Volume: 14 Issue: 02 Pages: 5385-5389(2022) ISSN: 0975-0290

A Study on Deep Learning Based Classification of Flower Images

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---ABSTRACT---

Deep learning techniques are becoming more and more common in computer vision applications in different fields, such as object recognition, classification, and segmentation. In the study, a classification application was made for flower species detection using the deep learning method of different datasets. The pre-learning MobileNet, DenseNet, Inception, and ResNet models, which are the basis of deep learning, are discussed separately. In experimental studies, models were trained with flower classes with five (flower dataset) and seventeen (Oxford 17) types of flowers and their performances were compared. Performance tests, it is aimed to measure the success of different model optimizers in each data set. For the Oxford-17 data set in experimental studies; With Adam optimizer 93.14% in MobileNetV2 model, 95.59% with SGD optimizer, 92.85% with Adam optimizer in ResNet152v2 model, 88.96% with SGD optimizer, 91.55% with Adam optimizer in InceptionV3 model, 91.55% with SGD optimizer Validation accuracy of 87.66, InceptionResnetV2 model was 86.36% with Adam optimizer, 83.76% with SGD optimizer, 94.16% with Adam optimizer in DenseNet169 model and 90.91% with SGD optimizer. For the dataset named Flower dataset; With Adam optimizer 91.62% in MobileNetV2 model, 80.80% with SGD optimizer, 92.94% with Adam optimizer in ResNet152v2 model, 85.03% with SGD optimizer, 90.71% with Adam optimizer in InceptionV3 model, 82% with SGD optimizer, 62, InceptionResnetV2 model, 88.62% with Adam optimizer, 81.84% with SGD optimizer, 90.03% with Adam optimizer in DenseNet169 model, 82.89% with SGD optimizer. When the results are compared, it is seen that the performance rate of deep learning methods varies in some models depending on the number of classes in the data set, and in most models depending on the optimizer type.

Keywords - **Convolutional neural network, deep learning, image classification, flower classification.**

Date of Submission: Jul 19, 2022 Date of Acceptance: Sep 12, 2022

I. INTRODUCTION

Reconnaissance, surveillance, and real-time image transmission are critical, there are many types of flowers in nature and flowers are widely used in fields such as health, industry, and cosmetics. It is important to determine flower types for correct use in different sectors [1]. In determining the flower types, it is necessary to determine the distinctive features of each flower. Therefore, species identification and classification is a very laborious and time-consuming process. Determining flower types with human abilities becomes more difficult as the number of varieties increases. With the developing technology, this classification process can be done with information processing methods [2].

For flower classification with information technologies, first of all, flower pictures must be taken from different angles. These flower pictures are evaluated in the presence of experts and completed with labeling, that is, the determination of the flower type. Afterward, systems were developed that separate the flower from each other by cleaning the foreground and background of the flower with image processing methods. Recently, adequate flower painting, experience and equipment development, artificial intelligence systems, and automatic classification methods are recommended. Characteristics that distinguish flowers from each other, such as flower texture, flower crown, color, and shape, are among the criteria that determine the flower type. Ready-made datasets were created together with the experiences obtained from artificial intelligence models [3-4]. Datasets such as Oxford and Flowers are widely used for flower classification processes in artificial intelligence applications [5].

In this study, flower classification was performed and performance evaluation was carried out using the flower dataset and MobileNet, DenseNet, Inception, and ResNet pre-learning models. In addition, learning models were optimized with Adam optimizer and SGD optimizer and the results were evaluated. The obtained accuracy results show that there can be positive improvements in flower classification depending on the optimizer and flower class number.

II. RELATED WORK

It is seen that there are similar studies in the proposed study type when the literature studies are examined.

Volume: 14 Issue: 02 Pages: 5385-5389(2022) ISSN: 0975-0290

Various algorithms have been proposed so far for flower classifications. First among these, first in flower classification, pairwise rotation invariant co-occurrence local binary pattern (PRICoLBP) [6], metric forests with GMM [7], generalized max-pooling (GMP) [8], color attention-based bag-of-words approaches have been used [9]. These methods are used, and classical classifiers such as SVM are preferred.

Recently, CNN, one of the deep learning algorithms, has been used in the semantic classification of images of flowers classifications. In addition, CNN learning is preferred based on transfer learning approaches. For this, using previously trained models, the experience of these algorithms has been turned into an advantage in flower classification [10]. The flower Dataset collected from Flickr, Google, and Kaggle is used as the dataset. In a proposed study, it is stated that for flower object detection, localization, and classification, ResNet 50, ResNet 101, Inception ResNet V2, Inception V2, NAS, and MobileNet V2 transfer learning methods were trained and evaluated on the flower 30 dataset containing 19679 flower images and flower 102 datasets. His proposed model gave an accuracy of 87.6% in the 102-flower class dataset and 96.2% in the 30-flower class dataset [11]. In another study, a deep learning-based approach is presented for flower image recognition systems using Oxford-17 and Oxford-102 datasets based on InceptionV3. In this study, it was stated that the classification success rate was 95% [12].

