BANGLADESHI LOCAL FLOWER CLASSIFICATION USING CNN

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Bangladeshi Local Flower Classification Using CNN**", submitted by Ikhtiar Khan Sohan, ID: 171-15-8668 and Jahid Hasan Shuvo, ID: 171-15-9074 and Ruhul Amin, ID: 171-15-8720 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 27 January 2021.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Ms. Rubaiya Hafiz, Sr. Lecturer, Department of CSE,** and co-supervision of **Mr. Majidur Rahman, Lecturer, Department of CSE,** Faculty of Science and Information Technology, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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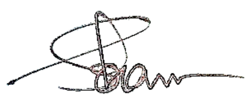

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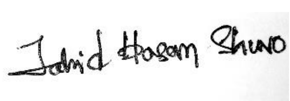

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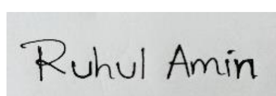

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ABSTRACT

A very beautiful gift, known to us as a flower, has been sent by our nature. Flowers have given us all kinds of colors and lovely fragrances as well, and only flowers enhance the beauty of our world. The fragrance of the flower brings immense peace of mind. It mesmerizes everyone. In various parts of our lives, technology will play an important role in helping aspects of our lives. Today's computer vision technology is powered by deep learning algorithms that make sense of images using a special form of the neural network, called a convolutional neural network (CNN). In deep learning, we can use the convolutional neural network (CNN) to get state-of-the-art accuracy in various classification problems, such as image info, CIFAR-100, CIFAR-10, MINIST data sets. In this work, we propose a new system to identify automatic self-ruling decision-making and predictive models using a convolutional neural network for different types of local image flower detections (CNN). A lot of research has been done previously on flower classification in image classification issues, but our related issue of local Bangladeshi flower detection problem does not work on any model and any datasets. We have retrained the final layer of the CNN architecture, MobileNet, Inception V3, VGG16 for classification approach, for solid architecture. Predicting between 6 different types of flower pictures (AKONDO, DADMORDON, DUTURA, KOCHURIPANA, SIALKATA, VATFUL). We suggested an overall accuracy of about 90 percent that can be used for various purposes, such as different implementations of the operating system.

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Introduction

1.1 Introduction

Last few years, artificial intelligence and computer vision are widely used for many human activities. Technology has applied in different ways. We can apply flower detections technology for detect flower using computer vision applications. Different kinds of flowers and new species of flowers have been discovered. Nowadays, human life is far away from pure nature. Most people live in the city. Sometimes they go to the village. There are many local flowers in the countryside that no one knows about. Bangladesh is no exception. There are many local flowers in the villages of this country. But many do not know much about these flowers. Many people are interested to know about these flowers. An ordinary person with less botanical knowledge will not be able to tell which species a flower belongs to. There is no way we can get more details about flowers without consulting botanists, including the figure alone. Search for information on the Internet, you need to know at least one keyword related to that flower. Whereas there is a way to search images by input image, the result we find of local flowers is often irrelevant to what we want. This work proposed Flower Identification System which helps to recognize the image of flowers to get more information about their species. The system assigns image classification based on existing databases. The user will be able to gain important information about the input flower image like scientific name of the flower, botanical information etc. We can use deep learning using convolutional neural network (CNN) that read every pixel of an image and successfully able to extract feature from images. There are different types of local flower, but we work only with 6 popular local flowers detections and whose name are bench AKONDO, DADMORDON, DUTURA, KOCHURIPANA, SIALKATA, VATFUL. Our main goal is to build a transfer learning model that can recognize a photo of different types of local flower that could be apply computer vision applications. For that, firstly we have to train our model with a different types of models, but we developed a new CNN model to train our images for better accuracy. And also train VGG16, InceptionV3, MobileNet models for comparison with our CNN model for more trustworthy. There are several parts to complete our task, for easy to understand we can divide our task into different following sections, such as in section 3 described our proposed methodology that's included in an implementation of our model, data collection, data augmentation, data preprocessing, define test set for evaluating our models and train data set to train our model. In section 4 are described as performance evaluation, result discussion, comparison. And future work and conclusions and future works are mentions in section 5.

