MACHINE LEARNING

TITLE: Classification of various flowers

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GROUP:06

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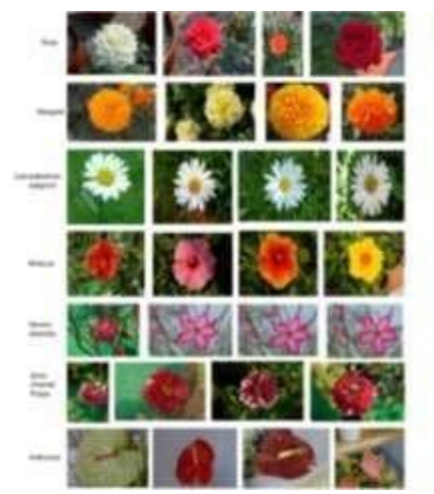
***Abstract*- Flower classification is a challenging task due to the wide range of flower species, which have a similar shape, appearance or surrounding objects such as leaves and grass. In this study, the authors propose a novel two-step deep learning classifier to distinguish flowers of a wide range of species. First, the flower region is automatically segmented to allow localization of the minimum bounding box around it. The proposed flower segmentation approach is modelled as a binary classifier in a fully convolutional network framework. Second, they build a robust convolutional neural network classifier to distinguish the different flower types. They propose novel steps during the training stage to ensure robust, accurate and real-time classification. They evaluate their method on three well known flower datasets. Their classification results exceed 97% on all datasets, which are better than the state-of-the-art in this domain.**

1. Introduction

This template, Unlike simple object classification such as distinguishing cats from dogs, flower recognition and classification is a challenging task due to the wide range of flower classes that share similar features: several flowers from different types share similar color, shape and appearance. Furthermore, images of different flowers usually contain similar surrounding objects such as leaves, grass etc. There are more than 250,000 known species of flowering plants classified into about 350 families **[1]**. A wide range of various applications including content-based image retrieval for flower representation and indexing **[2]**, plants monitoring systems, floriculture industry **[3]**, live plant identification and educational resources on flower taxonomy **[4]** depend on successful flower classification. Manual classification is possible but time consuming and tedious to use with a large number of images and potentially erroneous in some flower classes especially when the image background is complex. Thus, robust techniques of flower segmentation, detection and classification have great value.

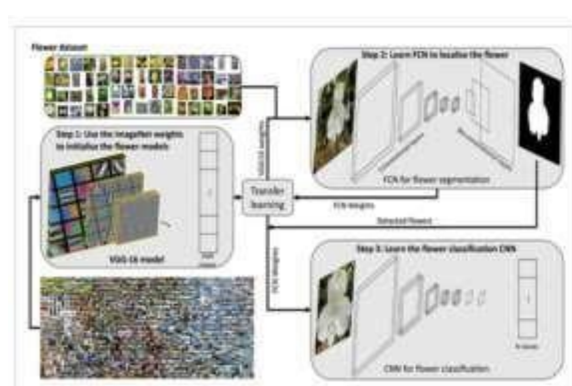
2. Literature review

In **[4]**, a standard visual vocabulary of flower species is created as images in multiple variations under a single flower name as label.The dataset was acquired from Kaggle The Kaggle consists of 102 species . The first process in the flower classification problem focuses on image segmentation. In **[5]** and **[6],** the authors use a supervised model based flower textures with graph cuts to extract flower content. This process models textures of flower as patch models and the model guides the graph cuts algorithm to initiate the minimum cut at the texture maximum locations in the flower image. The authors in **[7]** use color clustering and shape features to perform region of interest (ROI) based flower image retrieval. The color clustering is achieved using color histogram based features. Shape feature set is defined based on centroid contour distance (CCD) and Angle Code Histogram (ACH) characterizing the flower contours. They have tested the algorithm on 885 flower images from 14 species. A completely unsupervised model is proposed in **[8]** with simple color based holding. RGB color space is converted into Lab color space and OTSU holding is performed on all three color spaces. The best holded flower image is selected which is close to ground truth image. The authors claim that their model is faster compared to **[5].**



3. System architecture

We propose a two-step approach for the flower classification problem. The first step localizes the flower by detecting the minimum bounding box around it. The localization is performed by segmenting the flower region using an FCN method **[10]**. The second step learns a CNN to accurately classify the different flower classes. Fig. **1** shows the overall framework for the proposed method. Here, we show how the segmentation FCN is initialized by the VGG-16 model **[9]** while the classification CNN is initialized by segmentation FCN.



4. Equations

After generating cropped flower images, the task is simplified since the highly discriminative regions are mainly kept while other possible misleading regions are removed. In this work, we address the flower classification problem as a multi-class CNN classification of *N* classes. The problem is simply formulated as a function *F* which predicts the class *c* of an image *x* such as $c = F(x)$.

