Flower Classification using Deep Learning models

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***Abstract*— Deep learning techniques are used widespread for image recognition and classification problems. Gradually, deep learning architectures have modified to comprise more layers and become more robust model for classification problems. In this paper, the base VGG16 model is fine-tuned for the classification flowers into five categories, namely, Daisy, Dandelion, Sunflower, Rose and Tulip flowers. The fine-tuned VGG16 model is trained using 3520 flower images. The model is achieved a classification accuracy of 97.67% for validation set and 95.00% for testing dataset. The Kaggle dataset is used for training, validation and testing of the proposed fine-tuned VGG16 model. The goal of this work is to show that a proper modified VGG16 deep model, which is, pre-trained on ImageNet for image classification can be used for other image data set using very small dataset without over fitting. The VGG16 model uses mall size 3x3 filters.**

Keywords: convolution neural network; transfer learning, deep learning, Fine-tuning, VGG16.

I. INTRODUCTION

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. The system proposed in the paper can be used by botanists, campers and doctors alike. This can be extended as an image search solution where photo can be taken as an input instead of text in order to get more information about the subject and search accordingly for best matching results.

The importance of building automated flower recognition method stands out in many benefits such as providing fast recognition for harvesting robots. The automated flower recognition gives the people, with limited experience in flower species, the ability to recognize the species of a flower, with the advantages of saving time and effort. Also, recently there has been a demand for flower floriculture which has made it important commercial trades in agriculture. This system could help in the field of floriculture in a commercial way.

It is very tough mission to categorize different types of flowers due to several reasons. There is lot of variation in colors within a class of flowers and lot of similarity between several classes. Even expert botanists and gardeners cannot identify some of them accurately. Also flowers are not rigid objects; appearance can be affected by many external factors like temperature, sunlight, nutrition and humidity. There is a need for competent automated system to identify and recognize flower species.

II. LITERATURE SURVEY

Maria-Elena et al., (2008) performed a Flower Classification on dataset with 103 classes. The method uses features computed from local shape/texture, the boundary-shape, spatial distribution of petals, and the colour. Author conducted study using SVM classifier with a multiple kernel framework and achieved classification accuracy of 55.1% (single feature) and 72.8% (all features). Xiaoling Xia et al., (2017) proposed method for Flower Classification using Inception-v3 with transfer learning concept. Authors used Oxford-I7 and Oxford-I02 flower dataset. The back propagation neural network (BPNN) is used to train the last layer. The Classification accuracy is 95% on Oxford-I7 flower dataset and 94% on Oxford102 flower dataset is achieved. Hossam M. Zawbaa et al., (2014) proposed method for flower classification (eight categories) using Support Vector Machine (SVM) and Random Forests (RF) classifiers, which, are trained using Scale Invariant Feature Transform (SIFT) and Segmentation-based Fractal Texture Analysis (SFTA) based features. Ayşe ELDEM et al., (2018) proposed method for Iris Classification using a Deep Neural Network with different activation Functions. The Relu, sigmoid and Tanh functions are used in hidden layers with epochs (100 to 400). Yong Wu, Xiao Qin et al., (2018) conducted study using Oxford-17 and Oxford-102 flower dataset. Convolution neural network models VGG-16, VGG-19, Inception-v3 and ResNet50 models are used with transfer learning. Xie et al. (2011) proposed image classification and retrieval algorithms with LandUse-21 dataset, Indoor-67 dataset and SUN-397 dataset. Authors proposed (Online Nearest-neighbour Estimation), a unified algorithm for both image classification and retrieval. Guru et al., proposed a model for flower classification using KNN classifier. Authors created own dataset of 25 species. Segmentation is carried out using threshold based method followed by GLCM based feature extraction and Gabor filter response. Nilsback and Zisserman (2011) proposed method based on image features, including local shape/texture, boundary shape, colour and spatial distribution of petals colour for flower classification using SVM classifier with multiple kernels. Deshpande et al.(2019) proposed a methodology on Haar wavelet features for decease detection. Shantala et al.(2020), conducted study on fungal decease detection in maize leaves using deep learning models.

III. PROPOSED METHODOLOGY

The proposed method for the classification of flowers is shown in figure 1.

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Dataset : The Kaggle dataset is used in this study. The dataset set contains five categories of flower images i e. Daisy, Dandelion, Sunflower, Rose And Tulip.
Daisy : 813 images. Dandelion : 1055 images, Sunflower: 734 images, Rose : 784 images, and Tulip : 984 images. The dataset consist of 4326 images and Images are about size 320x240 pixels. The dataset is divided into training dataset (80 %), validation dataset (10%) and testing dataset (10%).
The methodology consists of five steps: Data Splitting, pre-processing, training Fine-tuning VGG16, model validation and finally testing the model on the test dataset

