IDENTIFICATION AND CLASSIFICATION OF FLOWERS USING DEEP LEARNING

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***Abstract*—Computer vision techniques play an important role in extracting meaningful information from images, analysing the extracted information and understanding it. In our everyday life, we come across numerous flowers, besides the rail line or in our garden. But in most case we have no knowledge about that flower.Some of them are identical in physical appearance like shape, size and colour. Hence it is difficult to recognize any species. In order to classify the flower in the broader sense as to whether it belongs to the category of rose,sunflower or tulips and subsequently identify the sub category or the specific species type we propose a Machine learning model to identify and classify the flowers.The project focuses on how Machine Learning algorithms can automatically recognize the class of flower with the help of high degree of accuracy rather than approximately. There are three phases to implement this approach namely segmentation, feature extraction and classification using Neural Network, Logistic Regression, Support Vector Machine. Further we propose to make a comparative analysis of different flower classification systems with the proposed Machine learning model based on the simulation results obtained based on the simulation results obtained.**

***Index Terms*—Machine Learning, Extraction, Classification, Convolutional Neural Network, Logistic Regression,Support Vector Machine**

I. INTRODUCTION

In research and development work plant identification is a vital plan, and also used as a powerful technique for plant protection for plant species differentiation and genetic relationship discovery. The leaves can commonly be easily acquired from the plant, and have appropriate recognizable attributes to determine between several species. Currently, plant analysis is primarily geared towards professional plant scientists. However, there are a vast number of plant species, which are complex for a plant scientist to completely identify. Hence computers and related machine learning algorithm need an automated plant species recognition method. Categorization of flowers is a difficult task even for humans — surely harder than refusing service against a human car from a bicycle. Picture classification is a vibrant area of research involving underlying object and machine vision. Readily available classifiers were proposed for various applications in the literature. Here the suggestions carried using convolution neural networks to identify floral images. While flowering plants play an important role in human activities, the ability to identify them is increasingly lacking in humans. Moreover, the typical plant classification system is a challenging and complicated process for un-experts, i.e. using a standard link recognition tree with dichotomies keys. However, due to substantial advancements in machine vision and machine learning, autonomous picture-based recognition presents an easy and quick way to determine the plants. In previous studies use of the leaf images for this function has been thoroughly explored. Although leaves can be identified during a year at almost any time, the processing of suitable leaf images introduces difficulties as the segmentation of the foreground is required to retrieve variables of the discriminative type. However, for most scenarios these shape variables are true only for some sort of leaf, i.e. simple single leaves. The most physically recognizable and noticeable part of a plant is its flower, a subject of extensive botanical research and sometimes the key to species identification. Flowers demonstrate wide variation in colour, shape and texture, permitting the use of a broad range of strategies built for object classification tasks. The specific challenge of classifying flower-based plants comes from visually small variances in the interclass as opposed to general variances in the interclass. In an accurate representation, very small differences in the nature of visually similar flowers must be taken into account. Therefore, the classification type of these operations is called fine grained classification. Using local image features, i.e. a series of image regions corresponding to artifacts or parts of them, allows for significantly greater classification accuracies compared to evaluating the overall image quality in equal measure for certain tasks. Initial flower type surveys supported exactly designed descriptors relying on contour parameters and coloration histograms for instance on foreground segmentation and corresponding flowers definition. Certain approaches are extremely limited and often apply only to some type of inflorescence and to a distinct viewpoint. The aim of this research is to analyse method variations on three separate datasets in relation to the representation accuracy in plant classification based on the flower image. In addition, here showing the beneficial use of excellently-defined constraint during image acquisition by comparing the findings obtained on those datasets.

We know machine learning is the subpart of computer science. Machine learning centers around the advancement of computer programs that can show themselves to grow and change at the point when exposed on new unseen data. It is an exploration field which has the intersection of both predictive and statistical analysis. There are two fundamental categories of machine learning. They are supervised and unsupervised learning and here in this paper, we focus on supervised learning approach, which uses a training set to teach models to get the desired output. The training dataset consists of training samples. In supervised learning each training sample consists of a pair of an input value with the desired output value. Supervised learning can be based on classification and regression. If the output value is categorical, then that is termed as classification or else if the output value is a real value, then that is regression.

