset has highest species number between datasets. The comparison of the results of models that used the Leafsnap dataset is shown in Table 9. Results were achieved by different classification methods using this dataset. Some researchers seem to have reduced species when used this dataset. In the studies used the same number of species, the second-best performance was obtained. The method that provides the best performance in this study is obtained from new CNN + SVM model.

Table 9. Comparison of classification performances for the Leafsnap dataset.

Published by	Method	Number of species	Number of images	Accuracy
Hu, 2018	MSF-CNN	184	-	85.28
Shah, 2017	SVM	150	7 710	85,37
Barre, 2017	CNN	184	272 300	86,30
Beikmohammadi, 2018	MobileNet + LR	184	29 107	90,54
Song, 2019	ABCNN	184	-	91.43
Ganguly, 2022	BLeafNet	184	-	92.22
Hewitt, 2018	SVM	183	7 440	92,40
Shah, 2017	CNN	150	7 710	95,61
Kumar, 2012	KNN	184	29 107	96,80
In this study	**New CNN + SVM**	**184**	**57 966**	**91,71**

The comparison of the results of methods that used the Swedish Leaf dataset is shown in Table 10. there are 15 leaf species in this database. Considering the studies used the Swedish Leaf data set, it was seen that high performance has been achieved. The methods proposed in this study has seemed to be as good as the results in the literature.

Table 10. Comparison of classification performances of the Swedish Leaf dataset with different classification methods.

Published by	Method	Number of species	Number of images	Accuracy
Wang, 2017	CNN + SVM	15	1 125	97,63
Hewitt, 2018	SVM	15	1 125	97,80
Zhang, 2020	SVM	15	1 125	97,93
Tsolakidis, 2014	Linear SVM	15	750	98,13
Sujith, 2020	ANN	15	1 125	98,23
Pearline, 2019	VGG + LR	15	1 125	98,52
Atabay, 2016	CNN	15	2 250	99,11
In this study	**MobileNet + SVM**	**15**	**13 500**	**99,82**

Flavia dataset is one of the most used datasets in the literature. The comparison of the results of methods used the Flavia dataset are given in Table 11. There are many models applied in literature to classify Flavia dataset. It was seen that the results obtained from the pre-trained models were quite high in the classification of the Flavia dataset.

Table 11. Comparison of classification performances of the Flavia dataset with different classification methods.

Published by	Method	Number of	Number of	Accurac
Lavania, 2014	KNN	33	1 907	87,50
Wu, 2007	PNN	32	1 800	90,00
Shah, 2017	SVM	32	1 907	93,22
Kadir, 2011	PNN	32	1 600	93,75
Kulkarni, 2013	RF - PNN	32	1 600	93,82
Kumar, 2019	MP - AdaBoost	32	1 907	95,42
Pearline, 2019b	VGG+ LR	32	1 907	96,25
Hewitt, 2018	SVM	32	1 907	96,66
Tsolakidis, 2014	MobileNet + LR	32	1 600	97,18
Atabay, 2016	CNN	32	3 814	97,24
Barre, 2017	CNN	32	44 623	97,90
Sujith, 2020	GLCM+LBP+PHOG+NCA	32	1 907	98,23
Zhang, 2020	SVM	32	1 907	98,53
Wang, 2018	DPCNN + SVM	32	1 907	98,53
Ganguly, 2022	BLeafNet	32	-	98,70
Shah, 2017	CNN	32	1 907	99,28
Lee, 2017	CNN + SVM	32	2 603	99,30
Beikmohammadi,	MobileNet + LR	32	1 907	99,60
In this study	**MobileNet + SVM**	**32**	**22 877**	**99,56**

