Classification of flower species using CNN models, Subspace Discriminant, and NCA

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Abstract— Flowers have an important place in human life. Because flowers can appear at every stage of human life. People want to know these types of flowers that they come across even in daily life. However, due to a large number of flower types, there are difficulties in recognizing these types. We used deep learning methods in this study to overcome these difficulties. Deep learning methods have been widely used in different fields recently. In this study, we used 3 different deep learning methods. In the first stage, we performed the classification process using the pre-trained Efficientnetb0, MobilenetV2 and Alexnet architectures. In the second step, we extracted the feature maps of the images in the dataset using these three pre-trained deep learning models. Then, we optimized these features using the NCA size reduction method to save time and cost. Next, we classified these optimized features in the features Subspace Discriminant classifier. In the final stage, we combined the features we obtained with three pre-trained deep learning architectures. After optimizing these combined features with the NCA method, we classified the features in the Subspace Discriminant classifier. In the first step, the highest accuracy we achieved in the three pre-trained deep learning architectures was 83.67%, while our accuracy rate was 94% in this hybrid method we recommend. This shows that our proposed model is successful.

Keywords— Classification, CNN, Deep Learning, Flowers, NCA

I. Introduction

Flowers are beings that every person encounters in daily life. People want to know what these types of flowers they come across are. It has always been a matter of curiosity whether it is harmful, beneficial or what kind of it is. However, due to a lack of knowledge, people often do not understand these flower types. In addition, the classification of flower species is of great importance for biologists [1]. Flowers can take different forms at different times or in different seasons. Because of all these difficulties, this study is of great importance. There are studies in the literature using traditional methods. However, the number of studies conducted with deep learning methods is limited. In this study, we propose a model so that people who are not experts in their field can learn the type of flower they have seen, even from their mobile devices. With this deep learning model, people can photograph and learn the type of flower they are curious about. This method, which we have proposed, performs feature extraction automatically, unlike traditional methods [2]. And feature selection is made so that the application responds quickly. In this way, unnecessary features will be eliminated [3]. Because when a flower is photographed, its surroundings can also be taken. Thanks to this optimization method, the model will work faster and more efficiently.

There are some studies in the literature on the subject. Wu et al. [4] used transfer learning models in their study. Vgg16, Vgg19, Inceptionv3 and Resnet50 are the main models they use. Oxford-17 and Oxford-102 flower datasets were used in this study. They achieved 94% accuracy on the Resnet50 architecture. Chen et al. [5] classified the images in the flower dataset using CNN networks in their study. Feature extraction was done in the proposed model. The accuracy rate obtained in the proposed model was 90.2%. Alkhonin et al. [6] classified these flower types using a dataset of 4 different flower types. The accuracy rate obtained by the researchers was 83.13%. Çıbuk et al. [7] used flower17 and flower102 datasets in their study. In their study, feature extraction was done with CNN models. They optimized their feature maps with the mRMR feature selection method. They classified these optimized features in the SVM classifier. They reached 96.39% accuracy in the flower17 dataset and 95.70% in the flower102 dataset. Gao et al. [8] pre-processed the images in the data set to eliminate the blurriness of the images in the data set. After applying the pre-processing step to the data set, the accuracy rate they obtained in the InceptionV3 model was 97.78%. Qi et al. [9] preferred the Sift method and SVM classifier to classify flower species in their study. They classified the features they obtained in the SVM classifier. The accuracy rate obtained by the researchers in this study was 87.73%.

In this study, we aimed to obtain feature maps of images in the dataset using pre-trained deep models. Later we combined the feature maps. We used the NCA dimension reduction method to optimize these combined feature maps. With our proposed model, we achieved a high accuracy value in the Subspace Discriminant classifier. The obtained accuracy value shows that the proposed model can be used in classifying flower species.

In the continuation of the article, the methods used in the study, the classifiers, the optimization method, the proposed method and the results obtained are emphasized. Finally, the conclusion section is given.

II. BackGround

This part of the study examined the data set, deep learning models, Subspace Discriminant classifier, and NCA dimension reduction method.