1.2 Motivation

Technology is an integral component of every human being's because with technology we can make more facile our quotidian life. Now we can utilize artificial perspicacity that able to make a decision like humans. When we fixate on an object or something then in a short time we can able to make a clear sense of that object. Our encephalon is very vigorous and more expeditious to make a clear sense, but it is not facile for us. Every time we processing a minimum of 60 images with high-resolution pixels to agonize that. When an object's light go through our retina with neurons to our encephalon then we can visually perceive and understand about that object but take remotely of time to give a result. To understand something, we have to train our encephalon, like that if we opiate to make a machine that can visually perceive the object and identify it prosperously. For that, we have to edify a machine to relegate objects near humans. At that conception, we can build a model that can relegate an image with a cognation of the training task.

1.3 Rationale of the Study

Using artificial perspicacity computer are becoming more and more human, because there are no any department we don't utilize computer. We can utilize artificial astuteness in anywhere like as internet, playground, home, office, factory, etc. For availing management system we can utilize it in different way and different places. By considering that's facts we can make a model that prosperously avail a human exercise zone management systems. Our proposed model make a vital role for prosperously apperceived human exercise activities efficiently. For making a model we can utilize sundry machine learning model like as deep learning utilizing a convolutional neural network.

1.4 Research Questions

In first time we can't understand what is our first work? because it is very arduous for us to identify our right path. At that time, we thinking some confusion questions.

- which programing language are perfect for implement our problems.
- How to collect data?
- Which types of picture are performed very well.
- How people are benefited?
- Is it possible to 90% correct classification rate?
- How easily we can use that?

1.5 Expected Outcome

We opiate to build a model that prosperously avail guides decision making. This model works on rural local flower detections accurately and can able to detect for availing about ken the flowers. In our project, we opiate to build a model utilizing popular most recent machine learning techniques for best performance. Our model impeccably identifies a flower and exhibit about the flower. Our model works in any situation and any weather impeccably. It's can able to detect 90% accurately for every input. Our model will be a light weight, because it take marginally time to give outputs for every input. Our model read only image form camera, video, text file, manually etc. But model's output can be different way. To build our model we utilize Deep Learning of Convolutional neural network. Because a convolutional neural network gives a good relegation performance for image data-sets. There is some main target to outcome of our project.

- Rural local flower classified.
- A little bit time to give output.
- It helps to know any people about the flower with provide information’s.
- It could able to performed any weather and any situation.

1.6 Layout of the Report

In this chapter one we already discourse about prelude of our project, objective, motivation, research questions, and last was expected outcome of our project.

CHAPTER 2

Background

2.1 Introduction

In this section, we discuss about cognate works of our project, background information, some scope of the quandaries and challenges. That discussion are subsidiary for our project to solve some quandaries because we can find pertinent information from our cognate works or literature reviews. In this section we can identify scope of the quandaries and challenges to how increase the precision level.

2.2 Related Works

Our data sets are totally new collected. Before the widespread works on image classifications we working with different data sets or different algorithms. But till now, there are many task done in ordinary flower image detection but not done the work Bangladeshi local flower detection. M.V.D Prasad proposed Convolutional Neural Network(CNN) model that able to classify ordinary flower image and got accuracy 97.78% [1]. Tanakorn Tiay use K-nearest neighbors(KNN) algorithm and they classify flower model and they got their accuracy more than 80% [2]. Many different ways to classify flower images. Formerly flower recognition system was raised by Das [3]. A color based flower segmentation algorithm was developed. It is very hard to relegate different flower species predicated pristinely on color; many different flowers and designates have kindred colors, and many flowers of the same species have different colors. Das color based approach was amended by [4]. Hong [5] use color clustering and shape feature to perform Region of Interest(ROI) predicted flower image retrieval. The color clustering is achieved utilizing color histogram predicated feature. Shape feature set is defined predicated on centroid Contour Distance(CCD) and angle code histogram (ACH) characterizing the flower contours. Hathaifa Almoydady [6] achive 81.19% accuracy using Artificial Neural

Network(ANN). Pardee [7] got 80.67% accuracy using python and random forest classifier method.

