CLASSIFICATION OF FLOWERS

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DECLARATION BY THE CANDIDATE

I hereby declare that the project report entitled **"CLASSIFICATION OF FLOWERS"** submitted to **Prof.B.S.Harish** represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that i have adhered to all principles of academic honestly and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission.

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ABSTRACT

This project presents classification of flowers using Convolutional Neural Network (CNN). In this study, the performance of CNN for flower identification using its images is investigated. Publicly available dataset, namely Flower Recognition dataset, have been used for the training and testing purposes. CNN has been proven to produce excellent results for object recognition but its performance can still be influenced by the type of images and the number of layers of the CNN architecture. Experimental results indicate that the utilization of the images of flowers arrive to the highest accuracy of 80% respectively.

1 Introduction

1.1 Problem Statement

Flower classification is a challenging task due to the wide range of flower species which have similar shape, appearance or surrounding objects such as leaves and grass. The proposed method classifies and recognises flower images using a powerful artificial intelligence tool, convolutional neural networks (CNN).Consequently, system shows the flower name and a short description to user.

1.2 General Introduction

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 colour, shape and appearance. Furthermore, images of different flowers usually contain similar surrounding objects such as leaves, grass, etc.
A wide range of various applications including content-based image retrieval for flower representation and indexing, plants monitoring systems, floriculture industry , live plant identification and educational resources on flower taxonomy 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. Conventional flower classification techniques use a combination of features extracted from the flower images with the aim of improving classification performance. Colour, texture, shape, and some statistical

information are among the main sources of features that are widely used to identify the different flower species. Some methods rely on human interaction to further enhance the classification results. In addition, Support Vector Machines (SVM) are among the most commonly used types of classifiers. Many flower classification techniques rely on learning their features from a segmented flower region to improve accuracy, but Deep learning techniques, especially Convolutional Neural Networks (CNNs), have recently gained wide interest due to superior accuracy compared to classical machine learning methods which rely on hand-crafted features.

Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learn by example. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Within the past few years, deep learning algorithms particularly Convolutional Neural Networks (CNNs) have proven their much powerful feature representation capabilities in computer vision. Data are trained by using a large set of labelled data with various numbers of layers of the CNN. Current advances in hardware technology have enabled the evolution of CNN and massive number of their applications, as well as complicated tasks like objects recognition and image classification. It has resulted in ground breaking decisions over the last decade in various fields related to pattern recognition. from image processing to voice recognition [4]. CNN's capabilities have become a known and used in various object recognition problems such as flower categorization, leaf recognition, voice analysis, image classification, fruit classification and ripeness grading recognition, food recognition , and plant disease identification.

However, a recent trend in machine learning has shown that learned representations are more practical and economical . Several parts of a plant can be used by a botanist in order to recognize a plant and various efforts have been done that includes flowers and leaves. However, some researches have also been made on flower recognition to identify the species of plants. Even though flowers have many different species, some of them have very similar characteristics and looks. This similarity and dissimilarity make the flowers recognition process with a highly accurate result is very challenging. The purpose of identifying plants is to categorize the plants for recording purposes. The process of identifying a plant using flowers is an easy task for botanists as they can simply recognize it using their knowledge. On the contrary, for machines to achieve the same recognition results requires performing image-processing techniques to extract visual information and compare them to existing sets of data. Structured learning or better known as deep learning, has been recognized as a new area in computer vision that has been reported to produce excellent results.

1.3 Block diagram

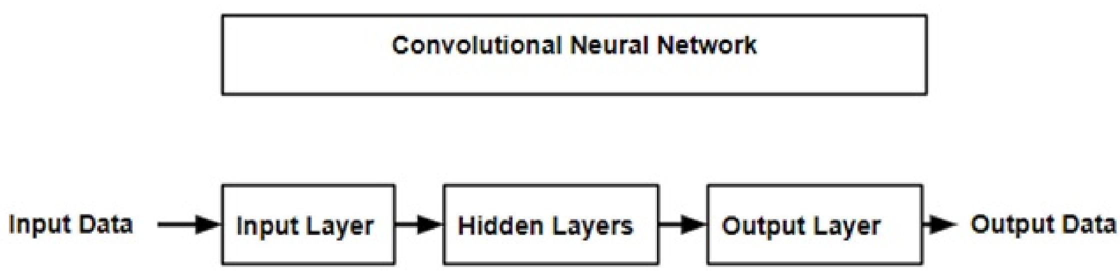


Figure 1: General block diagram

Figure shows the CNN is comprised of an input layer, an output layer and multiple hidden layers in between. The hidden layers of a CNN mainly consist of convolutional layers, pooling layers, and fully connected layers.