A. Dataset

Dataset used in the study consists of 10 different types of flowers. These species are Tulips, Orchids, Peonies, Hydrangeas, Lilies, Gardenias, Garden Roses, Daisies, Hibiscus and Bougainvillea. The dataset used was taken from Kaggle [10]. To clearly observe the results of the proposed approach, no pre-processing was applied to the data. Also, data multiplexing was not done. Sample images from the data set are given in Figure 1.

Fig.1. Images of Dataset

B. Models, Subspace Discriminant and NCA

Deep learning models have been widely used in recent years with the developing technology [11, 12, 13]. It is possible to define deep learning as a machine learning method consisting of multiple layers that predict results with a given dataset. In this study, we used three different state-of-the-art models to classify flower species. The first of these models is Efficientnetb0. Efficientnetb0 was published at a conference held in 2019. In the Imagenet classification problem, an accuracy value of 84.4% was obtained with the computational load of 66M parameters. There are eight different versions of the Efficientnet model available. These are named in the range Efficientnetb0 – Efficientnetb7. In this model, besides the concept of depth, the concepts of resolution and width are also examined [14, 15]. The second model we used in our study is MobilenetV2. Since this model contains much information in the datasets, it is a model developed mostly for mobile devices. In addition, this model significantly reduces the complexity of the network and the model size. This model, which is among the models that can be preferred for feature extraction, has been used in many studies recently [16]. The third model we used in this study is Alexnet. The Alexnet model is the winner of the Imagenet competition held in 2012. At the same time, the success of the Alexnet model in this competition marked the beginning of a new era for deep learning. It achieved an accuracy of 83.6% in the Imagenet competition [17]. The NCA method was used to reduce the size of the feature maps obtained in our study. The reason why we use the NCA method is that the size of the data held in the data sets is huge. Due to the high correlation between the features in the data sets, it is of great importance to eliminate unnecessary information. In this way, the time and resources spent while creating models are minimized. The Subspace Discriminant classifier was used to classify the features we optimized using the NCA method [18]. Machine learning classifiers are very widely used classifiers. Classification is the process of categorizing these data by drawing a conclusion from the existing data and determining which category the new data that will come later belong to. This method can be used if roughly used data is desired to be divided into categories. The number of classes does not matter here; the important thing is that the data is labelled [19, 20]. This classification method is accepted in the literature and is preferred in many studies.

C. Proposed Architecture

To compare the method we proposed to classify the Flowers image dataset with the pre-trained models, we first performed the classification with the Efficientnetb0, MobilenetV2 and Alexnet models. As a result, we can give the block diagram of pre-trained architectures as in figure 2.