2.3 Research Summary

Beginnings machine learning was very weak of algorithm but, day by day machine learning algorithm are developed. Now machine learning are used every sector. Machine learning is an Artificial Intelligence (AI) technology that provides the faculty with structures to learn and modify from experience automatically without being specifically programmed. Machine learning focuses on the creation of computer programs that learn for themselves and can access and use data. From few years ago image predicated relegation commenced utilizing some machine learning techniques. Utilizing Convolutional neural networks we can able to edifying machines to understand an image. In this image relegation part there are a plethora of works with different way. We get a better erudition from background of machine learning, and cognate works. We use machine learning for flower classification. We make new model that able to task very accurately and efficiently.

2.4 Scope of the problem

There are so many scope of problem when we start our new work. New data collection and use new algorithm are within them.

2.5 Challenges

There are various challenges to fulfill our project. In the beginning we have to collecting new data set form separate sector to train our model. We have to prepared data afore going through the CNN model. Build a new model with various layer was very challenging. Number of epoch, Define training set , avoid Overfitting and batch size pick are very challenging for us. Our work is so challenging but possible to fulfill prosperously. We taking that challenge and work hard we complete our work.

CHAPTER 3
Research Methodology

3.1 Introduction

In this chapter, we being to describe how our method working. Flower image classification we implement convolutional neural network in this paper, cause it is the most powerful and popular for deep learning. We are collect and created totally new data set and model of the convolutional neural network (CNN). We consult about test set and training, input, output, every convolutional layer, variants types of technical issues, performance, etc. purpose of cleaning concept we will give an appropriate example.

3.2 Research Subject and Instrumentation

The research topic makes a fresh concept of our research area. In this section, we implement and design our model, collect perfect data, prepare the data and train our model, performance discussion, and then apply our model to working. For complete our work we used windows platform. For completing our work we use python programing language and many other packages like tensorflow, keras, numpy, OpenCV, cv2, seaborn, matplotlib, etc. We use python another package anaconda on jupyter notebook and finally used google colaboratory free online cloud-based Jupyter notebook environment to complete all programming task . We choose python because it is free, simple syntax, foster fast testing for involute algorithms readability for machine learning applications.

3.3 Data Collection Procedure

For this thesis purpose, we make a new dataset to train the proposed networks. About our rural flower known very few person. So the flower images are very rare on online platform. Most of images we collected directly by our smartphone camera from rural area. Some collect from several platforms like as websites, Facebook, Instagram, reddit, etc. All images are JPG format and resolution are different. Our collected data more than 1343 images with six categories there are "AKONDO", "DADMORDON", "DUTURA", "KOCHURIPANA", "SIALKATA", "VATFUL". Every class have more than 200 images. Our dataset have total of 1343 images, we use 1004 images for training and 335 for testing.

AKONDO

DADMORDON

DUTURA

KOCHURIPANA

SIALKATA

VATFUL

Fig 3.3.1: Display a part of Dataset

3.4 Data Processing

Our first obstacle are collect data and how to process them. Our collected data set all image data resolution are not the same. So we need prepare all data for working. Data processing is the essential part for training the model and get a better accuracy, because it reduces the overfitting, computational cost etc.

3.5.1 Data Augmentation

The few training sets can outcome in overfitting [8]. The some kinds of new dataset samples was enhance for avoid overfitting [9] that we used to train our convolutional neural network model (CNN). Data augmentation are very essential because it makes more effective of model performance and put down classification loss.

3.5.2 Data Preparation

For avoiding cost many computational resources and overfitting chance we finished augmentation and minimized the input images dimension fixed into 150 X 150 pixels. After that pass images on CNN model for this purpose used RGB color that simply help to detect features by CNN that ensure that to get better accuracy. For the normalizing, we can less RGB values by dividing by 255 and get the range of [−0.5, 0.5].