1.4 Applications

(i) The applications of classification of flowers can be found useful in floriculture. The floriculture has become one of the important commercial trades in agriculture owing to steady increase in demand of flower. Floriculture industry comprises of flower trade, nursery plants and potted plants, seed and bulb production, micro propagation and extraction of essential oil from flowers.
(ii) Also flower recognition is used for searching patent flower images to know whether the flower image applied for patent is already present in the patent image database or not.
(iii) One of the most popular uses of flowers is as decoration. Floral arrangements are popular for events such as weddings.
(iv) Fragrant flowers inspire many perfumes and fragrances.
(v) Flowers and other plants have long since been used for medicinal purposes and they continue to be an important part of medicine in modern times.
(vi) Therefore there is need for classification of flowers for its effective usage.

1.5 Challenges

The key challenges involved in flower classification are categorised as:
(i) Developing a framework for a flower classification system is a difficult task because of lot of appearance variations caused due to variations in imaging conditions, deformations and variations between different instances of same category.

(ii) Creating a flower classification system is a difficult because of large intra-class variation present and small inter-class variation present among different classes .
(iii) The dataset of flowers contains the flower images are taken in natural environment where the shine of light changes with the time and weather.
(iv) In addition, flowers are often more or less transparent and specula highlights can make a flower appear light or even white causing an illumination problem.
(v) Also, there is a lot more variations in viewpoint, occlusions, scale of flower images.
(vi) It requires big data of labelled training images and to prepare this big data, it consumes a lot of time and cost as for the training purpose only.
(vii) Non availability of dataset(images) for certain rare species of flowers.
(viii) Non availability of high resolution images of certain hard to find flowers.
(ix) All these problems lead to a confusion across classes and make the task of flower classification more challenging.

1.6 Motivation

Flowers importance in nature is everywhere, they can feed insects, birds, animals and humans; provide natural medicines for humans and some animals. Without flowers, plants would merely be green, and the world would be a duller place. Floriculture is a fast emerging major venture in the world, especially as a potential money-spinner for many third-world countries. Many flowers and ornamental plants are being grown for domestic as well as for export market will provide more return than any other agricultural crops.

The reason for undertaking this project is that in this fast growing world , it is difficult to manually identify flowers by humans which may result in accidental errors. By utilizing this approach of computer vision it is possible to decrease the time taken by human workforce and also the errors that might be incurred.

1.7 Objectives

The objectives for classification of flowers are:-
1. To evaluate the current methods used in flower identification.
2. To divide the dataset into training and testing sets.
3. To train a convolutional neural network which is capable correctly classifying images of flowers with an average accuracy of 80% or more.
4. Recognizing each and every flower from image with less computation and high accuracy.
5. To validate the model and observe the results.

2 Literature Survey

Flower classification poses a unique challenge task because most flower categories have a significant visual similarity, indistinguishable on color (or shape) alone. Discriminating one flower from another mainly rely on a combination of different cues, such as shape, color, and texture patterns. We can find a couple of works carried out in this direction.
Nilsback and Zisserman [2] designed a flower classification system by extracting visual vocabularies which represent the color, shape, and texture features of flower images. In order to segment a flower from the background, the RGB color distribution is determined by

labeling pixels as foreground and background on a set of training samples, and subsequently the flower is automatically segmented using the concept of interactive graph cuts [3]. In order to extract the color vocabulary, each flower image is mapped onto HSV (hue, saturation, and value) color space, and the HSV values of each pixel of the training images are clustered and treated as the color vocabulary. Shift-invariant feature transform (SIFT) descriptors are used to represent the shape features and the responses of the MR8 filter bank in different orientations are used as texture features. Also, the authors use the combination of all the three visual vocabularies with different weights in order to study the effect of different features. Nilsback and Zisserman [2] considered a dataset of 17 species, each containing 80 images, and achieved an accuracy of 71.76% for a combination of all three features. In order to study the effect of classification accuracy on a large data set, Nilsback and Zisserman in their work [4] considered a dataset of 103 classes, each containing 40 to 250 samples. The low-level features such as color, histogram of gradient orientations, and SIFT features are used. They have achieved an accuracy of 72.8% with an SVM classifier using multiple kernels. Nilsback and Zisserman [5] proposed a two-step model to segment the flowers in color images, one to separate the foreground from background and the other to extract the petal structure of the flower. This segmentation algorithm is tolerant to changes in viewpoint and petal deformation, and the method is applicable in general for any flower class.

