Pre-trained Deep Neural Network Model of VGG 16 for Flower Image Classification

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***Abstract*— Flowers are everywhere around us. They can feed insects, birds, animals and humans. They are also used as medicines for humans and some animals. A good understanding of flowers is essential to help in identifying new or rare species when came across. This will help the medicinal industry to improve. As the classification of flower species is an important task, it is already in research and many different approaches have been developed. Currently, flower image classification methods can be divided into two categories such as methods based on manual feature extraction and methods based on deep learning to automatically extract features. Manual feature extraction methods mostly extract colour features, texture features, and shape features of images, and combine them with machine learning algorithms for classification. Aiming at the problem that the classification accuracy of the traditional flower classification method is low and the deep neural network requires a large amount of original data. In this work, we proposed a model based on fine-tuning of a pre-trained deep learning model, called VGG16. The experimental results on the international public flower recognition dataset, Oxford flower-102 dataset, show that by enhancing the original data, the accuracy of the network's recognition and classification of flowers is improved. At the same time, the model proposed in this work is superior to other traditional network models, with higher recognition accuracy and robustness.**

***Index Terms*— Image Classification, VGG Model, Convolutional Neural Network, 102 Flower Image Dataset**

I. INTRODUCTION

Information from Flowers are an integral part of our ecosystem. They are mainly used in floriculture, the cosmetic industry and herbal medicine. Given several flower images, it is very time-consuming to identify flower species manually. Species information on the various ranges of flowers is important to protect and manage biodiversity. Also, flowers are considered as the most important part of the food chain and habitat for almost all insect pollinators. Therefore, owning an adequate recognition of flower species is essential for biodiversity protection. There are thousands of flowers grow in a wide variety in different countries of the world. Manual identification of all these flower species is a time-consuming and challenging task for even botanical experts. What distinguishes one flower from another can sometimes be the colour, e.g. bluebell vs sunflower, sometimes the shape, e.g. daffodil vs dandelion, and sometimes patterns on the petals, e.g. pansies vs tigerlilies etc. The difficulty lies in finding suitable features to represent colour, shape, patterns etc., and also for the classifier having the capacity to learn which feature or features to use.

Automated flower classification is challenging due to a large number of similarities among classes, the complex structure of flowers and the unpredictable variety of flower classes in nature. Flower image classification is a vibrant research area in image processing and computer vision. Plenty of classifiers have been proposed in the recent past for different applications. Most traditional classifiers use local, global or both types of image features. Low classification accuracy due to inadequate feature descriptors is the major limitation of these methods. Recently, with the development of computer vision technology, flower classification has significantly progressed in computer vision. Especially that different types of flowers own similar shapes, colors, and petals. Therefore, the development of a computer-aided method is an urgent step for fast and accurate flower categorization. Various techniques have been developed for image classification, which can be divided into two groups such as traditional machine learning methods and deep learning methods. In the first group of methods, raw images should be transformed into a suitable format in which machine can easily extract handcrafted features such as color, shape and texture [1]. In the second group, raw images can be fed to Convolutional Neural Networks (CNNs) directly without doing much pre-processing. Most of the traditional methods require various pre-processing techniques. This is very challenging. Therefore many researchers have automatically done feature extraction instead of using manual methods. Deep learning has provided excellent results in the applications of computer vision like object detection, image segmentation, image classification etc. Different neural layers process an enormous amount of data in deep Convolutional Neural Networks (CNNs), like the human brain. Deep features are very much valuable for image classification.

Deep learning expands the scope of artificial intelligence and has made great achievements in recent years, among which the deep learning model of convolutional neural network can realize the extraction of relevant features through convolution and achieve great performance improvement in large-scale image classification tasks. The traditional image classification methods mainly extract the shape features, color features and texture features of the image. Using the manual feature extraction method, there will be difficulties in feature selection and insufficient feature extraction.

This paper presents a VGG16 model based on different kinds of flower image screening, classification and recognition method. In the proposed method, the image is passed through a stack of convolutional (conv.) layers, where we use filters with a very small receptive field of 3 × 3. The convolution stride is fixed to 1 pixel, the spatial padding of convolution layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for 3 × 3 convolutional layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the convolutional layers. Max-pooling is performed over a 2 × 2 pixel window, with stride 2. A stack of convolutional layers is followed by three Fully-Connected (FC) layers. The first two have 4096 channels each, the third performs 102-way ILSVRC classification and thus contains 102 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non-linearity.

