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Assessment Of Resnet Pre-Trained Networks For Flowers Classification Using Transfer Learning

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Abstract: Convolutional neural networks (CNNs), in particular, are deep learning approaches that have gained a lot of attention recently because of their greater accuracy compared to traditional machine learning techniques that rely on features that are manually generated. Advancements in hardware capabilities, specifically in the utilization of graphics processing units (GPUs), greatly accelerate deep learning techniques' processing times.

Utilize the most recent advancements in deep learning techniques, such as CNN, combined with the availability of adequately sized flower datasets in this work to robustly address the flower categorization challenge. In order to identify distinct flower classes, our automatic system first recognizes the area surrounding a flower in an image. Then, using the cropped images, it trains a powerful CNN classifier named as ResNet (18, 50 and 101). Our reliable approach is assessed on several well-known flower datasets, and the findings indicate that the suggested method performs at a suitable classification accuracy (CA) in the Kaggle datasets.

Keywords: Residual, ResNet, CNN, Classification Accuracy

1. Introduction

The process of recognizing an object as a particular entity inside an image or video is known as object recognition [1-3]. Deep learning, machine learning, and computer vision algorithms all produce important results, one of which is object recognition [4]. The technological foundation of many of the programs we use on a daily basis. The fundamental objective of object recognition is to educate a computer to perform a task that comes effortlessly to humans to recognize the contents of an image or video [1-4]. Deep learning approach has been widely used to classify object using pre-trained models. In this work, ResNet based pre-trained network has been used to classify flower objects using transfer learning approach.

A significant number of flower species have similar forms, appearances, or surrounding elements like grass and foliage, making flower categorization a difficult undertaking[3]. A novel two-step deep learning classifier is proposed by the authors of this study to differentiate flowers from a variety of species [1-5]. Initially, the flower-like area is automatically divided into pieces so that the minimum boundaries surrounding it may be identified. The suggested method for dividing flowers is represented as a multi classifier within a framework of fully convolutional networks. Secondly, they construct a strong convolutional neural network classifier to differentiate between the various kinds of flowers.

During the training phase, researchers propose methods that ensure reliable, precise, and simultaneous classification. Researchers test their method using the popular flower datasets. Five different flower species have been classified in this work using the well-known pre-trained network ResNet three versions 18, 50, and 101. It is noted that pre-trained network has been trained using fine tuning and transfer learning. This work has been divide into five section. In section one, introduction has been introduced about the work. In section two, related study has been discussed about the work. In section three, discussed methodology and dataset used in the proposed work. In section four, result has been discussed in brief. In section five, conclusion has been discussed.

2. Related Study

Object detection is a computational method for identifying target items in an image. It is a subclass of computer vision [2]. The object recognition task is to form a precise coordinates (boundary) surrounding these objects and associate the appropriate object category with each boundary [1-4]. The most comprehensive technique for recognizing objects is deep learning. This work includes a summary, benefits, and analysis of certain deep learning and the traditional learning methods that have been employed by researchers to implement and use object identification [5-8]. A brief overview of object detection techniques shown in Figure 1.

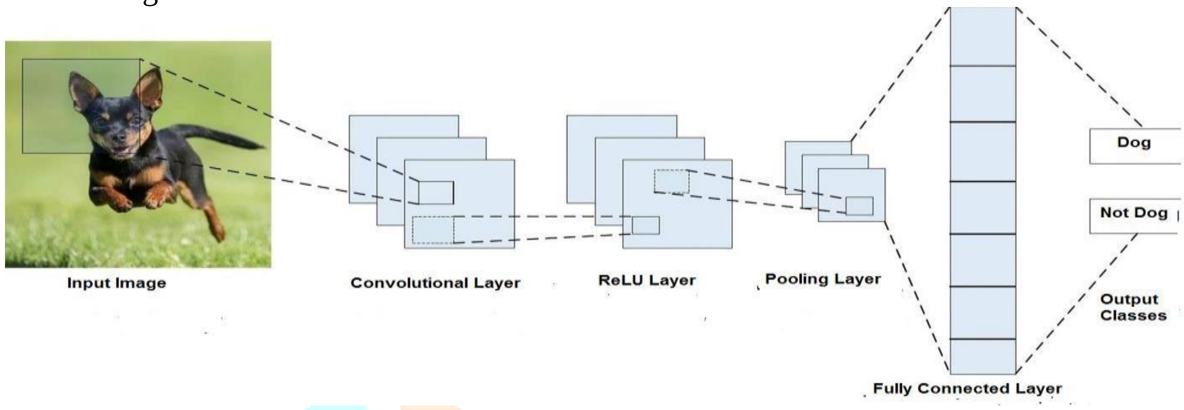

Figure 1. A brief overview of object detection techniques

This study conducted a thorough review of the literature on pre-trained ImageNet models for image classification in order to categorize test images. Much larger networks with millions of parameters has been needed to classify more different types of objects [1-12]. Without the need for training, this work learned and applied a variety of pre-trained methods for image classification [5-9]. The ImageNet researchers originally revealed their dataset in 2009, but the concept for this study originated more than 15 years ago with an investigation by an AI researcher [8-10].