Das et al. [1] proposed an indexing method to index flower patent images using domain knowledge. The flower was segmented using an iterative segmentation algorithm with domain knowledge driven feedback. In their work, the image color is mapped to names using the ISCC-NBS color system and X Window system. Each flower image is discretized in HSV color space, and each point on the discretized HSV space is mapped to a color name in the ISCC-NBS and X Window systems in order to index the flowers. Yoshioka et al. [6] performed a quantitative evaluation of petal colors using principal component analysis. They considered the first five principal components (PCs) of a maximum square on the petals. The quantitative evaluation indicates that the different PCs correspond to different color features of petals such as color depth, difference in color depth in upper and lower parts of the image, etc.

Varma and Ray [7] proposed a method for learning the trade-off between invariance and discriminative power for a given classification task. They learn the optimal, domain-specific kernel as a combination of base kernels corresponding to base features which achieve different levels of trade-off, such as rotation invariance, scale invariance, affine invariance, etc. The classification is carried out on the basis of vocabularies of visual words of shape, color, and texture descriptors. The background in each image is removed using graph cuts. Shape distances between two images are calculated as the statistic between the normalized frequency histograms of densely sampled, vector quantized SIFT descriptors of the two images. Similarly, color distances are computed over vocabularies of HSV descriptors and texture over MR8 filter responses. An entire set of weights is learnt, spanning the full range from shape to color.

In their work, Saitoh et al. [8] describe an automatic method for recognizing a blooming flower based on a photograph taken with a digital camera in a natural scene. They have also proposed a method for extracting the flower regions. It is based on "Intelligent Scissors" [9], which find the path between two points that minimizes a cost function dependent on image gradients. The method works under the assumption that the flower is in focus and in the centre of the photograph and that the background is out of focus. Under this assumption, the cost between any two points on the flower is smaller than the cost between a point in the background and a point in the foreground. The midpoint of the image is used as the starting point to identify the flower region. This method requires no prior color information. Saitoh et al. [10] designed a flower classification system which extracts features from both flowers and leaves, and used a piecewise linear discriminant analysis for recognition on a dataset of 34 species each containing 20 sets of wild flowers.

Nilsback and Zisserman [2] noted that color and shape are the major features in flower classification. This is true only when the flower classes considered have little intra-class variation. However, if there is a large variation within a class, for example where species of the same type have different colors, then color may not be the best suitable feature. Hence, in this work, we investigate the suitability of texture features in designing a system for flower classification. The flower is segmented using a threshold-based method, and texture features, namely the color texture moments (CTMs), gray level co-occurrence matrix (GLCM), and Gabor responses, are extracted from the segmented image and used for classification. In considering the color texture moments, we extract moments from different color spaces of the flower images. In the gray level co-occurrence matrix, features such as contrast, energy, entropy, correlation, and homogeneity are taken into account. In the Gabor analysis, we have extracted the first three moments of each of the Gabor responses obtained for different scales and orientations. These features are used for training and classification using a probabilistic neural network.

Dr. S.M. Mukane et.al [11] proposed Flower Classification Using Neural Network Based Image Processing. In this paper, it is proposed to have a method for classification of flowers using Artificial Neural Network (ANN) classifier. The proposed method is based on textural features such as Gray level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT).The ANN has been trained by 50 samples to classify 5 classes of flowers and achieved classification. accuracy more than 85% using GLCM features only. Feature database is created using wavelet decomposed sub bands up to forth level of decomposition. Experimentation has been conducted on databases of 50 images and 5 classes. The classification accuracy under ANN classifier has been investigated. As compared with all classes GLCM features shows highest result while combination of DWT and GLCM shows less success rate. Hence it is found that flower images can be classified easily with the GLCM features only. Only gray level features have been used. The neural network is trained using the back propagation algorithm. Own database of flowers of 5 classes, each containing 10 flower images has been created. It has been found that MLP offers accuracy 87% with GLCM features.