This paper is organized in 6 sections. The section 2 discusses about existing works proposed for image classification. The dataset characteristics are explained in section 3. The proposed approach and the components that are used in the proposed approach are explained in section 4. The experimental results of proposed approach are explained in section 5. The section 6 concludes this paper with future enhancements.

II. LITERATURE SURVEY

Previously, methods like Deformable Part Models [2], Histogram of Oriented Gradients [3] and Scale invariant feature transform [4] were used for feature extraction, linear classifiers and object detectors [5]. Later the work was focused on segmentation and classification using manual feature engineering. But nowadays, state-of-art performance is achieved by Convolutional Neural Networks. CNNs have fulfilled the demand of robustness and have removed the need of hand crafted features. They are similar to Artificial Neural networks but do not require feature engineering. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linear operation. At the last, CNNs also have a loss function which is to be minimized for optimization.

Several papers [6, 7] have proposed methods explicitly for the automatic segmentation of a flower image into flower as foreground, and the rest as background. The segmentation scheme proposed by Nilsback and Zisserman [6] proceeds in an iterative manner: first an initial flower segmentation is obtained using general (non-class specific) foreground and background colour distributions. These distributions are learnt by labelling pixels in a few training images of each class in the dataset as foreground (i.e. part of the flower), or background (i.e. part of the greenery), and then averaging the distributions across all classes. Given these general foreground and background distributions, the initial binary segmentation is obtained using the contrast dependent prior MRF cost function of [8], optimized with graph cuts. This segmentation may not be perfect, but is often sufficient to extract at least part of the external boundary of the flower. A generic flower shape model is then fitted to this initial segmentation in order to detect petals. The model selects petals which have a loose geometric consistency using an affine invariant Hough like procedure. The image regions for the petals deemed to be geometrically consistent are used to obtain a new image specific foreground colour model. The foreground colour model is then updated by blending the image specific foreground model with the general foreground model. The MRF segmentation is repeated using this new colour model. In cases where the initial segmentation was not perfect, the use of the image specific foreground often harvests more of the flower. The steps of shape model fitting and image specific foreground learning can then be iterated until convergence, when no or very little change has occurred between two consecutive iterations. This scheme was introduced the usage of a 13 class flower dataset, a subset of the 17 class flower dataset of [9]. It can be seen that it also works well for flowers very different in shape to those used in [6].

In recent computer vision research, the advent of the Vision Transformer (ViT) has rapidly revolutionized various architectural design efforts. ViT achieved state-of-the-art image classification performance using self-attention found in natural language processing, and MLP-Mixer achieved competitive performance using simple multi-layer perceptrons. In contrast, several studies have also suggested that carefully redesigned convolutional neural networks (CNNs) can achieve advanced performance comparable to ViT without resorting to these new ideas. Against this background, there is growing interest in what inductive bias is suitable for computer vision. In [10], they proposed a Sequencer which is a novel and competitive architecture alternative to ViT that provides a new perspective on these issues. Unlike ViTs, Sequencer models long-range dependencies using LSTMs rather than self-attention layers. They also proposed a two-dimensional version of Sequencer module, where an LSTM is decomposed into vertical and horizontal LSTMs to enhance performance. Despite its simplicity, several experiments demonstrate that Sequencer performs impressively well: Sequencer2D-L, with 54M parameters, realizes 84.6% top-1 accuracy on only ImageNet-1K.