A. Convolutional Neural Networks

Convolutional neural networks are a class of machine learning networks which are commonly applied to image visualization problems such as classification. CNNs were inspired by the connections of the neurons and synapses in the brain. The design of these networks is made up of series of convolutional, pooling, and fully connected layers. The convolutional layer does what its name describes, it applies a number of convolutional fifilters to the input images in order to acquire the learning parameters for the network. Pooling layers are placed in between convolutional layers, and are used to reduce the number of parameters used for learning, and thus reduce the computation required. Finally, fully connected layers are full connections to the previous layer, rather than the small window the convolutional layers are connected to in the input. Convolutional neural networks are commonly used for image classification, however, there are limitations to this application. A human can identify the contents of certain images much more quickly than a computer, but CNNs have proven to have a 97.6% success rate when applied to facial recognition. Basically, a Convolutional Neural Network consists of adding an extra layer, which is called convolutional that gives an eye to the Artifificial Intelligence or Deep Learning model because with the help of it we can easily take a 3D frame or image as an input as opposed to our previous artificial neural network that could only take an input vector containing some features as information.But here we are going to add at the front a convolutional layer which will be able to visualize images just like humans do.

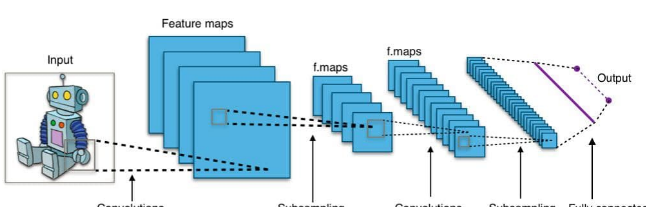

Fig. 1. Convolutional Neural Network

II. RELATED WORKS

Hsu, TH., Lee, CH [1] describes the usage of an interactive, color-and shape-based flower segmentation interface. In this work the user tries to picture a bounding box on the position of flower, and the algorithm like segmentation which make use of boundaries of flower to trace the algorithms to more accurately and to extract the flower regions. Studies were performed on OUFD, and results on a big collection of flower images indicate reliable boundary detection. Prashengit Dhar [2] discussed flower characterization framework as functions using LBP and SURF, and SVM is used as a classifier. Pre-processed image of the input to enhance picture quality. The image obtained after pre-processing is segmented using the active method of contour segmentation. The LBP and SURF features are deleted after image segmentation. The SURF functions are derived from MSER regions. Then they are undergone with the concatenation.Such concatenated features for classification are fed in to the SVM classifier. This employs Quadratic SVM trains to classify those features and controls. But they do produce bad results. Joylin Priya Pinto [3] explains the methods for the identification of Iris flower species. The Iris dataset or Fisher's Iris dataset is a multivariate data set presented by biologist and statistician Ronald Fisher in 1936. It is basically published at UCI Machine Learning Repository. .The paper describes the various methods and algorithms used in the analysis of iris dataset. SVM, KNN and Logistic Regression methods are used to get good accuracy result and we have also applied the cross validation technique to improve the accuracy. Md. Mizanur Rahman [4] explained Flower is a very important part of nature. Experienced botanists do this identification of flower but a naive person will have to consult flower guidebooks or browse any relevant web pages on the Internet through keywords searching. Our system can recognizes the flower in real time using mobile camera.With the rapid development of technology, AI is being used in various fields. Machine learning is the most basic method to achieve AI. This research describes the work principle of machine learning and an application of machine learning. Dr. Dayanand Lal Et.al,[7] analysed method variations on three separate datasets in relation to the representation accuracy in plant classification based on the flower image. In addition, they showed the beneficial use of excellently-defined constraint during image acquisition by comparing the findings obtained on those datasets.The total species of flower being image characteristics are retrieved from the training dataset using Convolution Neural Network and stored to format HDF5 files. Xuanxin Liu, Fu Xu, Yu Sun, Haiyan Zhang, and Zhibo Chen [15] proposed the C-RNN models for observation-centered plant identifification. The CNN backbones extract features and the RNN units integrate features and implement classification. The combination of MobileNet and GRU is the best trade-off of classification accuracy and computational overhead on the Flavia dataset. The test accuracy reaches 100%, while it has fewer parameters. Experiments on the BJFU100 dataset show that the C-RNN model trained by two-stage end-to-end training further improves the accuracy of majority voting method by 0.7%. The proposed C-RNN model mimics human behaviors and further improves the performance of plant identification, which has great potential in in-field plant identification.