3. Research Methodology

Residual Blocks is a concept proposed by this architecture to address the vanishing/exploding gradient problem [5]. It employ a method in this network called skip connections. The skip connection skips some layers in between to connect layer activations to subsequent layers [7-10]. Thus, a residual block is created. These residual blocks are stacked to create ResNet [6]. The idea behind this network is to let the network fit the residual mapping rather of having layers learn the underlying mapping [6].The sample residual structure used in the variant of ResNet network is shown in Figure 2.

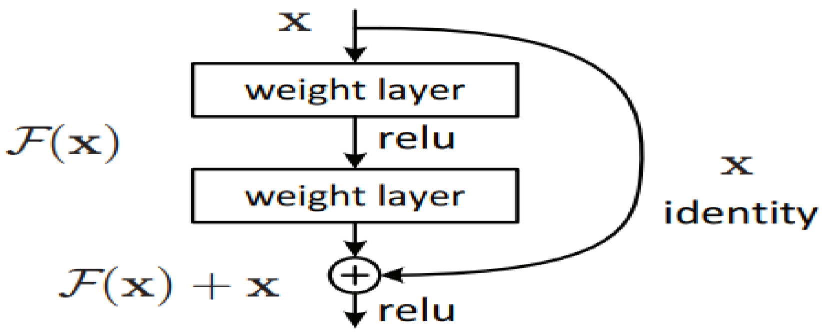

Figure 2. The sample residual structure used in the variant of ResNet network

$F(x) = H(x) - x$ which gives $H(x) = F(x) + x$.

Adding this kind of skip connection has the benefit of allowing regularization to bypass any layers that degrade architecture performance. As a result, training a very deep neural network is achieved without the vanishing/exploding gradient issues. The Research Methodology used to classify flower object is shown in Figure 3.