3.6 Research Methodology Convolutional Layer

There are many kinds of neural networks. Convolutional Neural Network (CNN) one of them. Mainly it is designed for image analysis. CNN is a specific part of artificial neural network architecture for deep learning that uses perceptron a grating machine learning unit algorithm for supervised learning to analyze different types of data. It can automatically eliminate high-level features from raw input features, which are more puissant than human-designed features. CNN operations-basically works depend on inputs for extracting pattern recognition and works well with data, that has spatial relationship CNN also has a learnable parameter like neural network [10]. Some of these layers are convolutional, using a mathematical operation and model to pass on results to gradual layers.

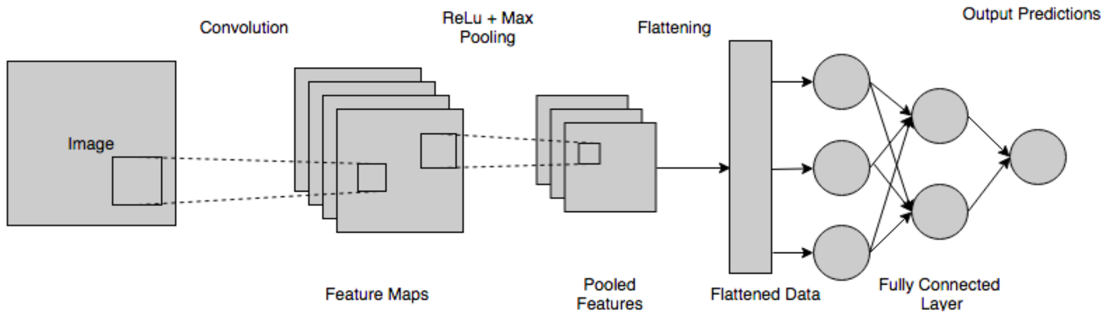


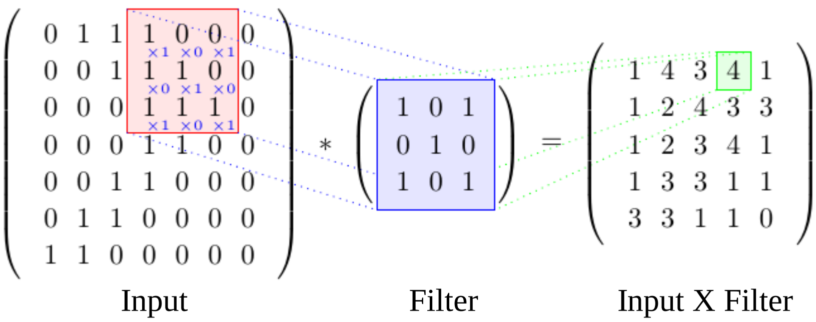
Fig 3.6.1: Architecture of CNN

3.6.1 Convolutional layer

A convolutional neural network has a many layer. It has an input layer, an output layer and many kinds of hidden layers. Every input is convoluted with various kinds of filter during the forward expansion or kernel [11]. We can Classification prediction problems, Regression prediction problems, object detection, face recognition, segmentation, etc. There are different types of layers to identify an image, such as the input layer of the first layer of CNN the read-only image pixel to pixel, the image can be grayscale category RGB. Then the filter used to the second step for extract the input image function in different way. Different forms of pooling layers are used to decrease the shape of input images for parameter reduction. The outcome of the convolution indicates momentum which has an effect on the classification[11]. These samples are called characteristics. Some model hyper-parameters have to be configured to create a convolutional layer like filter length, stride, and padding.

- Length of filters: The kernel acts as a filter, it works in the input data to extract unique features or pattern identifications that improve the classification efficiency. Filters are not specified in the CNNs. Throughout the training process, the importance of any filter is taught. CNN may find more sense from input images through filtering by people capable of understanding the values of various filters, but human-designed filters might not be able to find unique characteristics. As a

3X3 filter, which is small but probably simple to read input image pixels, the filter could be several different sizes.



1*1	0*0	0*1	1*0	1*1	0*0	1*1	1*0	1*1	Total (+)
1	0	0	0	1	0	1	0	1	4

Fig 3.6.1.1: Kernel

- Stride: The number of rows and columns that move pixels over the input matrix is defined by Stride. If the input matrix is used, Stride decreases the output dimension. If step is 2, then transfer the filters to an input matrix of 2 pixels. The stride number is always an integer, not a fraction, and the default stride is 1.