III. METHODOLOGY

A. Block Diagram

The objective of our methodology is to choose the best classification model which performs well on flower species identification. Learning models are created based on CNN machine learning algorithm. For developing this method five different flowers dataset features are used in the train and test datasets. This algorithm is implemented using tensorflow tool kit based on Python. In this analysis we are trying to find out which classification model holds good. To know the model accuracy, we have also evaluates the predictive models by dividing the original sample data into a training set in order to train the model and a test set to evaluate it.
The block diagram of our model is given below:

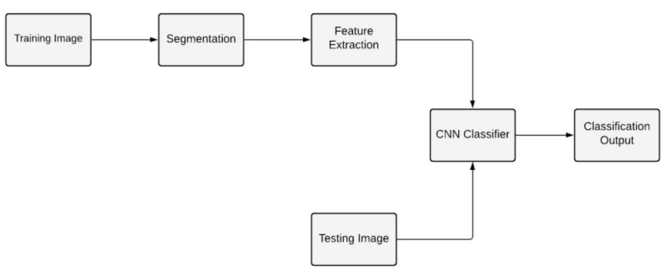

Fig. 2. Blockdiagram of Methodology

B. Data Collection

Accumulation of related dataset is a crucial for carrying out experiment and producing results.For implementation purpose we have used flowers dataset which is a multivariate dataset.There are a number of existing datasets which have images of specific flowers. These datasets were generally collected for very specific uses with neural networks that were designed to classify flowers based on certain characteristics. Collection of data set is very important for training and testing of network. The data which is used for training and testing should give high accuracy and should meet the project outcomes.The dataset for this project was produced by Github.com.The dataset consists of total 3670 flowers images of type Daisy,Roses,Dandelion,Tulips and Sunflowers.As a result, the images of the flowers are a diverse collection of plants in their natural setting. This adds the benefit of training the network for use outdoors.These were true-color photos with varied resolution. Since we have not managed the image acquisition and camera activity, the images in the dataset having completely different distinction and illumination. Therefore, it is very much required to apply a correct pre-processing technique.

C. Statistics of data

The following table consists the statistics of raw data

TABLE I
STATISTICS OF RAW DATA

Flower Name	No.of Images
Daisy	764
Dandelion	1052
Rose	784
Tulip	984
Sunflower	733

D. segmentation

The aim of Segmentation is image enhancement and image restoration. Image Enhancement is a significant process that aimed to recover the visual look of an image. It is provided for the better transform representation for the next phases of image detection. Segmentation is the process which is