In this context, the original aspects that distinguish our study from the literature are as follows.

- Training the classification model with datasets with 5 and 17 classes
- The use of different optimization algorithms for learning models and the evaluation of accuracy performance separately.

III. METRIAL AND METHOD

In this section, information about DenseNet121, Resnet50, Inceptionv3, and EfficientNet, which are the algorithms in which the study is classified, are given. EfficientNet is envisioned as a group convolutional neural network model. The EfficientNet algorithm scales with the parameters of depth, width, and resolution [13].

Inception V3 is basically a convolutional neural network model and consists of a large number of convolution and maximum pooling steps [14]. The last layer of the model contains a fully connected neural network. The most important feature that distinguishes it from Inception v2 is the addition of a batch-normalized (FC) layer as a helper classifier [15].

The densely connected convolutional network called DenseNet121 consists of forwarding linking of each layer to the other layers [16]. In the DenseNet learning algorithm, each layer uses the properties of all previous layers as input. DenseNet consists of a total of 121 layers, including four dense blocks and three transition layers [17].

ResNet50 is a 50-layer neural network trained on the ImageNet dataset. ImageNet is known as an image database with more than 14 million images belonging to more than 20 thousand categories [18]. Unlike standard ESAs, shortcut connections are used in ResNet architectures. Shortcut links do not contain extra parameters and do not cause computational complexity [19].

The development of pre-learning neural network models is based on an optimization problem. The accuracy of the neural network algorithms used in the study was evaluated with Adam and Stochastic Gradient Descent (SGD) optimizer algorithms. Here, Adam's optimization algorithm is the gradient descent algorithm proposed by combining the advantageous aspects of Rmsprop and momentum methods. SGD is an approach used for discriminant learning of linear classifiers under convex loss functions in different machine learning algorithms [20].

In the comparison of the proposed model in flower classification with pre-learning, with different optimizer algorithms, performance evaluation was made with accuracy. Accuracy is one of the most used metrics to measure the success of a model [21]. Accuracy is expressed as the ratio of all correct classifications (TP and TN) to all classifications (TP, TN, FP, FN) as shown in Equation 1. In addition, the error function is used for the error performance of the model. The error function calculates how far the flower type classified in the model is from the correct classification and is expected to approach zero overtime during training [22].

$$acc = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

3.1 Dataset

In the study, two different flower datasets, named “Flowers Dataset” and “Oxford-17”, were used (Fig 1). The Flowers Dataset contains 3673 flower images in five categories. Image data is collected from Flickr, Google, and Yandex images. The pictures are divided into five classes daisy, tulip, rose, sunflower, and dandelion, and are anonymous.

Fig. 1.Flowers Dataset dataset sample images

Oxford-17 is a flower dataset with 17 different flower categories and 80 images in each category (Fig 2). It was created by Nilsback and Zisserman, a flower species seen in England [http://www.robots.ox.ac.uk/~vgg/data.html]

Fig. 2.Oxford-17 dataset sample images

IV. RESEARCH FINDINGS AND DISCUSSION

In experimental studies, deep learning models with pre-learning were used. The study was carried out using Python Programming language and TensorFlow2 library on Kaggle and Google Colab platforms. 5-class Flowers Dataset and 17-class Oxford-17 dataset were used in the training of pre-learning models. 80% of the 3670 images in the Flower Dataset are reserved as training and validation (validation) and 20% as test data. Similarly, 70% of the 1360 images in the Oxford-17 dataset were classified as training, 15% as validation, and 15% as test data. Training of each model was run for 5, 15, 50, and 100 epochs for Adam and SGD optimizers. The results obtained using the Flower Dataset are given in Table 1 and the results obtained from Oxford-17 are given in Table 2.

Table 1. Results from training models with Flower Dataset

Model	Epoch	Optimizer	Train		Validation	
			loss	Acc	loss	Acc
Mobilenetv2	50	Adam	0.4864	0.9162	0.4960	0.9032
	50	SGD	0.7090	0.8080	0.5904	0.8521
Resnet152v2	50	Adam	0.4321	0.9294	0.4672	0.9178
	50	SGD	0.5908	0.8503	0.5534	0.8759
Inceptionv3	50	Adam	0.4864	0.9071	0.5093	0.9105
	50	SGD	0.6706	0.8262	0.5610	0.8759
inceptionResnetv2	50	Adam	0.5430	0.8862	0.5432	0.8795
	50	SGD	0.6743	0.8184	0.5822	0.8503
DenseNet169	50	Adam	0.5151	0.9003	0.4579	**0.9324**
	50	SGD	0.6638	0.8289	0.5111	0.9051