Finally, since there are no similar studies in the literature for the same combined dataset, a comparison cannot be made. Using similar approach Gajjar et al. (2022) evaluates the performance of EfficientNet model when applied to a combination of the Flavia, Folio datasets, LeafSnap, Swedish, and Middle European Woody Plants 2014, naming it the F2LSM dataset. They reported 98% of accuracy for combined dataset containing 374 different types. A study in the form of a combined data set obtained by merging all data sets was presented by Camgözlü & Kutlu (2021). They used 270 different types and 65100 images and 80% of the dataset was reserved for training and 20% for testing. 88% training accuracy and 79% test accuracy were achieved. In addition, the models used in this study were compared with each other (as shown Table 12). It is seen that the best model is performed with the new CNN model trained with leaf images and SVM. It is thought that this means that the number of samples is high and a new CNN model specially trained with leaf images provides better results.

Table 12. Comparison of classification performances of the Combined Dataset using different models.

Methods	Combined Dataset		Classification Accuracy	
for Feature Transformation	**Number of species**	**Number of images**	**with KNN**	**with SVM**
new CNN			81,18	86,00
InceptionV3			68,57	72,77
MobileNet	270	62 424	75,31	84,36
VGGNet			70,45	82,79
DenseNet			75,55	83,56

In the proposed study, the trained CNN model was used as a feature transformation tool and performances were examined with KNN and SVM classifiers. Since the obtained performances better describe the generalization performance, the 10fold Cross validation method was applied.

Classification of leaf datasets using convolutional neural networks is scarce in the literature. However, the long duration of the training and the need for high equipment in the models used in these studies make it difficult for the researchers. In the literature, there are leaf recognition models in which pre-trained models are used instead of training a new model.

In conclusion, in this study, 5 different image datasets were used. In order to achieve a generalization performance for rotation independent, amount of images were augmented by images rotated in 12 different angular positions. 4 different pre-trained models were used for feature extraction. In addition to these, training was carried out by creating a CNN model with lower parameters trained with leaf image datasets and this model was used for feature extraction as well. All developed models for leaf classification system were compared.

In general, In the results of the overall performance, a high performance has been achieved in all datasets. It is seen in detail in Tables. When the new trained CNN model is compared with the pre-trained models, it is seen that it performs close to each other's. As a result of the comparison, the increase in the number of class and images shows that the classification problem is getting bigger. Considering this situation, the new trained CNN model created for leaf classification has been achieved better result according to the results of the Leafsnap dataset, where the number of species is much higher than other datasets. The parameters of pre-trained models VGGNet model, InceptionV3, MobileNet , DenseNet and New CNN Model are 8192, 8192, 16384, 16384 and 1536 respectively. The new CNN model has achieved as good results as the pre-trained models, and sometimes even better. This shows that the model trained with own dataset could be good even if they have small parameters. As a result, it was observed that the performance of the specially trained CNN model increased. It has been seen that others can achieve good performance and the high number of data is another parameter that increases the performance of the models.

In this study, different classification methods and different data sets were used. When these results and the studies in the literature are examined, it has been determined what kind of method will be used in hardware with low processing power. As it can be seen in the comparison tables, many CNN models have been used in the literature. The common issue with them is the high hardware requirements used. But, it may not always be high hardware. In this case, instead of training deep learning models, it is possible to use their capabilities by using pre-trained models as a feature transformation. Nevertheless, it is necessary to say that training with the relevant data set is better than pre-trained models. However, in the absence of hardware, it can be used as an alternative.

Accordingly, it has been determined that the classification of the features extracted from the pre-trained models with different feature vector sizes according to the capacity of the system being processed requires both less time and less processing power. It should be taken into account that pre-trained models can be used, considering that the performance difference between the pre-trained and the trained models result is not very large. As a result, getting very good results by performing feature transformation with pre-trained models depends on the dataset. Pre-trained models don't require training, so they don't require high processing power. However, it should not be forgotten that the new CNN model requires serious hardware to perform training, especially in datasets with high samples.

Conflict of Interest

The authors declare that they have no competing interests.

Author Contributions

All authors' contributions are equal for the preparation of research in the manuscript.

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