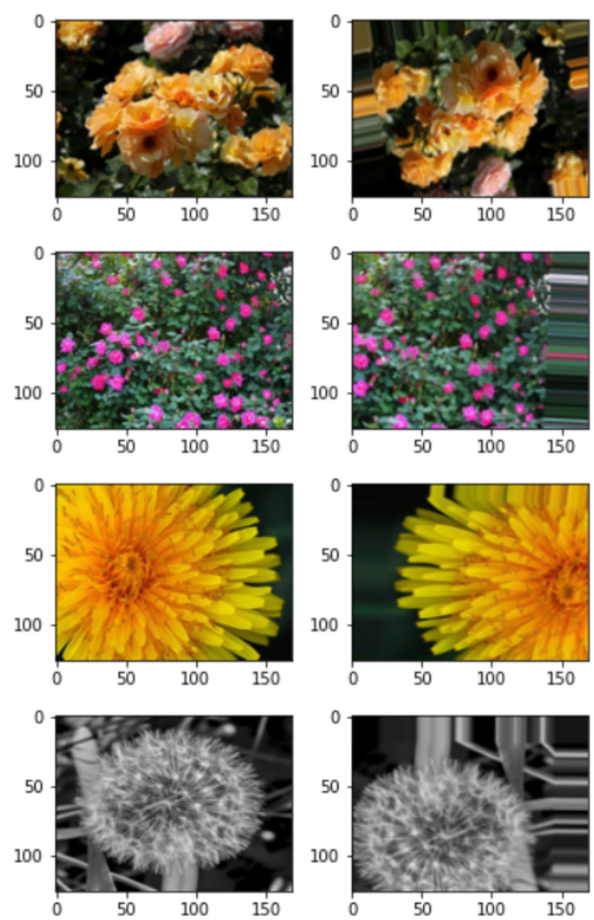

Fig. 3. Augmented Image

used to remove the inadmissible background and consider only the spotlight (foreground) object that is flower. Images that contains flowers are too contain parts of plant, leaves or grass in the background. In order to extract the correct features, it is required to separate the flower image from its background. To remove the background of images and improve the quality of flower image foreground, segmentation techniques are used.The main objective is to simplify the representation of the flower and to provide something which is more significant and easier to analyze. to increase the quality of images and removing the inappropriate noises presented in images.

E. Feature Extraction

After applying image segmentation, features are extracted from the segmented image. In the field of computer vision and image processing, feature describes an information that is used to identify or detect some object related to certain application.Within identical species, flowers could look completely different and generally flowers from different species contains high similarity. Moreover, some flowers area unit distinguishable by their colors, whereas others have special types of texture. The key challenge of classification is to figure out acceptable choices to infer the visual information of flower image and to produce a classifier in such a way, that it is able to differentiate between different species. In this work, features pertaining to flower image include color, texture, size of species have many attributes which are common with each other and produce less effective result. Therefore we have to measure the image by merging different feature descriptors which identify the image more efficaciously.

F. Classifier

In our dataset, we have all the images of five types of flowers in training as well as in the test set folders. We are going to train our CNN model on images of flowers like roses, daisy, tulips,dandelion,sunflower each respectively that are present in the training set followed by evaluating our model with the new images of Roses, tulips,dandelion,sunflower and daisy flowers, each respectively in the test set on which our model was not trained. So, we are actually going to build and train a Convolutional Neural network to recognize if there is a rose,daisy or tulip in the image.

For the implementation of CNN, we are going to use the Google Colab. So, we will start with importing the libraries, data preprocessing followed by building a CNN, training the CNN and lastly, we will make a single prediction. All the steps will be carried out in the same way as we did in ANN, the only difference is that now we are not pre-processing the classic dataset, but some images, which is why the data preprocessing is different and will consist of doing two steps, i.e., in the first, we will pre-process the training set and then will pre-process the test set.

IV. Proposed Algorithm

The proposed methodology for flower identification and classification is represented in figure 2. The process is started with image segmentation. After performing segmentation, the features are take out from segmented image including basic and morphology features of flowers. The outcome of data segmentation and feature extraction is the final training data set that is used during model building phase. In model building phase, a model builds and tests by applying appropriate machine learning method on training data set. The dataset containing training examples is considered as an input for the model building phase. It is generally divided into three categories: training, validation, and testing. 80% of the data is contained by training data set including of the validation data set and 20% of the data is contained by the test data set. During experimental work, CNN is emerged as a most efficient algorithm and it has been tested over a dataset containing 4317 flower images. After a model has been trained and tested, it is able to identify and classify a flower image and generates the predicted output.

A. Loading Image data

There are five flower categories. The images are loaded in a numpy array as matrix and associated categories are loaded in an independent array. We resize images so they all have the same width and height. We select the width as the mean width of all images and the height as the mean height of all images. images are loaded and resized with a width of 169, and a height of 126 and stored in the numpy array.So we have 4317 tensor images of width 169 and height 126, each pixel being defined by three colors R, G, B.We can check by random images that each of them have the same size.

