# FLOWER IMAGE DETECTION USING TRANSFER LEARNING

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## ABSTRACT

*Image processing is an important part of removing features from photos. However, image processing and image interpreting process in the distribution of low-level statistical statistics is a challenging task. These processes are complex as the captured image contains a lot of noise, and the target objects are touched by light, light. In the case of flower classification, photo editing or pre-processing is an important part of the automatic flower photo recognition system. The classification of a flower image depends on low-level elements, for example, color and texture, in order to define and define the content of the image. In this project, a Convolution Neural Network (CNN)-based approach was proposed in which the pre-trained VGG-16 model was used to extract features from flower images and before the model was trained, further analysis was performed to remove the noise. , improve brightness and improve image quality using the Digital Image Processing (DIP) algorithm. The model is trained with about 2000 images in three classes, and the classification is done by FC, SVM, Naive Bayes classifier and DT; high accuracy achieved with FC layer and SVM 91.56% and 91.36%.*

**Keyword: -** *Machine Learning, Python, Numpy, CNN, Tensorflow.*

## 1. INTRODUCTION

Knowledge of the various kinds of flowers is essential to the protection and control of biodiversity. Also, flowers are considered to be the most important part of the food chain and habitat for almost all pollinators. Therefore, adequate recognition of flower species is essential to the protection of biodiversity. There are thousands of flowering plants in various parts of the world. Personal identification of all these flower species is a time consuming and challenging task for even the botanist. Recently, with the advent of computer vision technology, flower classification has greatly improved computer vision. Especially that different types of flowers have the same shapes, colors, and petals. Therefore, the development of a computer-assisted approach is an urgent step for the rapid and accurate flowering of flowers. A variety of image classification techniques have been developed, which can be divided into two groups: traditional machine learning methods and in-depth learning methods. In the first set of methods, immature images should be converted to a suitable format where the machine can easily extract hand-made elements such as color, shape and texture. In the second group, immature images can be fed to Convolution Neural Networks (CNNs) directly without much processing. This is one of the reasons why these methods work so well in application recognition. In addition, CNNs are able to learn hierarchical features automatically with the goal of separating or separating images. Due to CNN's impressive progress in various areas, we use CNN-based model learning to automatically distinguish different types of flowers. Learning-based transmission methods improve the performance of our network on a small database. Our proposed model is based on the development of a pre-trained in-depth learning model, called DenseNet121. Recently, we saw Dense Net’s excellent performance in image classification. This network is very accurate and easy to train, as each layer is directly connected to all the other layers. Therefore, this model is an interesting case to deal with the problem of flower separation. Our pre-trained model is trained and tested in the kaggle flower database and achieves good accuracy compared to other models.

In this study method of passing the test is introduced. In this process a pre-trained CNN model is used to extract elements from flower images and segmentation function. Basically, the purpose of the project is to obtain high phase accuracy with the minimum set data of that VGG16 used in the network data set.

## 2. LITERATURE REVIEW

In-depth learning methods are based on neural networks and power-based models. In-depth learning uses multiple layers of processing to extract features. Each completed layer receives the output in the previous layer as input. In in-depth reading, the first layers produce the most common features such as the information at the end, while the subsequent layers produce the most obvious features. High-quality features are reproduced from low-key features to build a consistent presentation. This diagram represents the study of multiple levels associated with different intake levels. In-depth learning is basically based on learning from data representation. In-depth learning methods algorithms are used to solve many machine learning problems. The image separation area, is one of the areas where in-depth learning is used. Photo classification is the subject of the most comprehensive image processing. It is an important technology that many people apply to every aspect of human life. Scheduling length of time to allow non-class images to be included in their classrooms. . Divisions can be binary or multiple. There are many studies done on picture classification books. CNN Architecture is the most preferred method. This was due to the Image net competition organized in 2012. A. Krizevsky et al. Participated in the competition with a model they created using convolutional neural networks and showed the best performance result of recent times. Y. Seo et al., used the Convolutional Neural Network (CNN) to differentiate the image of clothing from the fashion business. In this study, it was revealed that segregation of clothing may be difficult due to the lack of tagged image data for different categories of clothing and each category. Therefore, they recommend GoogLeNet architecture training for the ImageNet database as well as a well-prepared data set based on design features. N. Hnoohom et al., introduced a predictive model for classifying fast food images in Thailand. The model was trained in natural photography (Google Net database) and used a well-tuned in-depth learning process to create a speculative Thai fast food model. Y. A. L. Alsabahi et al., used the transmission study based on the Inception V3 model to classify DR images. They used the weight of the Inception V3 model trained in the ImageNet database and optimized their data sets. In the study, the problem of classification was investigated. To this end, the training process is carried out using pre-trained models and Kaggle floral detection database.