Automatic classification of flowers is essential in research on flowers, medicinal use of flowers, flower patent analysis etc. Traditionally, flower classification is done using low-level features like color, shape, texture and geometry. There exist large intra-class variation and interclass similarity among flower classes. Search engine-based flower identification and classification system are not efficient and robust because they are based on visual search. The accuracy and robustness of flower classification depend highly on the feature descriptor. Deep features have shown excellent performance in the last few years on high-resolution images, but they cannot extract accurate global features from low-resolution images. In [11], the researchers proposed an efficient flower classification system using a fusion of handcrafted features and deep features. Low-level features are extracted using Colour Coherent Vector (CCV), Centre Symmetric Local Binary Pattern (CSLBP) and Edge Histogram Descriptor (EHD). Deep features are extracted from pre-trained networks: ResNet-50 and AlexNet. Further, a Multiclass Support Vector Machine (SVM) is used to yield high classification accuracy. Experiments are carried out on Oxford Flower 17, Flower102, Kaggle flower dataset and Corel-1K dataset. Classification accuracy of 100, 95.3, 94 and 92% is obtained on the Corel dataset, Oxford Flower 17, Kaggle flower dataset and flower 102 dataset, respectively, which is better than existing approaches. A remarkable achievement in classification accuracy of 86.4% is observed on the pooled dataset.

M. Ghazi et al., [12] employed pre-trained AlexNet, GoogleNet and VGG-16 CNNs for the flower classification. They used the image augmentation technique to obtain the new augmented image dataset and observed an accuracy of 80%. Tian et al., [13] classified images from Flower 17 dataset using the data augmentation method with their CNN model. The classification was done using the Softmax function. The authors reported a classification accuracy of 92%. The base Vgg-16 model was fine-tuned in [14] to classify flowers into five categories. The authors reported a classification accuracy of 95%. However, this approach could classify only five types of flowers. It was reported in [15] that deep features outperform handcrafted features. The authors analysed classification accuracies using OverFeat, Inception-v3 and Xception architectures on Flower 102 dataset, and it was reported that Inception-V3 yields the highest accuracy among the three architectures. In [16], an analysis of the performance of VGG-16, VGG-19 and Resnet-50 on the ImageNet dataset was presented. The arbitrary set of annotated images was given as input to these three networks for classification. It was reported by the authors that the performance of ResNet-50 was better compared to VGG-16 and VGG-19.

In the recent past, Deep CNN has been used popularly for solving complex problems with a massive amount of data [17]. Authors obtained good classification accuracy using the ImageNet dataset [18] consisting of 1000 categories. The motivation for using deep features was to eliminate the difficulty in feature extraction. Nowadays, deep learning technology is considered a promising research topic in machine learning, artificial intelligence, data science and analytics because of its learning capabilities from the given data [19]. In [20], AlexNet, GoogleNet, ResNet-50, and VGG-16 CNN models were used for feature extraction. Efficient features were selected and classified by SVM. Excellent classification success on the Kaggle flower dataset demonstrated the importance of deep features. However, four deep networks were used by authors. In [21], authors have explained advancements in image classification using different Convolutional Neural Networks.

In recent times, deep learning methods play a pivotal role in complicated tasks, such as extracting useful features, segmentation, and semantic classification of images. These methods had significant effects on flower type's classification during recent years. In [22], they are trying to classify 102 flower species using a robust deep learning method. To this end, the authors used the transfer learning approach employing DenseNet121 architecture to categorize various species of oxford-102 flowers dataset. In this regard, they have tried to fine-tune their model to achieve higher accuracy respect to other methods. The researchers performed pre-processing by normalizing and resizing of their images and then fed them to their fine-tuned pretrained model. They divided our dataset to three sets of train, validation, and test. They achieved the accuracy of 98.6% for 50 epochs which is better than other deep-learning based methods for the same dataset in the study.

The fast progress of deep learning makes Convolutional Neural Network (CNN) emerges at the historic moment, and as an important achievement, it has been extensively used in all sorts of fields. Compared with traditional machine learning, CNN has more advantages, on the one hand, it has more hidden layers and complex network structure, and on the other hand, it has a stronger ability of feature learning and feature expression. With the fast progress of computer technology, the application research of fast and accurate recognition and classification of flowers by obtaining flower images through mobile devices has received extensive attention. In [23], authors observed that the flowers images collected under natural conditions have large background interference, and it is difficult to recognize flowers because of their inter-class similarity and intra-class diversity. Therefore, in view of the lack of flower image data and low classification accuracy, the experiment sorted out the data sets of four kinds of flowers, and used the CNN to classify the images. Compared with the traditional approaches, the classification precision can be largely enhanced.