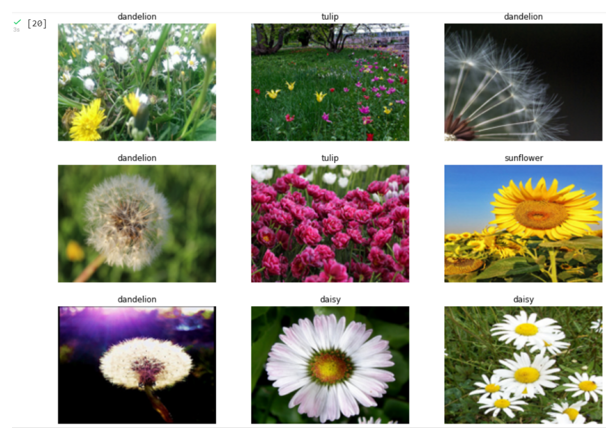

Fig. 4. Loading Random Images

B. Train and Test Split

We used the random seed 43 and a test set size of 20% of the dataset. Moreover, we use the parameter stratify set to target so that the class repartition is maintained.

C. Preparing data and Target Encoding

To ease the convergence of the algorithm, it is usefull to normalize the data. We see here what are the maximum and minimum values in the data, and normalize it accordingly.And again we check the images randomly.Then we convert targets. First, from string to numerical values, each category becoming an integer, from 0 to 4 (as there are five different flower categories).Then we have fitted the encoder on training set.Then applied on both training and testing sets.And then, we convert

```
[24] print(X_train.shape)
     print(X_test.shape)
     print(y_train.shape)
     print(y_test.shape)

     (3453, 126, 169, 3)
     (864, 126, 169, 3)
     (3453,)
     (864,)

[25] pd.DataFrame(y_train).value_counts()/len(y_train)

     dandelion    0.243846
     tulip        0.227918
     rose         0.181581
     daisy        0.176948
     sunflower    0.169708
     dtype: float64

[26] pd.DataFrame(y_test).value_counts()/len(y_test)

     dandelion    0.243056
     tulip        0.228009
     rose         0.181713
     daisy        0.177083
     sunflower    0.170139
     dtype: float64
```

Fig. 5. Train and Test split

the result to one-hot encoded target so that they can be used to train a classification neural network. We use to categorical from tensorflow library. Then we built the CNN network.

D. Design Implementation

The image data is reduced to a size of 169x126 pixels in order to not overwhelm the hardware the program was normally tested on. Batches of 32 images are fed into the convolutional layer and 16 filters of 8x8 pixels are applied to the images.Then,Each pooling layer uses a pool size of 2x2 and a stride size of 2.Each fully connected layer performs an activation on each of its inputs. The first, however, performs a RELU activation function on the data. Then we set an early stopping after 5 epochs and set the parameter restore best weights to True so that the weights of best score on monitored metric - here val accuracy (accuracy on test set) - are restored when training stops. This way the model has the best accuracy possible on unseen data. Then we have plotted the graphs with 70% accuracy.

E. Training

When one train networks for machine learning, it is often useful to monitor the training progress. By plotting various metrics during training, one can learn how the training is progressing. For example, one can determine how quickly the network accuracy is improving, and whether the network is starting to over fit the training data. When one specify 'training-progress' as the 'Plots' value in training Options and start network training, train Network creates a figure and displays training metrics at every iteration. Each iteration is an estimation of the gradient and an update of the network parameters. If one specify validation data in training Options, then the figure shows validation metrics each time train Network validates the network.

Training accuracy: Classification accuracy on each individual mini-batch.

validation accuracy: Classification accuracy on the Test set

Training loss and validation loss: The loss on each mini-batch, its smoothed version, and the loss on the validation set, respectively.

If the final layer of your network is a classification Layer, then the loss function is the cross entropy loss. Once training is complete, train Network returns the trained network. When training finishes, view the Results showing the final validation accuracy and the reason that training finished. The final validation metrics are labeled Final in the plots. If one's network contains batch normalization layers, then the final validation metrics are often different from the validation metrics evaluated during training. This is because batch normalization layers in the final network perform different operations than during training.