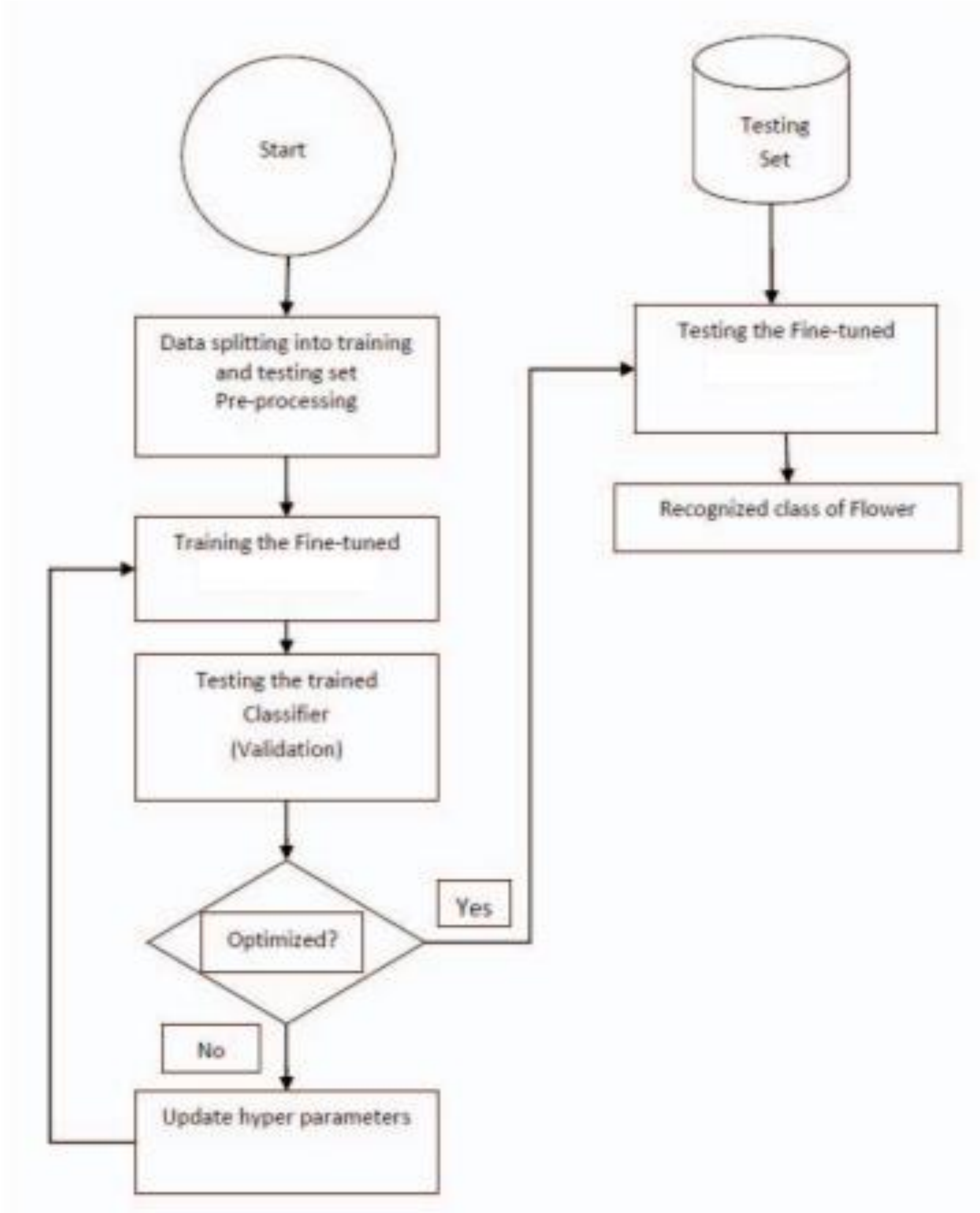

Figure 3. The Research Methodology used to classify flower object

3.1. Dataset

This study utilizes of the Kaggle dataset. There are five types of flower images in the dataset set: daisy, dandelion, sunflower, rose, and tulip. Daisy: 633 images. 898 images of dandelions, 699 images of sunflowers, 641 images of roses, and 799 images of tulips. The 3670 images in the collection have an approximate 320x240 pixel size. The dataset is split up into three categories: testing (10%), validation (10%), and training (80%). The five phases of the methodology are as follows: (a) splitting the data; (b) pre-processing; (c) training; (d) fine-tuning; (e) validating the model; and (f) testing the model on the test dataset. The sample image of Flower is shown in figure 4.

Figure 4. The sample images of Kaggle dataset

4. Results and Discussion

ResNet that has been tuned is used to implement the proposed algorithm on MATLAB. The images are in RGB color space and JPEG format. In this paper, the improved ResNet model is trained, validated, and tested using the Kaggle dataset. There are five categories of floral images in the dataset collection, i.e. I.E. 633 images of Daisy, Dandelion, Sunflower, Rose, and Tulip. 898 images of dandelions, 699 images of sunflowers, 641 images of roses, and 799 images of tulips. The 3670 photos in the collection have an approximate 320x240 pixel size. The dataset is split up into three categories: testing (10%), validation (10%), and training (80%). The suggested refined ResNet50 model is analysed using the accuracy performance metric, and its results are contrasted with transfer learning-based ResNet models. The Table 4.1 shows the performance of these models.

Table 4.1. Performance of deep Learning models.

S.No.	Model	Validation Accuracy	Testing Accuracy
1	ResNet18 (scratch)	88%	90%
2	ResNet50 (scratch)	90%	91%
3	ResNet101(scratch)	94%	96%
4	ResNet18 (Fined tuned)	94%	96%
5	ResNet50 (Fined tuned)	95%	97%
6	ResNet101 (Fined tuned)	96%	98.5

The study used CNN, Base ResNet, and Fine-tuned ResNet, three different deep learning models, to classify flowers. The Kaggle flower dataset is available. From the beginning, the Fine-tuned ResNet is trained. Pretrained models, known as Base ResNet, were trained using the ImageNet dataset. CNN is a convolution neural network that consists of dense layers with Relu and Softmax activation layers, max pooling layers, and convolution layers. The photographs are processed using 3x3 small-size filters. The authors used Fine-tuned ResNet101, which was trained using the flower dataset, to get the best accuracy of 98.5%.

5. Conclusion

Deep learning techniques are widely used for image recognition and classification problems. Over time, deep learning architectures have evolved to include more layers and become more robust models for classification problems. In this paper, 3670 flower images are used to train the base ResNet (18, 50, and 101) models for the classification of flowers into five categories: daisy, dandelion, sunflower, rose, and tulip flowers. The model achieves a classification accuracy of 97% for the validation set and 98.5% for the testing dataset. To train, validate, and test the proposed ResNet models, the Kaggle dataset is used.

The purpose of this work is to demonstrate that by using a very small dataset and suitable modification, ResNet deep models that have been pre-trained on ImageNet for image classification can be utilized to other image data sets without overfitting. 3x3 filters of small size are used in the ResNet models. Using a variety of deep learning models, the authors studied the classification of flowers. The ResNet-tuned model, trained from scratch using the flower dataset, has the highest accuracy. Since testing error decreases with huge data and the model can generalize better from more knowledge, larger data sets can be employed to further improve the results.

Using a ResNet (Residual Neural Network) to classify floral images is an excellent use of deep learning. Using residual connections, ResNet is a potent convolutional neural network (CNN) architecture that is well-known for its capacity to train incredibly deep networks. Prepare the dataset by gathering a picture collection of flowers. For this reason, a number of datasets are available, like the Kaggle Flower Dataset, which has five distinct kinds of flowers. Select a ResNet model that has already been trained from a deep learning framework like MatLab. Replace the final classification layer in the ResNet model with a new one that corresponds to the number of classes in your flower dataset after training the model with pre-trained weights on a sizable dataset (such as ImageNet).

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