## 3. PROBLEM STATEMENT

Similar projects have recently been undertaken to identify flowering plants and plants. An important challenge developer’s face is finding the right ingredients for plants and flowers as there are so many variations in shape, color and texture of flowers. During the development of the project, it was noted that most of the programs focused on mathematical thinking involved in image representation. So the biggest challenge identified was the semantic gap that occurs due to differences in representation of digital imagery and human perception.

## 4. PROPOSED MODEL

From previous discussion we can understand that transfer learning is basically utilize the previous knowledge form source network in a target task. The important discussion in this section is how to transfer, what to transfer and when to transfer. What to transfer is the initial step for transfer learning, once we know our target task we can figure out what to transfer. Then it comes when to transfer, because using transfer learning we always want to improve the performance and we don't want the degrade so it is very important to decide when to transfer. After deciding what to transfer and when to transfer we can proceed for how to transfer, there are few techniques available for transfer learning we need to choose proper technique according to source and target data to get best optimal result. There are diverse Transfer learning procedures and methods, which can be applied, dependent on the area, job that needs to be done, and the accessibility of information. Based on that there are three category these are following: Inductive Transfer learning, Unsupervised Transfer Learning, Transudative Transfer Learning.

**1. Boredom Education.**

In this case, the source locations and the target locations are the same, however the source and target function are not the same. Statistics attempts to use inductive predispositions of source space to help improve objective function. Depending on whether the source material contains fictional information or not, this can be further divided into two categories, such as performing multiple learning and learning activities, each.

**2. Learning Uncontrolled Transfer**

This setting is similar to reading Subsequent Transfer by paying attention to unattended tasks in the policy field. Source and target locations are compared, yet functions are not the same. In this case, the label data is not accessible to both spaces.

**3. Transformational Transmission Studies**

In this case, there are similarities between the source and the targeted shares, however the related areas are different. In this setting, the source area has a lot of labelled data, while the policy space does not. This can be further organized by the categories below, referring to settings where feature fields are different or peripheral possibilities.

## 5. EXPERIMENTAL RESULTS

The proposed system is tested for 10 flower species. There are 50 test images for each species. This system uses 100 training images. The experimental results shown in table 1 indicate that the accuracy of our system to be more than 80%. Two examples, red rose and butterfly pea, yield 100% accuracy because of their distinct color. Marigold has the least accuracy because its color set is similar to sunflower color set and its edge characteristic set is similar to globe amaranth edge characteristics.

**Table 1: The Experimental Results**

| Flower species | | % correction |
|---|---|---|
| White plumeria |  | 90 |
| Red rose |  | 100 |
| Butterfly pea |  | 100 |
| Purple lotus |  | 90 |
| Orange cosmos |  | 96 |
| Globe amaranth |  | 92 |
| Chinese rose |  | 82 |
| Marigold |  | 80 |
| Periwinkle |  | 84 |
| Sunflower |  | 86 |

## 6. CONCLUSION AND FUTURE SCOPE

From the proposed method it can be concluded that using transfer learning method good accuracy can be achieved without having a large number of data set. Using SVM classifier with rbf kernel better accuracy can be achieved for multiple class classification although SVM works better for binary classification.

Some of the future scopes that can be done to this system are:

1. To provide more information of flower and their family, that might help Botany student for study and research purpose.
2. This helps in predicting the flower present in data set.

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