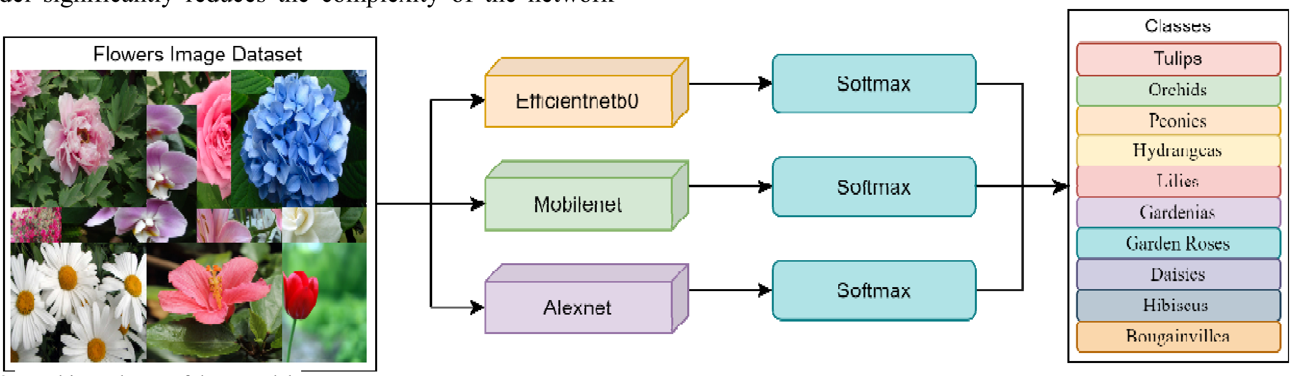

Fig.2. Working scheme of deep models

Then, we obtained individual feature maps of the images in the dataset using the Efficientnetb0, MobilenetV2 and Alexnet architectures. The resulting feature maps are 733 x 1000 in size. Then, we performed the size reduction process to make our model work faster and more efficiently. We preferred the NCA method for size reduction. We applied NCA to each of the 733 x 1000 feature maps we obtained. The size of the new feature maps we obtained is 733 x 291 in Efficientnetb0 architecture, 733 x 345 in MobilenetV2 architecture and 733 x 340 in Alexnet architecture. These optimized feature maps are classified in the Subspace Discriminant classifier. This phase of the study is given in Figure 3.

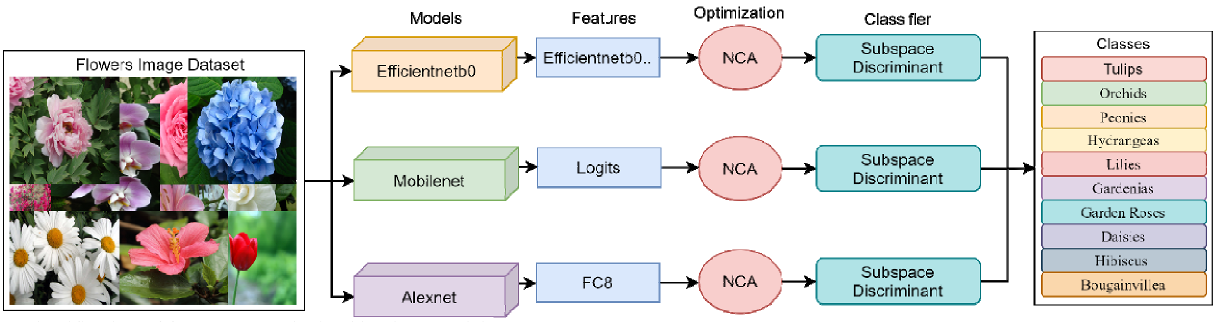

Fig.3. Classification of feature maps obtained by deep models

In the last step of our work, we combined the features we obtained from Efficientnetb0, MobilenetV2 and Alexnet architectures. The size of the feature map, which was 733 x 1000 in each architecture, became 733 x 3000 after merging. Then we used the NCA method to improve the performance of the model. As a result, the size of the new feature map we optimized was 733 x 236. Finally, we classified these features, which we obtained in the last stage, using Subspace Discriminant. The model we recommend is in figure 4.

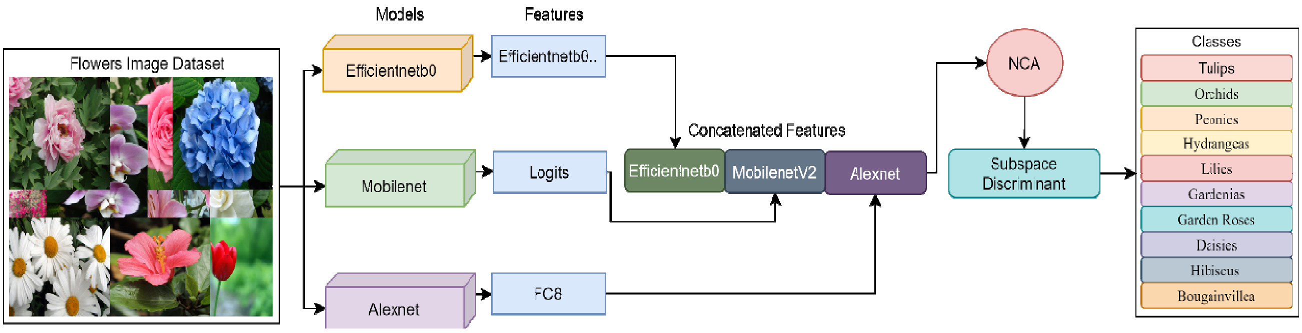

Fig.4. Classification of the combined feature maps obtained by the deep models

While obtaining the feature maps, the layer before the Softmax layer was preferred in all three architectures used in the study.