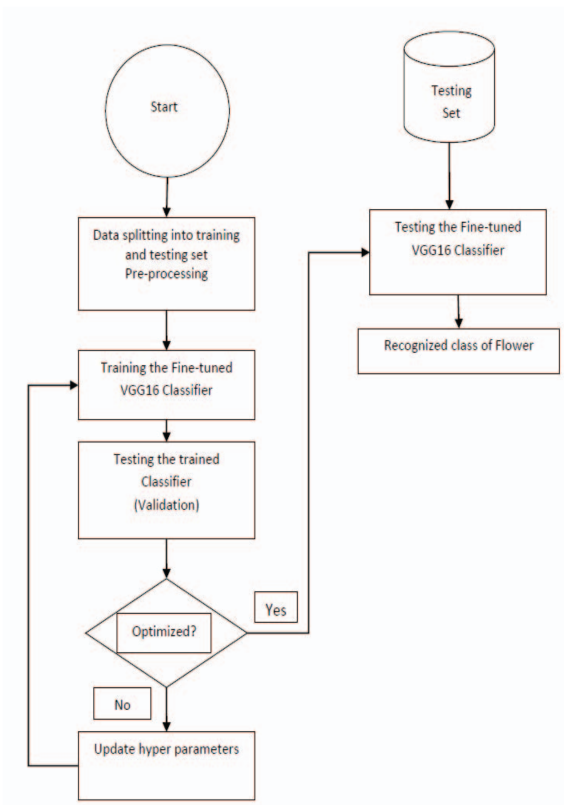

Figure 1. Proposed Methodology

A. Data Splitting: In this phase, the dataset is divided into training dataset, validation dataset and testing dataset. Training dataset is used to train fine-tune VGG16 model, validation dataset is used to validate VGG16 model and testing dataset is used to test the accuracy of the trained VGG16 model.

B. Pre-processing: In this phase, image features are enhanced for further processing, and all images are resized to 224x224 and this done using Keras pre-processing library Image Data Generator. In this phase, flowers are extracted from the given image. The Data augmentation is done using Image Data Generator.

C. Training: In this phase, the top layer of the pre-trained model was removed and replaced with a new fully connected layer with a Softmax classifier. The Dense layer is the densely-connected Neural Network layer of size 1024 with the Rectified Linear Unit (relu) as the activator. In the Fine Tuning phase, all convolution layers of the model are trained using Stochastic Gradient Descent (SGD) optimizer with learning rate (0.0001) and a momentum (0.9). The 20 epochs and batch size of 32 (number of samples propagating through the network) .

D. Validation: In this step, the trained model is validated or evaluated by comparing training accuracy and validation accuracy.

E. Testing: In this phase, the fine-tuned VGG16 model is tested by predicting the classes of given flower images retrieved from testing dataset folder.

Implementation: The VGG16 pre-trained model, which is implemented using convolution layers, max pooling layers and dense layers is used by training last three layers using Adam optimizer with learning rate of 0.001, 20 epochs and batch-size of 32 for flower dataset. The VGG16 consists of 13 convolution layers, 5 max pooling layers and 3 dense layers and which sum up to 21 layers and only 16 weight layers are considered. The small size 3x3 filters are used for the processing the images in this model. The performance of the pre-trained VGG16 model is enhanced by fine-tuning VGG16 model.
The sample images used for training and validation of fine-tuned VGG16 model is shown in the Figure 2.

Figure 2. The sample images of Kaggle dataset.

IV. CONVOLUTIONAL NEURAL NETWORKS

Deep Learning is an emerging field of research and Transfer Learning is one of its benefits. In image classification, for example, Transfer Learning makes use of features learned from one domain and used on another through feature extraction and fine-tuning. Convolutional Neural Network (also known as ConvNet) models trained on the ImageNet's million images with 1000 categories can be successfully used on other similar or dissimilar datasets, large or small, with great success.

The small datasets can benefit from these pre-trained networks because the lower layers of these pre-trained networks already contain many generic features such as edge and color blob detectors and only the higher layers need to be trained on the new datasets.

Convolution Neural Network formed with the help of different layers to perform the image classification task. The architecture of the CNN contains the different layers as follows:

Input Layer: Used to accept input images, and dispatched to next layers for feature extraction.

Convolution Layer: Used to extract features from input image using image matrix and a filter (Kernel).

ReLU (Rectified-Linear Unit): ReLU replaces all negative values in the matrix to zero, which, helps faster and effective training. Thus, negative values are not passed to the next layer.

Pooling: It is used to reduce spatial size of the feature map and thus reduces the parameters required to preserve significant information.

Fully Connected Layer: Used to build feature vector of input images and thus used for the classification of images.

Softmax Layer: It is used to normalize output of the neural network (between zero and one) and used to represent network output as probability.

The first four stages are called feature extraction stages and last two are called classification stages (K indicates number of classes) are shown in Figure 3.

