Image Classification: Classification of Flower over Oxford 102 Dataset

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Introduction

- Classification of flowers is our main purpose.
- Features that distinguish one flower from another are colour, texture, shape and number of petals or sepals.
- Flowers are widely used in various fields namely horticulture , medical. For example, Fig 1

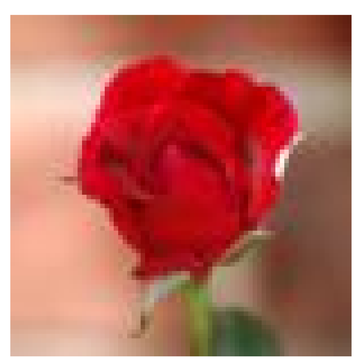

Figure 1: Rose petals are widely used in medical like rose water, cosmetics, decorations and for culinary purposes.[1]

Problem Statement

- Given the different categories of flowers, aim is to *classify* the flowers according to their categories by using conventional and deep learning approaches.

Dataset

- Oxford 102 flower dataset comprises of 102 categories of flowers having minimum of 40 and maximum of 258 images , Table 1.
- Images were collected by searching the web and taking pictures. Images are of different resolution.
- Out of 102 categories of flowers we selected 23 categories containing at least 100 images in each category and re-sized images to 100 × 100 and for transfer learning re-sized images to 70 × 70 .

Data Attributes	Brief Explanation	Example
Class Label	Unique identifier of each class	21
Image description	RGB images with different resolution. Each category contains minimum 40 images	Category lotus contains 137 images.

Table 1: Details of images (Oxford image dataset)

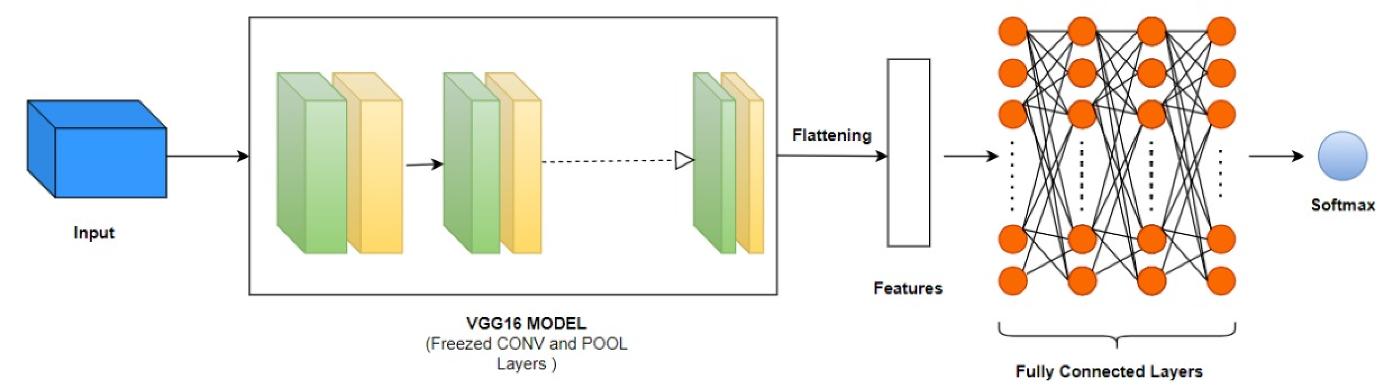

Figure 2: Input given to the model are RGB images which were fed into VGG16 CNN model pretrained on ImageNet dataset whose convolution and pool layers were freezed and extracting significant features of an image, then these features were feeded into fully-connected layer after flattening.

Methodology

Data Preprocessing

- Downsampling : The dataset was downsampled to 23 classes where each class was having at-least 100 images.
- Resizing : The images are resized to 70 × 70.

Transfer Learning Implementation

- The base model incorporates VGG16 model trained on ImageNet dataset.The model was set as not trainable.
- The transfer learning model has base model followed by four fully connected layer and a predictive layer.
- The model first extract significant features of images using conv and pool layer of VGG16.
- Those features were passed to fully connected layers in flatten format .
- Softmax function predicted the probability for each class of an image .