- Padding: After the convolution layer, the dimensions of the output matrix are reduced, but we can retain the output dimension as an input matrix using padding. Two types of padding exist: the same padding and legitimate padding. Valid padding means "no-padding and reduces the dimensions of the performance matrix". The same padding means that the same dimension as the input matrix is the output matrix. Add an extra block to the same padding, and symmetrically allocate zero to the input matrix for the same dimension.

To classify those features that are important for classification after each convolutionary process, use the activation function (denoted σ) [12].

3.6.2 Rectified Linear Units (ReLU):

When developing networks today, ReLU is the most commonly used activation function. The work of the ReLU is nonlinear and enables backpropagation. The constant gradient of ReLUs results in faster learning but at the same time it does not stimulate all neurons, as if the input is negative, it will translate to zero and it will not activate the neuron. So few neurons, not all neurons, are active at a time, so ReLU is much faster, quicker and more effective for this purpose. More biological inspiration for preparation.

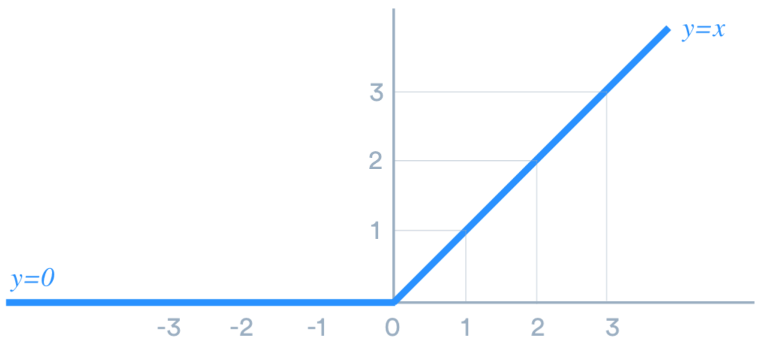


Fig 3.6.2.1: ReLU Activation Function

3.6.3 Pooling layer:

The pooling layer is a non-linear layer dividing the input dimension and reducing the number of parameters, controlling overfitting and retaining the most important information. The Pooling Layer size that can remove unnecessary features and retain the required features can be specified. MaxPooling, AveragePooling, and MinPooling are three forms of pooling sheet. Three pooling features in deep learning.

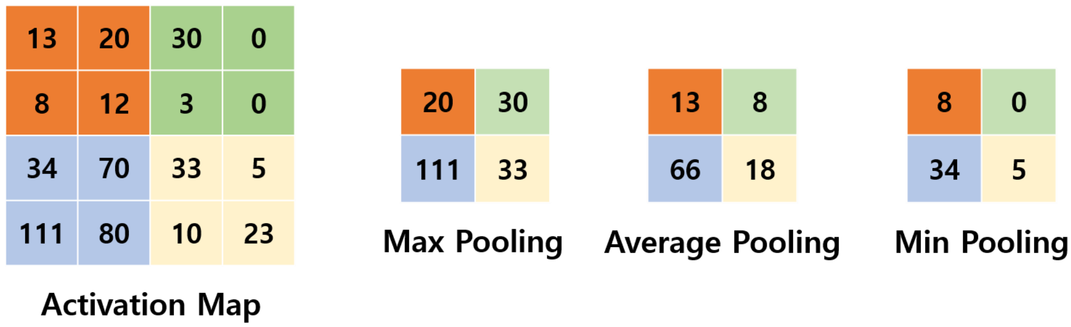


Fig 3.6.3.1: Poling Layer

- MaxPooling: It only selects the maximum value that the pooling window holds. MaxPooing is often used in the CNN architecture to identify related features because Max Pooling offers a better result from the layers of Average Pooling and MinPooling.
- AveragePooling: It selects only the average value in the pooling window.
- MinPooling: Choose just the minimum value in the pool pane.