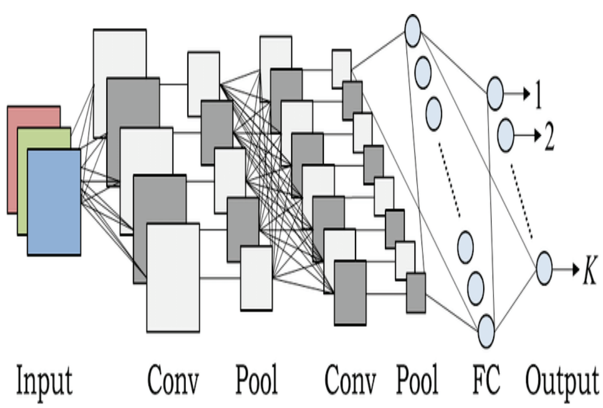

Figure 3: Convolution Neural Network Layers.

In VGG16, RGB images of size 224x224 are processed by five blocks of convolution layers. Each block is composed of growing numbers of 3x3 filters. The stride = 1 is used and the convolution layer inputs are padded to preserve spatial resolution. The blocks are joined by max-pooling layers. Max-pooling is applied over 22 windows with stride 2. The five blocks of convolution layers are followed by three fully-connected (FC) layers. The final layer is a soft-max layer that outputs class (Five classes) probabilities. The Figure 4 shows the layers present in VGG16 model.

Conv 1 uses 64 filters, Conv 2 uses 128 filters, and Conv 3 uses 256 filters. Both Conv 4 and Conv 5 use 512 filters.In the proposed fine-tuned VGG16 model, all layers are trained using flower dataset. The fine-tuning process adjusts the abstract representations of the model and thus used for flower classification.

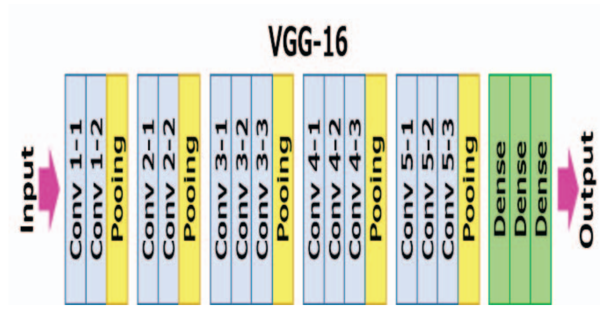

Figure 4: VGG16 layer definition

In transfer learning model, bottom layers in convolution block encode generic features whereas top layers encode specialized features based on the new dataset. Hence, retraining of fourth and fifth convolution block in VGG16 enables capture specialized features of flower dataset. The steps followed for fine-tuning of VGG16 model is as follows.

1. Set up fine tuning on pre-trained ImageNet VGG16 model – train all layers of VGG16.
2. Compile the revised model using SGD optimizer with a learning rate of 0.0001 and a momentum of 0.9
3. Fit the revised model, log the results and the training-time
4. Evaluate the Model
5. Save the Fine Tuning Model
6. Predict Unseen Images(Testing the model)
7. Stop

CNN Implementation: The base CNN model is implemented using 4 Convolution layers, 4 max pooling layers and 3 dense layers with Relu and Softmax activation layer. . The small size 3x3 filters are used for the processing the images in this model. The model was trained with Adam optimizer, learning rate of 0.001, The 20 epochs and a typical batch size of 32 (number of samples propagating through the network) were used for training this model.

V. Results and Discussions

The proposed algorithm is implemented using fine-tuned VGG16 on Google colab. The images are in JPEG format and in RGB color space. The Kaggle dataset is used in this study for training, validation and testing of fine-tuned VGG16 model. The dataset set contains five categories of flower images i e. Daisy flower dataset has 813 flower images. Dandelion flower has a 1085 flower images, sunflower dataset has a 734 flower images, rose flower dataset has a 784 flower images, and tulip flower dataset has 984 flower images. The dataset consist of 4400 images and Images are about size 320x240 pixels. The dataset is divided into training dataset (80 %), validation dataset (10%) and testing dataset (10%).

The performance metric, namely accuracy is used for analyzing the proposed fine-tuned VGG16 model, and is compared with transfer learning: base VGG16 model and convolution neural network (CNN). The Table 1 shows the performance of these models.

Serial No.	Model	Validation Accuracy (%)	Testing Accuracy (%)
1	Fine-tuned VGG16	97.67	95.00
2	VGG 16 (Transfer learning)	87.78	85.45
3	CNN	75.46	72.39

Table 1. Classification accuracies of various models.

The study conducted on classification of flowers using various deep learning models namely Fine-tuned VGG16, Base VGG 16 and CNN. The flower dataset is from kaggle. The Fine-tuned VGG16 is trained from the scratch. Base VGG 16 is pretrained model which is pretrained with Imagenet dataset. CNN is convolution neural network with 4 Convolution layers, 4 max pooling layers and 3 dense layers with Relu and Softmax activation layer. . The small size 3x3 filters are used for the processing the images. The authors obtained highest accuracy of 95% with Fine-tuned VGG16 which is trained with flower dataset.

VI. CONCLUSION AND FUTURE SCOPE

Authors carried out study on flower classification with various deep learning models. Highest accuracy is obtained with VGG fine tuned model which is trained from scatch with flower dataset. To further improve the results, larger data set can be used since testing error reduces with large data and the model is able to generalise better from a higher amount of information.

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