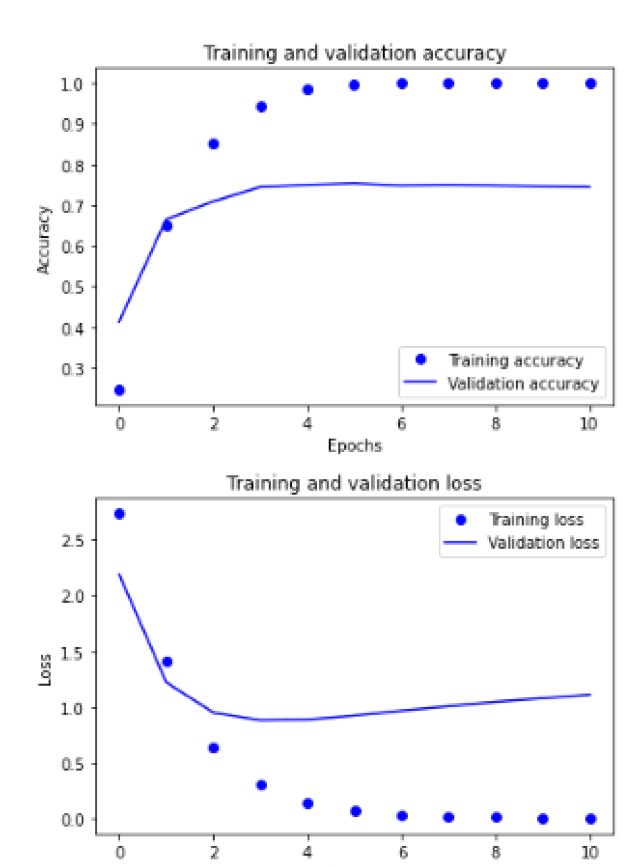

Figure 3: It depicts transfer learning model accuracy and loss during training as well as validation.

Experiments

KNN algorithm with hyperparameter tuning , selected best k values from **0 to 40** and with **manhattan distance** metric . **5 cross** fold validation performed.
Accuracy achieved = 32%

NN algorithm with input size of **100*100*3** having **100** neurons in input layer and **two hidden** layers having **80 and 50** neurons in each layer with **relu** activation function. Output layer having **23 neurons** with learning rate of **0.0001** with **softmax** activation function and **categorical crossentropy loss**. Trained the model on **50** epochs with batch size of **30.**
Accuracy Achieved = 39.7 %

CNN algorithm with input shape of (100,100,3) using **3** convolution layers with 100 filters of **3 x 3** size, **3** maxpool layers of filter size **2 x 2 and relu** activation function 3 FC layers having **90,80 and 70 neurons** each layer and output layer having **23** neurons with **softmax activation** function and **categorical cross-entropy loss** and learning rate of 0.001. 50 epochs with batch size of 30. Split is 0.2 between training and validation data.
Accuracy Achieved = 53.92 %

CNN algorithm with regularization input shape of (100,100,3) using **3** convolution layers with 100 filters of **3 x 3** size, **3** maxpool layers of filter size **2 x 2 and relu** activation function, 3 FC layers having **90,80 and 70 neurons** each layer and L2 regularization is used with learning rate of 0.01. output layer having **23** neurons with **softmax activation** function and **categorical cross-entropy loss**. 50 epochs with batch size of 30. Split is 0.2 between training and validation data.
Accuracy Achieved = 58.51 %

Transfer Learning input shape (70,70,3), selected **VGG16** model with imagenet weights, and **4 dense** layer with **120,100,80 and 60** neurons each layer with relu activation function and predictive layer of **23** neurons with softmax function. Hyperparameter i.e. learning rate of **0.0001** with an **adam** optimizer. Fitted model on **50** epochs and with **84 steps_per_epochs**.
Accuracy achieved = 75.85%

Data Augmentation input shape **(70,70,3)**, augmented the data by **feature wise centering, sample wise centering, feature wise std normalization, rotation range 20, zoom range 0.2 ,width shift range and height shift range 0.2, horizontal and vertical flip.** And used augmented data on transfer learning model and fitted on 50 epochs with 84 steps per epochs .
Accuracy Achieved = 46.07 %

Figure 4: It depicts the performed experiments and their architecture.

Results

We selected Nilsback et al. [2] as our **base paper** and **Oxford 102 category flower dataset** to perform our experiments. Our transfer learning model outperformed the baseline with an accuracy of 75.85 % whereas they achieved 72.8 % accuracy for the combination of features using SVM classifier.

Table 2: Results

Model	Training Accuracy %	Validation Accuracy %	Testing Accuracy %
KNN	100	24.33	32
NN	94.12	42.22	39.7
CNN	100	49.63	53.92
CNN Regularization	100	62.22	58.51
Transfer learning	100	74.44	75.85
Data Augmentation	80.28	83.93	46.07

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