Fadzilah Siraj et al [12] proposed the system for classification of Malaysian blooming flower. In this paper they present the application of NN and on image processing particularly for understanding flower image features. For predictive analysis, they have used two techniques namely, Neural Network (NN) and Logistic regression. The study shows that NN obtains the higher percentage of accuracy among two techniques. The Otsu's method was applied in order to compute a global threshold. The image is then converted to RGB color space again. In color extraction, the images were transformed from RGB color space to HSV color space the image texture is calculated based on gray-level co-occurrence matrix (GLCM) to obtain the contrast, correlation, energy and homogeneity of the image. The prediction accuracy of logistic regression is 26.8%. Therefore based on 1800 samples of Malaysian flower images, NN has shown a higher average prediction results vs. logistic regression. However this paper cannot present recognition of flower type, its only recognize flower features so in future studies can be focused on developed flower model system which can recognize Malaysian blooming flower or extending the dataset built and Verities sample of images can be captured for different flowers and recognize their types.

3 Proposed Method

For this project we used a convolutional neural network. This type of network makes use of convolutional layers, pooling layers, ReLU layers, fully connected layers and loss layers. In a typical CNN architecture, each convolutional layer is followed by a Rectified Linear Unit (ReLU) layer, then a Pooling layer then one or more convolutional layer and finally one or more fully connected layer.
A characteristic that sets apart the CNN from a regular neural network is taking into account the structure of the images while processing them. A regular neural network converts the input in a one dimensional array which makes the trained classifier less sensitive to positional changes. Convolutional layers are named after the convolution operation. In mathematics convolution is an operation on two functions that produces a third function that is the modified (convo-

luted) version of one of the original functions. The resulting function gives in integral of the pointwise multiplication of the two functions as a function of the amount that one of the original functions is translated.
In purely mathematical terms, convolution is a function derived from two given functions by integration which expresses how the shape of one is modified by the other

$$(f * g)(t) \overset{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$$

A convolutional layer consists of groups of neurons that make up kernels. The kernels have a small size but they always have the same depth as the input. The neurons from a kernel are connected to a small region of the input, called the receptive field, because it is highly inefficient to link all neurons to all previous outputs in the case of inputs of high dimensions such as images. For example, a 100 x 100 image has 10000 pixels and if the first layer has 100 neurons, it would result in 1000000 parameters. Instead of each neuron having weights for the full dimension of the input, a neuron holds weights for the dimension of the kernel input. The kernels slide across the width and height of the input, extract high level features and produce a 2 dimensional activation map. The stride at which a kernel slides is given as a parameter. The output of a convolutional layer is made by stacking the resulted activation maps which in turned is used to define the input of the next layer.

A convolutional layer is defined like this:
conv2d (

input ,
filter ,
strides ,
padding ,
use cudnn on gpu=True ,
data format ='NHWC' ,
dilations =[1 , 1 , 1 , 1] ,
name=None
)
Applying a convolutional layer over an image of size 32 X 32 results in an activation map of size 28 X 28. If we apply more convolutional layers, the size will be further reduced, and, as a result the image size is drastically reduced which produces loss of information and the vanishing gradient problem. To correct this, we use padding. Padding increases the size of a input data by filling constants around input data. In most of the cases, this constant is zero so the operation is named zero padding. "Same" padding means that the output feature map has the same spatial dimensions as the input feature map. This tries to pad evenly left and right, but if the number of columns to be added is odd, it will add an extra column to the right. "Valid" padding is equivalent to no padding.
The strides causes a kernel to skip over pixels in an image and not include them in the output. The strides determines how a convolution operation works with a kernel when a larger image and more complex kernel are used. As a kernel is sliding the input, it is using the strides parameter to determine how many positions to skip.
ReLU layer, or Rectified Linear Units layer, applies the activation function max(0, x). It does not reduce the size of the network, but it increases its nonlinear properties.