Aiming at the problem that the classification accuracy of the traditional flower classification method is low and the deep neural network requires a large amount of original data. in [24], they designed a flower classification model that combines generative adversarial network and ResNet-101 transfer learning algorithm, and uses stochastic gradient descent algorithm to optimize the training process of the model. The experimental results on the international public flower recognition dataset, Oxford flower-102 dataset, show that by enhancing the original data, the accuracy of the network's recognition and classification of flowers is improved. At the same time, the model proposed in this paper is superior to other traditional network models, with higher recognition accuracy and robustness.

III. DATASET CHARACTERISTICS

In this work, the oxford 102 flower dataset is used in the experiment. The dataset consists of 8189 images divided into 102 flower categories. The flowers are chosen to be flower commonly occurring in the United Kingdom. Each class consists of between 40 and 258 images. This dataset is more challenging since it has more images and categories. The images have large scale, pose and light variations. In addition, there are categories that have large variations within the category and several very similar categories. The Figure 1 shows the class labels of 102 flowers.

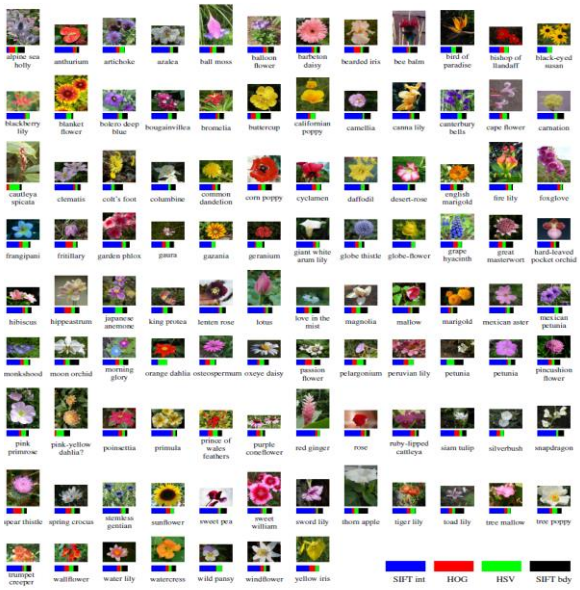

Figure 1: The 102 flower dataset.

IV. PROPOSED APPROACH

In this proposed approach we used VGG pretrained model for image classification. VGG stands for Visual Geometry Group, it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The “deep” refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG16 model was trained using Nvidia Titan Black GPUs for multiple weeks. The VGGNet-16 supports 16 layers and can classify images into 1000 object categories, including keyboard, animals, pencil, mouse, etc. Additionally, the model has an image input size of 224-by-224. VGGNets are based on the most essential features of convolutional neural networks (CNN). The VGG network is constructed with very small convolutional filters. The VGG-16 consists of 16 convolutional layers and three fully connected layers. Figure 2 shows the architecture of VGG model.

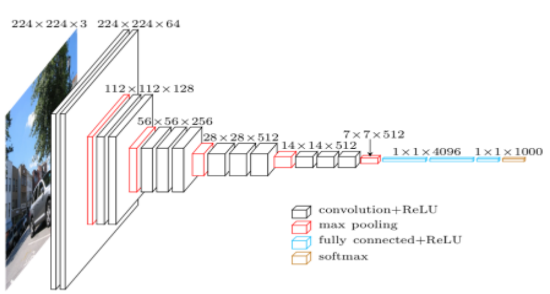

Figure 2: The Architecture VGG model

In the training, load a pre-trained network of VGG, define a new, untrained feed-forward network as a classifier, using ReLU activations and dropout. Train the classifier layers using the pre-trained network to get the features. Track the loss and accuracy on the validation set to determine the best hyperparameters. We passed an image into the network and predict the class of the flower in the image. The input to any of the network configurations is considered to be a fixed size 224 x 224 image with three channels – R, G, and B. Image is passed through the first stack of 2 convolution layers of the very small receptive size of 3 x 3, followed by ReLU activations. Each of these two layers contains 64 filters. The convolution stride is fixed at 1 pixel, and the padding is 1 pixel. This configuration preserves the spatial resolution, and the size of the output activation map is the same as the input image dimensions. The activation maps are then passed through spatial max pooling over a 2 x 2-pixel window, with a stride of 2 pixels. This halves the size of the activations. Thus the size of the activations at the end of the first stack is 112 x 112 x 64.