III. Experimental Results

Matlab environment was preferred for this study. Obtained results are given step by step with confusion matrices. In addition, Accuracy, Sensitivity, Specifity and F-measure values were calculated separately to measure the performance rates of the models. While getting results in deep models, 80% of the images in the data set are used for training, while the rest is reserved for testing. In the study, firstly, we obtained results with three pre-trained deep learning architectures. While obtaining these results, no made no changes to the architectures. The confusion matrix obtained in the Efficientnetb0 architecture and the confusion matrix obtained when the features obtained using the Efficientnetb0 architecture are classified are given. While the confusion matrix given in Table 1.a) is taken from the pre-trained Efficientnet architecture, in Table 1.b), the feature maps obtained using the Efficientnetb0 architecture are optimized using NCA. These features were then classified in the Subspace Discriminant classifier.

TABLE I.a) Efficientnetb0 + Softmax

True Class \ Predicted Class	Bougainvillea	Daisies	Garden_roses	Gardenias	Hibiscus	Hydrangeas	Lilies	Orchids	Peonies	Tulip
Bougainvillea	5		3	1	2				4	
Daisies		12		2		1	1		1	
Garden_roses	2	1	6					1	4	1
Gardenias				11		1	1	2		
Hibiscus			1	1	10		1	1	1	
Hydrangeas	1		1	1		9				
Lilies							12	1	2	1
Orchids		1	2	1			5	4		
Peonies			3						12	
Tulip	1						2	3		8

TABLE I.b) Efficientnetb0 + NCA + SVM

True Class \ Predicted Class	1	2	3	4	5	6	7	8	9	10
1	67		5					1		1
2		82					1			
3	4		57	3	1		1	1	6	1
4	1		1	75						
5			1		71			1	1	
6	1					57			2	
7				1			79		1	
8	1			3	1		4	55		
9			4		1	1			69	
10	1		1							69

As seen in Table I.a), the pre-trained Efficientnetb0 architecture correctly predicted 89 out of 147 test images, while it mispredicted 58 images. The accuracy rate of this model in the flowers data set is 60.54%. Table I.b), when the obtained features were classified after being optimized, the accuracy rate was 92.9%. In this step, the second step of our study, the accuracy rate increased from 60.54% to 92.9%. Out of 733 images in the data set, 681 were predicted correctly, while 52 were incorrectly predicted.

Table II shows the confusion matrix obtained in the pre-trained MobilenetV2 architecture and the confusion matrix obtained when the features obtained using this architecture are classified. While the confusion matrix given in Table 2.a) is taken from the pre-trained MobilenetV2 architecture (Table 2.b), the feature maps obtained using the MobilenetV2 architecture are optimized using NCA. These features were then classified in the Subspace Discriminant classifier.

TABLE II.a) MobilenetV2 + Softmax

True Class \ Predicted Class	Bougainvillea	Daisies	Garden_roses	Gardenias	Hibiscus	Hydrangeas	Lilies	Orchids	Peonies	Tulip
Bougainvillea	10		3			1			1	
Daisies		16		1						
Garden_roses	3		9					1	2	
Gardenias	1		1	10	1			2		
Hibiscus					14		1			
Hydrangeas	1					11				
Lilies							15	1		
Orchids				1			2	9		1
Peonies			3	1					11	
Tulip	1									13

TABLE II.b) MobilenetV2 + NCA + SVM

True Class \ Predicted Class	1	2	3	4	5	6	7	8	9	10
1	64		7	1				2		
2		83								
3	4		61	2					7	
4	2			75						
5			1		68		2	1	2	
6	1			1		56			2	
7							78	1	2	
8	4			1	1		3	55		
9			5		1	1			68	
10			1						1	69