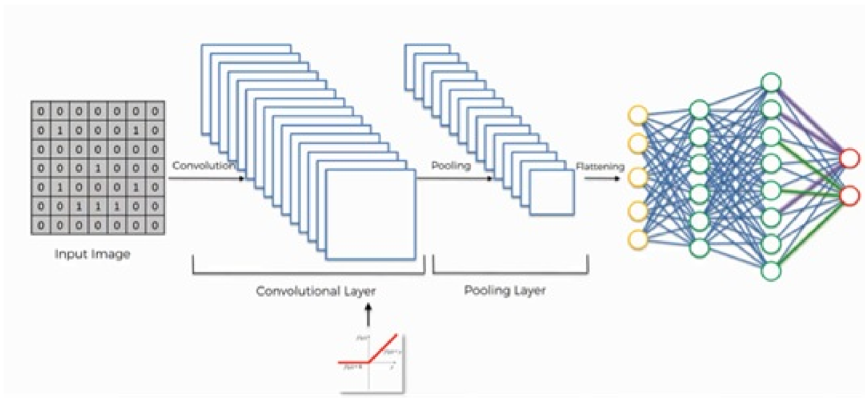


Figure 2: CNN Architecture Model

Pooling layers are used on one hand to reduce the spatial dimensions of the representation and to reduce the amount of computation done in the network. The other use of pooling layers is to control overfitting. The most used pooling layer has filters of size 2 x 2 with a stride 2. This effectively reduces the input to a quarter of its original size.

Fully connected layers are layers from a regular neural network.Each neuron from a fully connected layer is linked to each output of the previous layer. The operations behind a convolutional layer are the same as in a fully connected layer. Thus, it is possible to convert between the two.

This is normally the last layer of the network. Various loss function exist: softmax is used for predicting a class from multiple disjunct classes, sigmoid cross-entropy is used for predicting multiple independent probabilities (from the [0, 1] interval). Loss layers are used to penalize the network for deviating from the expected output. Finally, the class label with the highest prediction value is considered as the actual class of input image object.The input that we used consists of standard RGB images of size 150 x 150.

One of the beneficial feature of CNN is that it can overcome model over fitting using dropout technique. In this process, an image is feed as input into the network, which goes through multiple convolutions, subsampling and fully connected layer and finally outputs the class name of the input flower image. Where convolution layer computes the output of neurons that are connected to local regions or receptive fields in the input, each computation leads to the extraction of a feature map from the input image. Figure shows a general structure of the proposed CNN based recognition model that includes CNN, subsampling, fully-connected and dropout layers.

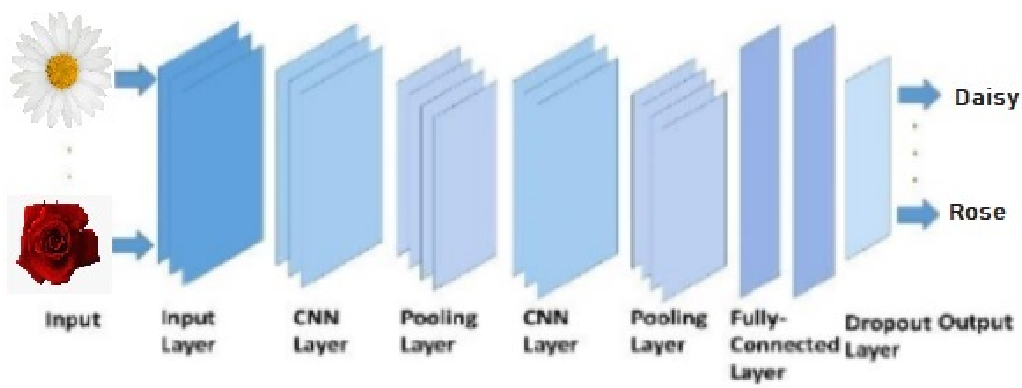


Figure 3: CNN Recognition model

4 Experimental Analysis

The images above were from the Kaggle's dataset "Flowers Recognition" by Alexander. The title of each image consists its class name and index number in the dataset. This dataset contains 4242 images of flowers. The pictures are divided into five classes: daisy, tulip, rose, sunflower and dandelion. For each class there are about 800 photos. . Photos are not in high resolution, 320x240 pixels. Photos are not reduced to a single size, they have different proportions. The data collection is based on scraped data from flickr, google images, and yandex images.