The activations then flow through a similar second stack, but with 128 filters as against 64 in the first one. Consequently, the size after the second stack becomes 56 x 56 x 128. This is followed by the third stack with three convolutional layers and a max pool layer. The number of filters applied here are 256, making the output size of the stack 28 x 28 x 256. This is followed by two stacks of three convolutional layers, with each containing 512 filters. The output at the end of both these stacks will be 7 x 7 x 512. The stacks of convolutional layers are followed by three fully connected layers with a flattening layer in-between. The first two have 4,096 neurons each, and the last fully connected layer serves as the output layer and has 102 neurons corresponding to the 102 possible classes for the 102 flower dataset. The output layer is followed by the Softmax activation layer used for categorical classification.

During training, the input to ConvNets is a fixed-size 224 × 224 RGB image. Image pre-processing techniques play an important role to improve the performance of proposed approach. In this approach, we used different pre-processing techniques like image resizing, conversion of values, and normalization. First, resize the images where the shortest side is 256 pixels, keeping the aspect ratio. Color channels of images are typically encoded as integers 0-255, but the model expected floats 0-1. We need to convert the values. The network expects the images to be normalized in a specific way. For the means, it's [0.485, 0.456, 0.406] and for the standard deviations [0.229, 0.224, 0.225]. Subtract the means from each color channel, and then divide by the standard deviation. The dataset is split into three parts, training, validation, and testing. For the training, apply transformations such as random scaling, cropping, and flipping. This will help the network generalize leading to better performance. We also need to make sure the input data is resized to 224x224 pixels as required by the pre-trained networks. The validation and testing sets are used to measure the model's performance on data it hasn't seen yet. For this we are not performing any scaling or rotation transformations, but we need to resize then crop the images to the appropriate size. The pre-trained networks we used were trained on the 102 flower dataset, where each color channel was normalized separately. For all three sets we need to normalize the means and standard deviations of the images to what the network expects.

A. Convolutional Neural network

The birth of convolutional neural network is closely related to biological natural visual cognition, which is generally composed of input layer, convolutional layer, pooling layer, full connection layer and output layer, among which the convolutional layer and pooling layer are usually carried out in turn. Due to image after convolution layer calculation diagram output characteristics, the characteristics of the output figure with the input of each neuron are local connection, and through the weighted average of the corresponding connection weights, and then sum, increase after the offset feature map is obtained by nonlinear activation function, then the feature map using filter convolution [26], was also named the convolutional neural network. ReLU activation function is used to add some nonlinear factors to the neural network, so that the neural network can better solve complex problems.

B. Convolutional layer

The convolution layer is composed of several convolution units, and the parameters of each convolution unit, such as the size of the convolution kernel, are optimized by the back propagation algorithm. The convolution operation is mainly used to extract the features of the input image. The primary convolution layer can only extract some small image features, such as lines, shapes, edges, etc., while more multi-layer convolution layers can extract more complex image features from these small features. Just as we human beings recognize pictures, the brain cannot recognize a picture instantaneously, but first locally recognize some features in the picture, and then comprehensively operate the local features of the image from a higher level, so as to get the global information of the whole picture [27].

C. Pooling layer

Pooling is also called subsampling, and its main function is to reduce the size of the feature image while maintaining the features of the image. In general, there is a pooling layer between the two convolution layers. The pooling layer does not contain parameters, and it only makes a subsampling of the characteristic map transmitted by the convolution layer, that is, data compression, to prevent overfitting. The pooling layer can play a role because the features of the image will not be changed, that is, the original features of the image will not be missing through the subsampling. According to this feature, the image can be shrunk down for convolution calculation, which can greatly reduce the time of convolution operation. There are usually two types of pooling such as maximum pooling and average pooling. Maximum pooling is to select the maximum value within the defined neighbourhood, while average pooling is to take the mean value within the neighbourhood.