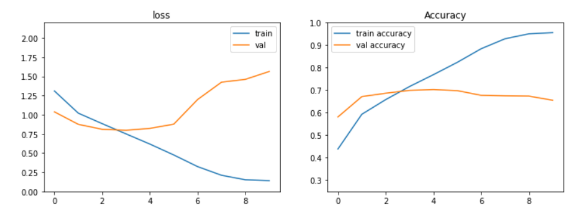

Fig. 6. Accuracy before augmentation

Then, We try to improve the model accuracy by using the data augmentation. It consists in applying little transformation to input images without changing its label. For this, we use ImageDataGenerator from tensorflow. It will generate images a little bit different from an original image so that it will be like the algorithm is training on more data.Then we have trained the model and we got accuracy improved by 10%

```
[52] plot_history(history_aug, title='', axs=None, exp_name="");
```

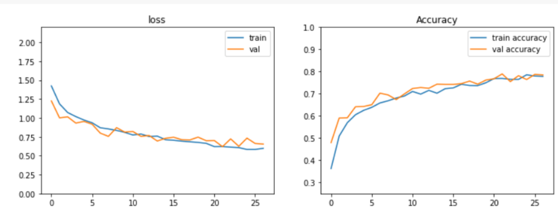

Fig. 7. Accuracy after augmentation

F. Pre-Trained Networks

Then we further improved our model using pre-trained networks like VGG16,ResNet50,MobileNetV2.

1) VGG16: VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR(Imagenet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx) parameters.

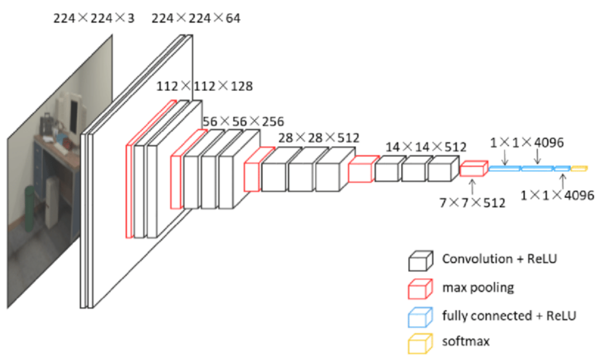

Fig. 8. VGG16 Architecture

2) ResNet50: ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

3) MobileNetV2: MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices. It is based on an inverted residual structure where the residual connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity. As a whole, the architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.

G. Testing

Testing is the process of evaluating the network. Testing the network gives how efficiently network is classifying the data, how accurately classifying the data. In Google COLAB we tested the images between the true labels and predicted labels.

H. Performance Metrics

To measure the performance of the classification algorithms can be obtained through accuracy.

Accuracy: The comparison of a measurement with a known standard, used to determine whether the measurement is reliable. Measurement accuracy is identified as the difference between the measurement of a factor and the accepted value for that factor from a trusted external source, or the percentage by which the two values differ.

$$Accuracy = TP + TN/TP + TN + FP + FN \quad (1)$$

True Positive:A true positive is an outcome where the model correctly predicts the positive class.

True Negitive:A true negative is an outcome where the model correctly predicts the negative class.

False Positive: A false positive is an outcome where the model incorrectly predicts the positive class.

False Negative:A false negative is an outcome where the model incorrectly predicts the negative class.