No.	Type of Flowers	No of Images
1.	Daisy	769
2.	Dandelion	1055
3.	Roses	784
4.	Sunflower	734
5.	Tulips	984
Total number of flower images		4242

Table 1 : Number of images according to the type of flowers

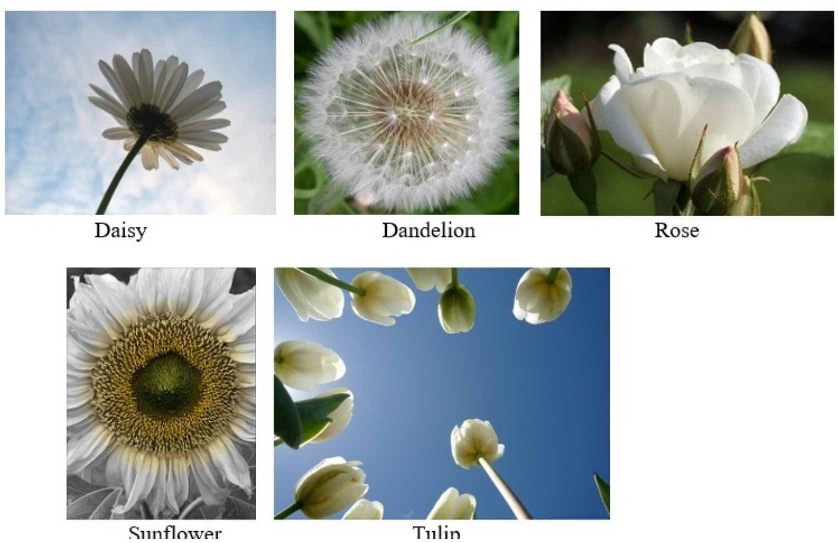


Figure 4: Flower recognition database

Table 1 shows number of images according to the different type of flowers which includes Daisy, Dandelion, Roses, Sunflower and Tulips. Figure 4 shows some example images from this dataset.
The laptop used to run the CNN for this project was HP Pavilion with Windows 10, Intel Core i7 processor, 8.00 GB RAM and the operating system is 64-bit while the software used is Jupyter notebook. The datasets used for this experiment is Flower Recognition dataset. All of the images were resized to 150 by 150 pixels to ensure the consistency of the data for the experiment.
The first layer is a convolutional layer which applies 32 5 x 5 filters. On this layer we apply max pooling with a filter of shape 2 x 2 with stride 1 which specifies that the pooled regions do not overlap. This also reduces the width and height to 50 pixels each.
The second convolutional layer applies 64 3 x 3 filters which outputs 64 activation maps. We apply on this layer the same kind of max pooling as on the first layer, shape 2 x 2 and stride 2.
The third convolutional layer applies 96 3 x 3 filters. Following is another max pool layer of shape 2 x 2 and stride 2.
The fourth convolutional layer applies 96 3 x 3 filters after which we apply a final max pool layer. Because of the four max pooling layers, the dimensions of the representation have each been reduced by a factor of 16, therefore the fifth layer, which is a fully connected layer, has 5 x 5 x 16 inputs.
This is the fifth unit of the proposed model. Here the output of the previous layer is taken as input to the Fully Connected Layer (FCL). This layer feeds into another fully connected layer with 1024 inputs and 256 outputs.
The last layer is a softmax loss layer with 256 inputs. The output of fully connected layer is fed to softmax layer. The purpose of using the softmax function as the loss function, is to convert the linear in-

puts to probabilities i.e., to range the scores between 0 and 1 which is easier to compute. The number of outputs is equal to the number of classes.

	Type of Layer	No of Filters	Feature Map Size (Height * Width * Depth)	Kernel Size	No of Stride	No of Padding
	Image Input Layer	-	150 x 150 x 3	-	-	-
1st Convolutional Unit	Conv - 1 (1st Convolutional Layer)	32	150 x 150 x 32	5 x 5	1 x 1	1 x 1
	Max-Pooling - 1 (1st pooling layer)	1	75 x 75 x 32	2 x 2	-	0
2nd Convolutional Unit	Conv - 2 (2nd Convolutional Layer)	64	75 x 75 x 64	3 x 3	1 x 1	1 x 1
	Max-Pooling - 2 (2nd pooling layer)	1	37 x 37 x 64	2 x 2	2 x 2	0
3rd Convolutional Unit	Conv - 3 (3nd Convolutional Layer)	96	37 x 37 x 96	3 x 3	1 x 1	1 x 1
	Max-Pooling - 3 (3nd pooling layer)	1	18 x 18 x 96	2 x 2	2 x 2	0
4th Convolutional Unit	Conv - 4 (4th Convolutional Layer)	96	18 x 18 x 96	3 x 3	1 x 1	1 x 1
	Max-Pooling - 4 (4th pooling layer)	1	9 x 9 x 96	2 x 2	2 x 2	0
Fully Connected Unit	Fully Connected Layer	-	4143749 x 1	-	-	-