3.6.4 Flatten Layer:

Flatten Layer There is a 'Flatten' layer between the convolutional layer and the completely connected layer. This process is called flattening, which transforms all the resulting 2-dimensional arrays into a 1D function vector. For the final classification layer, this flattening structure allows a single long continuous linear vector to be used by the dense layer.

3.6.5 Fully connected layer:

For a CNN network, the completely connected layer is the last level, which represents the feature vector for the input. Weights, biases, and neurons are included in the FC layer. In one layer, it binds neurons to neurons in another layer. To define each input efficiently and correctly, FC layers recombine each neuron. It is used by training to distinguish images between distinct categories. It is possible to contrast FC layers with Multilayer Perceptron (MLP), where each neuron has maximum connections with all previous activations of the layer[11].

3.6.6 Dropout layer:

A neural network is forced by the dropout layer to learn more efficient features that are helpful in combination with several different random subsets of other neurons [13]. Such layer layers boost over-fitting, reducing the training set's dependency and complexity.

3.6.7 Softmax layer:

In neural network functions, the Softmax layer is the last layer or output layer and is used to determine the likelihood of multiple groups. This function calculates the probabilities for each target class and returns the values for the specified inputs to evaluate the target class[14].

3.7 Test Set

For each class, this dataset includes 6 different classes and contains an average of 200 images. 1339 photos for all groups after augmentation. In this section, we construct a test set to evaluate our CNN model's classification results. We have split into two distinct test-set and train-set portions after data preprocessing. First use of the train-set for training our model. If we have successfully trained our model, then we can use the test set to validate our model. To get more valid accuracy, we pick test-set and train-set using random state = 42 and do well on the unseen test set. The training set is generated using 75 percent of the 1339 images and the remaining 25 percent is used for the test set[9]. Thus there are a total of 1004 images in the train set and 335 images in the test set.