As seen in Table II.a), the pre-trained MobilenetV2 architecture correctly predicted 118 out of 147 test images, while it mispredicted 29 images. The accuracy rate of this model in the flowers data set was 80.27%. In Table II.b), when the features obtained using the MobilenetV2 architecture were classified after being optimized, the accuracy rate was 92.36%. The MobilenetV2 architecture predicted 677 of the 733 flower images correctly, while it mispredicted 56. While the accuracy rate obtained in the MobilenetV2 architecture is 80.27%, it is 92.36% in the recommended approach.

In Table III, the confusion matrix obtained in the pre-trained Alexnet architecture and the confusion matrix obtained when the features obtained using the Alexnet architecture are classified are given. While the confusion matrix is given in Table III.a) is taken from the pre-trained Alexnet architecture, in Table III.b). The feature maps obtained using the Alexnet architecture are optimized using NCA. These features were then classified in the Subspace Discriminant classifier.

TABLE III.a) Alexnet + Softmax

True Class \ Predicted Class	Bougainvillea	Daisies	Garden_roses	Gardenias	Hibiscus	Hydrangeas	Lilies	Orchids	Peonies	Tulip
Bougainvillea	14								1	
Daisies		17								
Garden_roses	1		12	1					1	
Gardenias				15						
Hibiscus			1		11		2		1	
Hydrangeas	1					8			3	
Lilies		1					14			1
Orchids				1			4	7	1	
Peonies			1		1				13	
Tulip	1							1		12

TABLE III.b) Alexnet + NCA + SVM

True Class \ Predicted Class	1	2	3	4	5	6	7	8	9	10
1	65		3				2	1	3	
2		82						1		
3	7		53	3		1			10	
4			1	75			1			
5				1	63		3	3	4	
6	1		2	1		51			5	
7		1	1	5	1		71			2
8	1				1		3	57	2	
9			4	1		1		2	66	1
10			2				2	1	1	65

As seen in Table III.a), the pre-trained Alexnet architecture correctly predicted 123 out of 147 test images, while it predicted 24 images incorrectly. The accuracy rate of this model in the flowers data set is 83.67%. Alexnet was particularly unsuccessful in classifying images of the Orchids type. While he predicted 7 of 13 Orchids images used for the test correctly, he predicted 5 of them incorrectly. In Table III.b), the accuracy rate was 88.4%. In this step, 648 images were classified correctly, while 85 images were classified incorrectly. The accuracy rate increased from 83.67% to 88.4% at this step.

In the last step of the study, the proposed approach was evaluated. While obtaining the results at this stage, first of all, the feature maps obtained from the three architectures used in the study were combined. Then, after applying the NCA dimension reduction method to these feature maps, the obtained features were classified. The resulting confusion matrix is given in Table IV.

TABLE IV. Confusion matrix of proposed approach

True Class \ Predicted Class	1	2	3	4	5	6	7	8	9	10
1	71		2					1		
2	1	82								
3	4		57	3				1	8	1
4				77						
5			2		70			1	1	
6	1					59				
7				2			78		1	
8			1	1	1		4	57		
9			4			1			70	
10			3							68

In the proposed method, predicted 689 of 733 images correctly. The number of incorrectly guessed images is 44. The accuracy rate obtained with this approach is 94%.

IV. Conclusion

Flowers have an important place in human life. Knowing these flower types is both a critical and difficult process for most people. In this study, we have classified the images in the flowers image dataset. Our proposed model was more successful than both similar studies in the literature and the three pre-trained deep learning architectures used in the study. Thanks to the proposed model, even amateur people can take pictures of the flower species they are curious about and learn the genus quickly. In addition, this study is of great importance for biologists. This method produces faster and more accurate results than traditional methods. The study obtained an accuracy value of 94%. As can be understood from this value, this model can be used to classify flower types. It is among our aims to develop a faster classification method for more flower species in the future.

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