Table 2 : Layers in Convolutional neural network model

The time complexity of matrix multiplication for Mij x MjkMij x Mjk is simply O(i x j x k)O(i x j x k).
In order to be able to detect flowers from images we used the previously described neural network which was trained over many iterations with batches of 50 images selected at random from the training set. Every 50 steps we calculated the accuracy using cross valida-

tion. This showed steady improving of the network until reaching 100 percent accuracy on cross-validation. For the testing phase, we used the testing set and the calculated accuracy was 80 percent.
Choosing a convolutional neural network architecture for real time object detection and recognition is not an easy task because it is very difficult to estimate exact number of layers, kind of layers and number of neurons to use in each layer. Plotting is very useful as it allows you to see whereas the model is underfitting or overfitting. Underfitting, or under-learning is pretty easy to spot: the training lines don't converge as expected. Overfitting is a little bit trickier. For a clean dataset, any sudden changes in the validation line is a sign of overfitting. If the accuracy stops improving is also a sign of overfitting, this is when the early stopping feature might become handy.
As shown in Figure 5 and 6, the accuracy and loss curves are set to 50 with the training epoch during training. The number of epoch determines the number of repetitions of all the training data .The highest accuracy on test images was found to be 76%, corresponding to a training accuracy 88%.

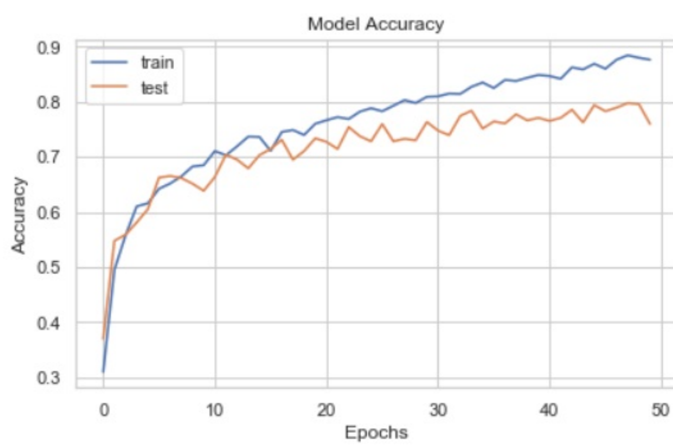


Figure 4 : Model validation and training accuracy curve

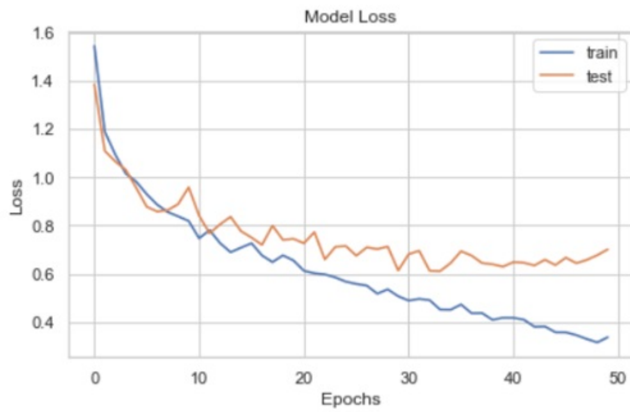
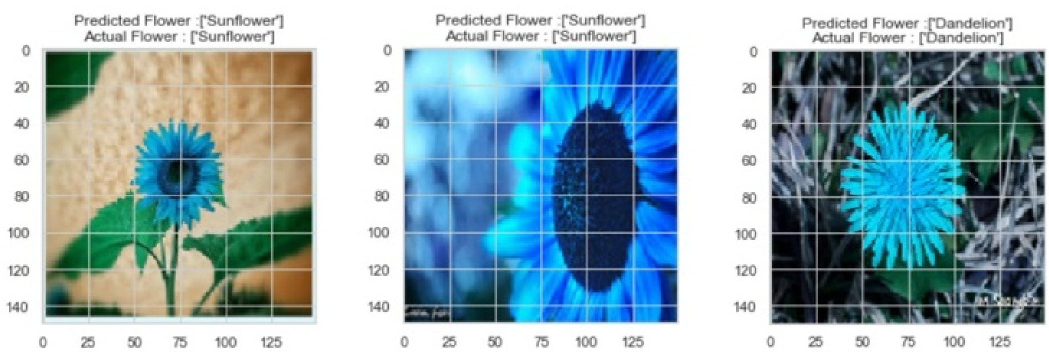


Figure 5 : Model validation and training loss curve

<u>Accuracies and loss functions versus the number of epochs</u>

Figure 7 shows some of the images that were classified correctly. On the top we have the predicted class of the flowers that was given by the network and below it we have the class to which it actually belongs to.