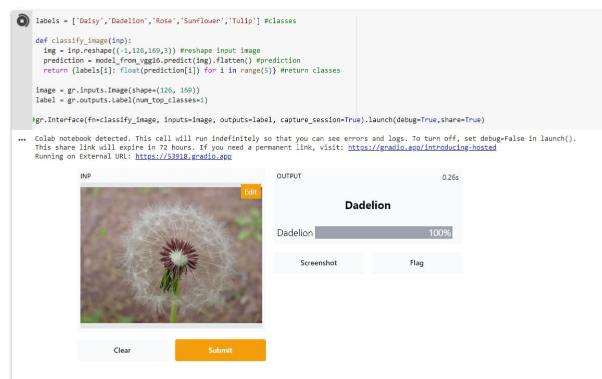

Fig. 9. Identification of flower

Overall Design Development

The initial step of this project was to research the available machine learning libraries, convolutional neural network design, and collect datasets. Though there exist some other libraries, but Tensorflow was chosen because there are many tutorials and documentation for the library.the goal of this project was to learn how to develop and optimize a neural network. The initial designs of the CNN for this project were based on several different tutorials about how to use Tensorflow to design an image classifier. The next step was to begin modifying the initial network to try and find a design that worked for the application of this project. The design of CNN which we tested is being submit as a deliverable for this project. This model also was trained using the dataset at the genus-species level, which uses approximately 800 images average per class, which is almost enough. But we are working to add more images per class. This model is currently being trained and tested. The parameters of the network such as number of training steps, output directory, and image input directory can all be specified, however, their defaults will place all the output directory in the current working directory. The input image directory must be specified, and the contents of the directory must be folders of images in tf files folder.The other lists which images were selected for training, testing, and validation.The classifier uses these to read result for each image classification and show the output result

Results and Discussion

The results obtained in identifying and classifying the flowers using Machine learning. A reasonable dataset has been collected through internet, labelled according to the application and trained using Convolutional neural networks. In this project we implemented the CNN network using TensorFlow

as per our requirements and trained under supervision.We have used pre-trained models VGG16, ResNet50. MOBILENETV2 A desirable training options are used to make the network stable so that one can ensure that the network will give high accuracy in classifying the data. So this training has gone under several trail and error methods to get the best out of all. The Python script which uses to the trained Tensorflow model is very simple, because most of the time spent on this project was for collecting the data and learning how to design a CNN. The classifier is designed to take a directory of images, a text file of the labels used in the network, and the trained model itself as inputs. The classifier tests the images with the specified model and displays the results comparing the correct label with the top four classes based on the confidence level of the predictions. The results of this project is almost successful and has the potential for future improvements. Now the application can identify flowers of different classes. We deeply focused to the accuracy rate. The accuracy rate depends on the amount of data. So that we use more images with different angel to improve the confidence level. Currently some flower identify with 100% confidence level. It is one of the success of our research and project. We used average of 850 images for per flowers for training step. The dataset contains around 4317 flower images. The CNN and the classifier are inconsistent, with some tests resulting in nearly 100% confidence during a correct classification, and other tests which entirely fail to produce a correct classification.
The experiment was carried out using Google COLAB. The images of the dataset is resized with dimension of 169x126 pixels. After applying the appropriate pre-processing and segmentation techniques, the features are extracted and the dataset is prepared to apply the proposed CNN algorithm with the integration of multi-label power dataset. Individually, for 5 classes (flower species), the classification of flower images with CNN achieves better classification accuracy compare to other classifiers with multi-labeling.The prediction model is predicted the name of the flower.

TABLE II
PERFORMANCE ANALYSIS

Name	Actual Output	Predicted Output	Prediction
Dandelion	Dandelion	Dandelion	Correct
Sunflower	Sunflower	Sunflower	Correct
Rose	Rose	Tulip	Incorrect
Daisy	Daisy	Daisy	Correct
Sunflower	Sunflower	Sunflower	Correct
Rose	Rose	Sunflower	Incorrect
Daisy	Daisy	Dandelion	Incorrect
tulip	tulip	tulip	Correct
Daisy	Daisy	Daisy	Correct
tulip	tulip	tulip	Correct

CONCLUSION

In this project, the identification and classification of flower images with its species is discussed. A dataset is accumulated that contains 4317 flower images of 5 classes. Basic and morphology features of flower images are extracted using computer vison techniques with image pre-processing and image segmentation methods. A prediction model using machine learning CNN algorithm is built with the integration of TensorFlow to classify different flower species easily, and the process becomes very fast, helping them in further research and study. Transfer learning technique with advanced pretrained networks has high rate of accuracy. The ultimate goal of this project is to design and optimize a convolutional neural network for use with flower classificationIt is observed the proposed approach achieved relatively a good classification accuracy with optimum possible extracted features.We will continue our research to make the system more efficient.

I. Future Work

This project has plenty of room for future work, by myself or a future interested student.
1. Improved CNN design. There much more research and practice is needed to optimize the design.
2. Improve the dataset and add more data.
3. Specific Identification of duplicate flower which is same to look at.

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