D. Activation function

When the activation function works, some neurons are stimulated to continue the activation information into the later layer. The neural network can solve the nonlinear problem because of the lack of linear model expression force and the activation function adds the nonlinear factors, supplementing the expression force of the linear model, so the characteristics of the activated neurons are saved and mapped to the next layer through the activation function. There are many kinds of activation functions, where ReLU functions are more used, and the formula of ReLU functions is $f(x) = \max(x, 0)$.The ReLU function is all equal to 0 at $x < 0$, and the f (x) derivative is 1 at $x > 0$, so the ReLU function can make the gradient unattenuated at $x > 0$, which can not only prevent the gradient from disappearing, but also converge faster, compensating for the sparse expression ability of the neural network. The activation function used in this convolutional neural network model is the ReLU function.

E. Fully connected layer

The Fully connected layer is usually at the end of the convolutional neural network. The nodes in the Fully connected layer are connected to all the nodes in the upper layer. The main function of the Fully connected layer is to integrate the features extracted from the front. After convolution, activation function and pooling, enough features are extracted to identify the image, and then the image can be classified. Normally be enough to help identify the characteristics of the image by the neural network into a cuboid, at the end of the convolutional neural network will get into a vertical rectangle vector, the input to classify all connection to cooperate in the output layer, is about to get 2 d feature graph into a one dimensional vector. The layers preceding the full connection layer are mainly used to extract different features, while the fully connected layer integrates local information after convolution, activation functions and pooling.

F. Softmax classifier

Softmax classifier is the output layer of convolutional neural network. After receiving the real number vector of the fully connected layer by Softmax, the output is also a real number vector. Each value of the real number vector output by Softmax represents the probability that this sample belongs to each class. Each value of the output real vector has a size between 0 and 1.

V. EMPIRICAL EVALUATIONS

In this work, we used VGG16 pretrained model for image classification. The experiment performed on the 102 flower dataset. We used 3 epochs in the experiment. The experiment results after 3 epochs are represented in Table 1.

Table 1: The accuracies of proposed approach for image classification

Evaluation Measure	Image Classification
Validation Accuracy	0.851
Test Accuracy	0.762
Validation loss	0.709

In Table 1, it was observed that the proposed approach attained best validation accuracy of 0.851 for 102 flower image classification. The proposed approach obtained test accuracy of 0.762 for 102 flower image classification. The proposed approach attained less validation loss of 0.709 for image classification.

VI. CONCLUSIONS AND FUTURE SCOPE

In this work, we trained an image classifier by using VGG16 to recognize different species of flowers. Our proposed model is based on fine-tuning of a pre-trained deep learning model, called VGG16. This model utilizes transfer learning of a CNN-based model to automatically differentiate various types of flowers. The proposed approach attained best validation accuracy of 0.851, test accuracy of 0.762, and validation loss of 0.709 for 102 flower image classification.

In future work, we are planning to develop an app to identify any type of image after scanning through this app. We are planning to implement this model for classification of other varieties of images.

REFERENCES

[1] R.Shaparia, N. Patel, and Z.Shah, “Flower classification using texture and color features”, 2: p. 113-118, 2017

[2] P. Felzenszwalb, D. McAllester, D. Ramaman, “A discriminatively trained, multiscale, deformable part model”, Proceedings of the IEEE CVPR 2008.

[3] Navneet Dalal and Bill Triggs, “Histograms of oriented gradients for human detection”, Proceedings of the IEEE CVPR 2005.

[4] DG Lowe, “Distinctive image features from scale-invariant keypoints”, International Journal of Computer Vision, 2004.

[5] Seeland M, Rzanny M, Alaqraa N, Wäldchen J, Mäder P, “Plant species classification using flower images—A comparative study of local feature representations”. PLoS ONE 12(2): e0170629. doi:10.1371/journal.pone.0170629

[6] M.-E. Nilsback and A. Zisserman. Delving into the whorl of flower segmentation. In Proc. BMVC., volume 1, pages 570–579, 2007.

[7] T. Saitoh, K. Aoki, and T. Kaneko. Automatic recognition of blooming flowers. In Proc. ICPR, volume 1, pages 27–30, 2004.

[8] Y. Y. Boykov and M. P. Jolly. Interactive graph cuts for optimal boundary and region segmentation of objects in ND images. In Proc. ICCV, volume 2, pages 105–112, 2001.