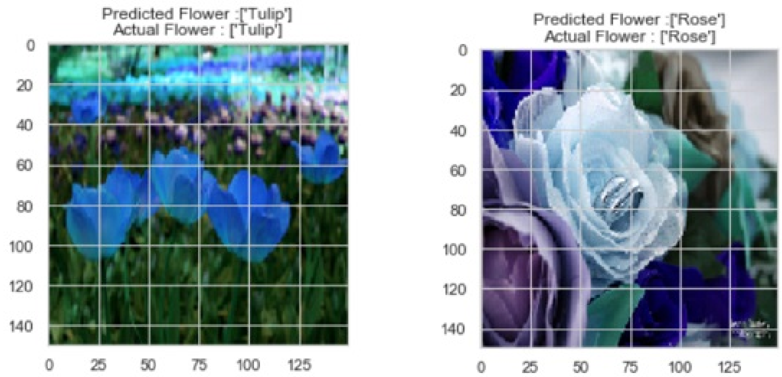


Figure 6 : Some of the correctly classified images are given

Figure 8 shows some of the images that were classified incorrectly. On the top we have the predicted class of the flowers that was given by the network and below it we have the class to which it actually belongs to.

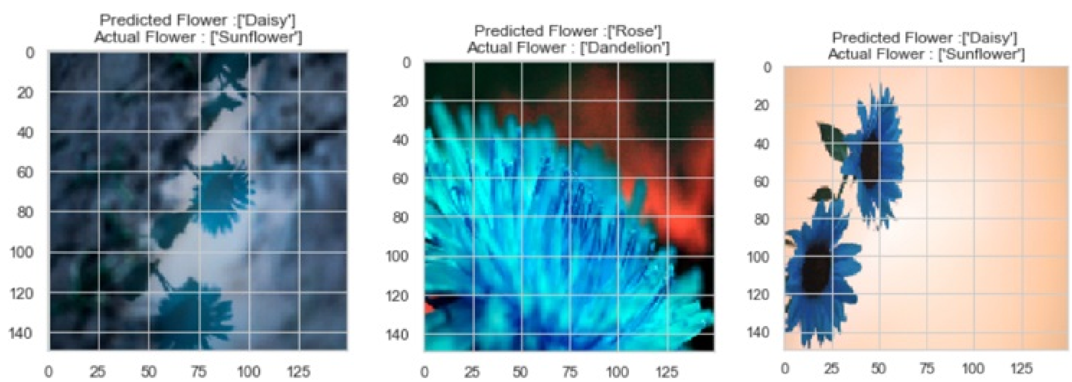


Figure 7 : Some of the incorrectly classified images are given

5 Conclusion and Future Scope

This project tries to set up a start to an area that is less explored at the current time. During this project we were able to explore part of the deep learning algorithms and discover strengths and weaknesses. We gained knowledge on deep learning and we obtained a software that can recognize flowers from images.
We hope that the results and methods presented in this project can be further expanded in a bigger project. From our point of view one of the main objectives for the future is to improve the accuracy of the neural network. This involves further experimenting with the structure of the network. Various tweaks and changes to any layers as well as the introduction of new layers can provide completely different results.
Another option is to replace all layers with convolutional layers. This has been shown to provide some improvement over the networks that have fully connected layers in their structure. A consequence of replacing all layers with convolutional ones is that there will be an increase in the number of parameters for the network. Another possibility is to replace the rectified linear units with exponential linear units.
According to project , this reduces computational complexity and add significantly better generalization performance than rectified linear units on networks with more than 5 layers. We would like to try out these practices and also to try to find new configurations that provide interesting results In the near future we plan to create a mobile application which takes pictures of flowers and labels them accordingly. Another objective is to expand the data set to include more flowers. This is a more time consuming process since we want to include items that were not used in most others related papers.

6 References

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