We propose a CNN which initializes its first five blocks from the FCN model which was already initialized by the VGG-16 model. However, instead of using 3 fully connected layers in blocks 6–8, we use 3 convolutional layers with 512 feature maps. The kernel size of the convolutional layer in block 6 is 7×7 , while the number of output parameters from the convolutional layer in block 8 is *N*.

We use a multi-class Softmax loss function as a measure of the quality of a particular set of parameters based on how well the predicted outcomes match the ground truth labels in the training data. Softmax computes the probabilistic distribution over *N* different possible outcomes. We also use stochastic gradient descent (SGD) to optimize and update the set of parameters aiming to minimize the loss function. SGD and Softmax loss are commonly used in other CNNbased applications such as **[[9], [10], [11], [12]]**. Our loss function takes as input an *N*-dimensional vector $\boldsymbol{X}$ and outputs an *N*-dimensional vector $\boldsymbol{Y}$ of real values between 0 and 1. This function is a normalized exponential and is defined as

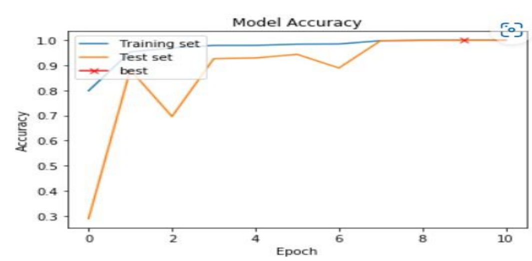
$$\sigma(\boldsymbol{X})_j = \frac{e^{X_j}}{\sum_{n=1}^{N} e^{X_n}} \quad (4)$$

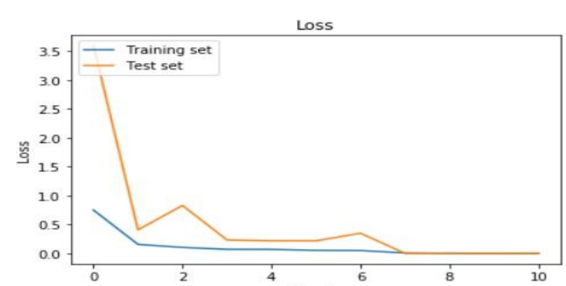
where $j = 1, \ldots, N$. We have noted that the loss function was not performing well initially during CNN parameter optimisation. There are several possible reasons for this but it is mainly due to the complexity of the multi-class classification problem compared with the learnt weights in the binary segmentation FCN. In addition, the function we are learning is not convex, not smooth and has many local minima with flat regions. Therefore, we propose two novel steps to improve the convergence of the algorithm.

First, since we have more convolutional layers in the CNN than the FCN, we propose to learn kernel parameters in a three-step approach. First, we let the CNN learn the kernels in the convolutional layers at blocks 6–8 while fixing the first five blocks. We then allow the CNN to learn the parameters in blocks 3–5. Finally, we let all parameters from all blocks be learned simultaneously. This provides better convergence for the CNN.Second, because of the existence of a large number of flat local minima, the optimiser is prevented from reaching a good solution. Therefore, it is important to allow the optimiser in some scenarios to restart its search while finding a good minimum. To address this issue, we propose a multi-step training approach during which we force the learning rate to decrease in each step and then make a sudden large increase. The increase in the learning rate allows the optimiser to 'restart' itself to allow searching for other nearby solutions. More details about different approaches to restart SGD are described in **[8]**.In addition, thanks to the flower detection step described in Section 3.2, a wider range of augmentation can be used. For instance, a larger range of rotation angles and vertical flipping are used here than in the FCN model because the image is already cropped around the flower and large rotation does not affect the overall appearance of the whole cropped image. However, performing a large rotation on the whole (non-cropped) flower image may create a completely unrealistic image. Finally, with possible

5. Result and Figures

The model reached a validation accuracy of 99.94% which is quite decent. And we can seethat the model did not overfit a lot. So it's quite a good model





6. Acknowledgments

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7. Conclusion

CNN is a powerful artificial intelligence tool in pattern classification. In this paper, we proposed a CNN architecture for classifying flower image classes. The CNN architecture is designed with four convolutional layers. Each convolutional layer with different filtering window sizes is considered which improves the speed and accuracy in recognition. A stochastic pooling technique is implemented which combines the advantages of both max and mean pooling techniques. Training is performed in different batches to know the robustness of enormous training modes required for CNN's. In Batch-V of training, the training is performed with four sets of data and maximizing the classification rate. Training accuracy and validation accuracies for this CNN architecture are better than the other models. A less amount of training and validation loss is observed with the proposed CNN architecture. The average recognition rate of proposed CNN model is 99.99 % and is higher compared with the other state of the art classifiers.

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