[9] M.-E. Nilsback and A. Zisserman. A visual vocabulary for flower classification. In Proc. CVPR, volume 2, pages 1447–1454, 2006.

[10] Yuki Tatsunami, Masato Taki, “Sequencer: Deep LSTM for Image Classification”, 36th Conference on Neural Information Processing Systems (NeurIPS 2022), arXiv:2205.01972v4 [cs.CV] 12 Jan 2023

[11] M. R. Banwaskar, A. M. Rajurkar, “An Efficient Flower Classification System using Feature Fusion”, International Journal of Engineering Trends and Technology, Volume 70 Issue 11, 70-80, November 2022

[12] M. Mehdipour Ghazi, B. Yanikoglu, and E. Aptoula, "Plant Identification Using Deep Neural Networks via Optimization of Transfer Learning Parameters," Neurocomputing, vol. 235, pp. 228-235, 2017.

[13] M. Tian, H. Chen, and Q. Wang, "Flower Identification Based on Deep Learning," Journal of Physics: Conference Series, vol. 1237, no. 2, 2019.

[14] Giraddi, S. Seeri, P. S. Hiremath and J. G.N, "Flower Classification using Deep Learning Models," International Conference on Smart Technologies in Computing, Electrical and Electronics, pp. 130-133, 2020

[15] I. Gogul and V. S. Kumar, "Flower Species Recognition System using Convolution Neural Networks and Transfer Learning," IEEE Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), pp. 1-6, 2017.

[16] Sushma L, and K.P. Lakshmi, "An Analysis of Convolution Neural Network for Image Classification using Different Models," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 10, 2020.

[17] Huthaifa Almogdady, Dr. Saher Manaseer, and Dr.Hazem Hiary, "A Flower Recognition System Based on Image Processing and Neural Networks," International Journal of Scientific and Technology Research, vol. 7, no. 11, pp. 166-173, 2018.

[18] A. Krizhevsky, I. Sutskever, and G.E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems, pp. 1-9, 2012.

[19] Fei Hu, Fuguang Yao, and Changjiu Pu, "Learning Salient Features for Flower Classification Using Convolutional Neural Network," 2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS), pp. 476-479,2020.

[20] Mesut Togˇaçar a, Burhan Ergen, and Zafer Cömert, "Classification of Flower Species by using Features Extracted from the Intersection of Feature Selection Methods in Convolutional Neural Network Models," Measurement, vol. 158, 2020.

[21] Farhana Sultana, Abu Sufian, and Paramartha Dutta, "Advancements in Image Classification using Convolutional Neural Network," Fourth IEEE International Conference on Research in Computational Intelligence and Communication Networks, pp. 122-129, 2018.

[22] Neda Alipour, Omid Tarkhaneh, Mohammad Awrangjeb, Flower Image Classification Using Deep Convolutional Neural Network, Conference Paper · May 2021 DOI: 10.1109/ICWR51868.2021.9443129

[23] Zhao Jiantao1, Chu Shumin, Research on Flower Image Classification Algorithm Based on Convolutional Neural Network, 2021 International Conference on Big Data and Intelligent Algorithms (BDIA 2021), Journal of Physics: Conference Series 1994 (2021) 012034

[24] Xiaoxue Li, Rongxin Lv, Yanzhen Yin, Kangkang Xin4, Zeyuan Liu and Zhongzhi Li, Flower image classification based on generative adversarial network and transfer learning, IOP Conf. Series: Earth and Environmental Science 647 (2021) 012180

[25] Nilsback, M-E. and Zisserman, A. “Automated flower classification over a large number of classes”. Proceedings of the Indian Conference on Computer Vision, Graphics and Image Processing (2008)

[26] Lin Peijun, Geng Zengmin, Hong Ying, Li Xuefei. Application of Convolutional Neural Network in Textile and Clothing Imagery [J]. Journal of Beijing Institute of Clothing (Natural Sciences), 2021,41 (01): 92-99

[27] Wang Bin, Gao Jiaping, Si Shtao. Image Classification and Application Based on Convolutional Neural Network [J]. Electronics and Packaging, 2021,21 (05): 76-80