3.8 Training the Model

After generating data preprocessing and defining train set, test set then we ready to train our model with training data sets that consist of 1004 photos. We update our model several times and adjust the optimizer, learning rate, loss function to increase accuracy and decrease loss as possible. Using Adam optimizer, we train our model to decrease the loss function as much as possible and apply it to a 75% training set and 25% validation set. For less memory, we use 128 batch size and quicker for training our model. As the method continues, we can see that training accuracy and validation accuracy are not greatly improved in 70 to 80 epochs. At that point, validation accuracy reached 97.01 percent, 1.00 percent training accuracy and 0.1884 percent validation loss. Then for final test evolution, our model is ready to predict unseen data.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      2432
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 37, 37, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 37, 37, 96)        55392
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 18, 18, 96)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 18, 18, 96)        83040
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 9, 9, 96)          0
_________________________________________________________________
flatten (Flatten)            (None, 7776)              0
_________________________________________________________________
dense (Dense)                (None, 512)               3981824
_________________________________________________________________
activation (Activation)      (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 3078
=================================================================
Total params: 4,144,262
Trainable params: 4,144,262
Non-trainable params: 0
_________________________________________________________________
```

Fig 3.8.1: Model Summary

3.9 Execution Requirements

For implement this Bangladeshi local flower classification experiments must be needs –

- Operation System (Windows 7 or above)
- x64-based processor
- SSD or HDD (Minimum 500 GB)
- RAM (Minimum 4 GB)

Necessary Tools

- Python Environments
- Jupyter Notebook (Anaconda) or online based platform Colab

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

This chapter we discuss about evaluated our model performance, number of parameters, accuracy level. Compare our CNN model with MobileNet, InceptionV3 and VGG16. For this comparison we use training and testing graph image

4.2.1 Number of Parameters

In our convolutional network model decorated with some of different layers, input size, number of filters, activation shape, etc. that generate weights, biases and that makes total 4,144,262 numbers of the parameter. First input image shape is 150X150 using RGB color to read-only image without generating parameters. Here used 4 kinds of Conv2D layers and MaxPool layers one Flatten layer, 2 dense layers with one output layer or softmax layer. The pool size (2, 2), strides (2,2) are same but number of filters (32,64,96,96) and kernel size (5,5), (3,3) are different in different layers.

Number 1: In input layer use for read image pixel to pixel. For Input Size that's activation shape are (150X150X3) for that activation size are 67,500 because input image wide 150, hight 150, and 3 for RGB color. In input layer are no parameters.

Number 2: Conv2D 1 is the first layer of convolutional network. It mainly works for extract features from image with filtes. In this model 32 number filter used and for that activation shape are (150X150X32) and activation size is 720,000. In Conv2D 1 generate (((5X5X3)+1)X32) = 2,432 number parameters. Here (5X5) is kernel size, and for RGB color 3.

Number 3: MaxPooling 1 layer use for reduce the number of parameters, avoid chance to overfitting. Here pooling size f = (2X2), stried s = 2, Image wide w = 150, hight h = 150.

So activation shape formula is (w-f+1)/s. so activaton shape is ((150-2+1)/2) = 74.5 = 75. Pooling layer reduce the image dimension 150 to 75 for that activation size is (75X75X32) = 180,000. Here 32 is filter size. Pooling layer don’t generate parameters.

Number 4: Conv2D 2 is the second layer of our model. It complete the same work for activation size (75X75X64) = 18,496 activation shape, and with 64 is number of filters make (((3X3X32)+1)X64) = 18,496 number of parameters. Here (3X3) are kernel size, and 64 is filter size.

Number 4: In section contain MaxPool 2. It is the second layer of MaxPool 2 for this model. At that same way pooling layer reduce the number of image shape 75 to 37 and make activation size 87,616 without generating parameters.