Table 2.Results from training models with Oxford-17

Model	Epoch	Optimizer	Train		Validation	
			loss	Acc	loss	Acc
Mobilenet_v2	50	Adam	0.2019	0.9517	0.2967	0.9314
	50	SGD	0.0033	0.9996	0.2100	**0.9559**
Resnet152v2	50	Adam	0.6748	0.9133	0.6374	0.9285
	50	SGD	1,1389	0.7229	0.7570	0.8896
Inception_v3	50	Adam	0.6962	0.9179	0.6979	0.9155
	50	SGD	0.9229	0.8080	0.7294	0.8766
InceptionResnet_v2	50	Adam	0.6248	0.8359	0.8242	0.8636
	50	SGD	1,1886	0.7177	0.9087	0.8376
DenseNet169	50	Adam	0.6575	0.9253	0.5846	0.9416
	50	SGD	0.9537	0.8012	0.7344	0.9091

It is observed that the accuracy values are compatible with the studies in the literature when the findings obtained as a result of the training of the models are examined. It was seen that the highest accuracy for the Flower dataset was obtained for the Adam optimizer in the DenseNet model. The lowest accuracy was obtained for the SGD optimizer in the InceptionResnet model. For the Oxford-17 dataset, the highest accuracy was obtained for the SGD optimizer in the MobileNet model, while the lowest accuracy was obtained for the SGD optimizer in the InceptionResnet model. The training and validation graphics of the DenseNet model, which has the highest success rate among the results obtained using the Flower dataset, are given in Fig. 3, and the training and validation graphics of the DenseNet model, which has the highest success rate for the Oxford-17 dataset, are given in Fig. 4.

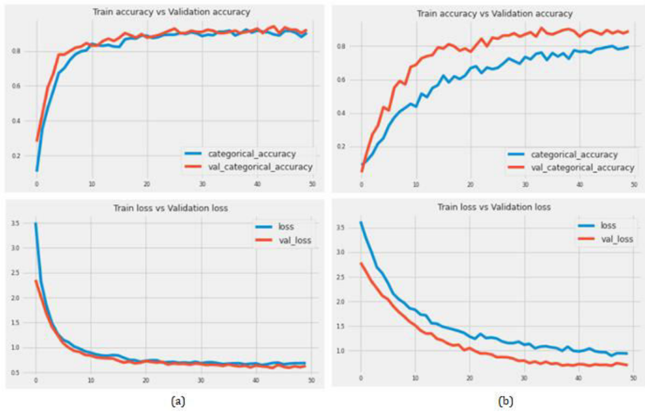

Fig. 3. Flower Dataset dataset accuracy and loss graph for DenseNet model, a) Adam, b) SGD optimizer

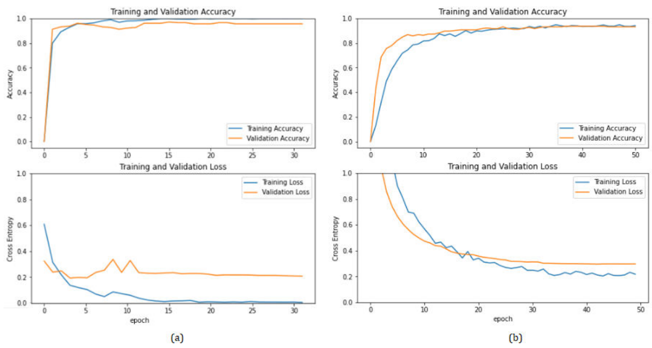

Fig. 4. Oxford17 dataset accuracy and loss graph for MobileNet model, a) SGD, b) Adam optimizer

When the research findings are examined, Adam optimizer; For the 5-class data set, it has been found that all five models have a higher success rate than the SGD optimizer. When the Adam optimizer was selected as the parameter for the 17-class data set, it achieved a higher performance rate than the SGD optimizer in the other four models, except for the MobileNet model.

When the models are evaluated according to the number of classes (5-17) in the data set; it was seen that Mobilenet_v2, Resnet152v2, Inceptionv3, and DenseNet169 models achieved almost the same accuracy in the both datasets, they reached relatively higher accuracy in the 17-class dataset. On the other hand, the InceptionResnetv2 model has a relatively lower accuracy in the 17-class dataset than the 5-class dataset.

V. CONCLUSION

In the study, using flower datasets containing different numbers of classes, separate training of pre-learning deep learning models for man and SGD optimizer parameters were carried out. It was observed that the Adam optimizer achieved higher classification accuracy than the SGD optimizer in both data sets. Considering the optimizers, it was concluded that the accuracy rates of the models were not significantly affected by the number of classes 5 and 17.

Comparisons can be made by including the Oxford-102 dataset with 102 classes as a third dataset for subsequent studies. In addition, different deep learning models such as VGGNet and EfficientNet, which were not used in the study, can be involved in model training for different optimizer parameters (RMSprob, AdaGrad, etc.).

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BIOGRAPHIES AND PHOTOGRAPHS

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