Number 10: After convolutional layer and pooling layer are flatten layer. It transforms all the resulting 2-dimensional arrays into a vector of 1D features. Activation shape (7776X1) = 7,776 number of activation size.

Number 11: Dense layer or fully connected layer have in this section. In this, layer has activation shape (512) but no activation size. It generates only parameters ((1+7776)X512) = 3,981,824.

Number 12: The final layer of this model is the Softmax layer. We can say that it is the output layer of our model. The Softmax layer creates parameters that have a final output form. Here (6X(512+1)) = 3,078 number of parameters.

After adding total number of parameters are 4,144,262. CNN's Conv2D and MaxPool layers use the activation form to produce the activation scale. MaxPool layer uses for reducing dimension size, and there are no parameters. Total parameters generate only Conv2D layers. For stable generalization, we don't increase CNN layers.

Table 4.2.1.1: Number of parameters

Layer		Number of Filters	Activation Shape	Activation Size	Parameters
Number	Operation				
1	Input Size	-	150,150,3	67,500	-
2	Conv2D 1	32	150,150,32	720,000	2,432
3	MaxPool 1	-	75,75,32	180,000	-
4	Conv2D 2	64	75,75,64	360,000	18,496
5	MaxPool 2	-	37,37,64	87,616	-
6	Conv2D 3	96	37,37,96	131,424	55,392
7	MaxPool3	-	18,18,96	31,104	-
8	Conv2D 4	96	18,18,96	31,104	83,040
9	MaxPool4	-	9,9,96	7,776	-
10	Flatten	-	7776,1	7,776	-
11	Dense 1	-	512	-	3,981,824
12	Softmax	-	6	-	3078
Total Parameters					4,144,262

4.2.2 Performance Evaluation

We applied the proposed CNN architecture to the data sets mentioned above to identify the best practices, achieving substantially better results with an average accuracy of 97 per class. In this picture, we can see the loss going downwards, and the accuracy of validation is increasing at this time, so we can tell at that point that the training model learns perfectly from the collection of training data.

Table 4.2.2.1: Classification result

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Number of epochs
MobileNet	92	94	92	92	80
InceptionV3	96	96	95	95	80
VGG16	94	94	95	94	80
CNN	97	97	97	97	80

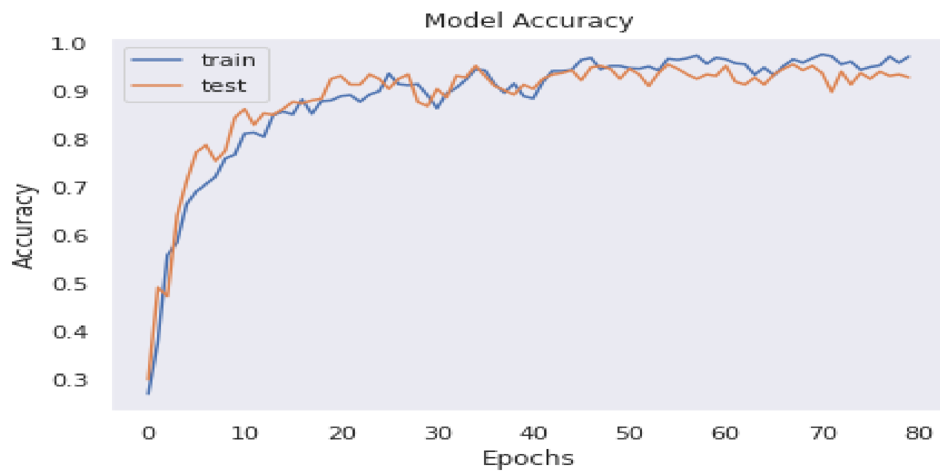


Fig 4.2.2.1: CNN Training and Validation Accuracy

Fig 4.2.2.2: CNN Training and Validation Loss

4.3 Result Discussion

We know that the classifier's performance was established on a test set from the training, validation and testing accuracy [11]. Our CNN model give a high accuracy of precision, recall and every weighted average up to 97. Total test dataset images are 335, and after classification, only 10 images are false predictions, another way 325 is a correct prediction.

The final test of our model gives 97% accuracy, so our model gives a better test accuracy for unseen data. To make a clear assume we can observer the confusion matrix.

Table 4.3.1: CNN Classification Report

Class	Precision (%)	Recall (%)	F1 (%)
Akondo	96	98	97
Dadmordon	1	98	99
Dutura	94	95	95
Kochuripana	94	96	95
Sialkata	1	95	97
Vatful	1	1	1

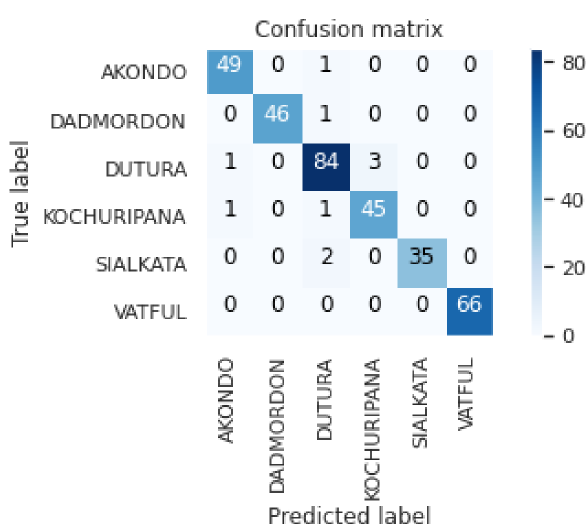


Fig 4.3.1: CNN Confusion Matrix

4.4 Comparison

In this segment, we compared different models with our CNN model with their test accuracies, such as InceptionV3, VGG16, and MobileNet, and used the same number of epochs and batch-size for best comparison. 25 percent of the test set and 75 percent of the train set are the same for each train model used, but the consistency of validation and testing accuracy varies from a separate model summarized in Table 2[17]. From the table, we find that VGG16 provides 94 percent accuracy with a little bit noisy, and sometimes comparable validation accuracy and train accuracy rate. The precision of MobileNet is 92 percent, but the accuracy of validation and train accuracy are very noisy. For these datasets, InceptionV3 provides low validation accuracy. But for a decent train accuracy with a little bit of noise, our CNN model offers the highest validation accuracy.

Finally, we noted that the accuracy of each model is met under the same conditions, but among them, our CNN performs perfectly with a validation accuracy of 95 percent. We suggested a new architecture for CNN.

4.5.1 MobileNet

MobileNet gives 92 percent validation accuracy but it allows a very high noisy result for training accuracy and validation accuracy. In Fig 4.5.1.1 we show training accuracy is good but validation accuracy is very noisy. And for training loss and validation loss, give the same result in Fig 4.5.1.2.

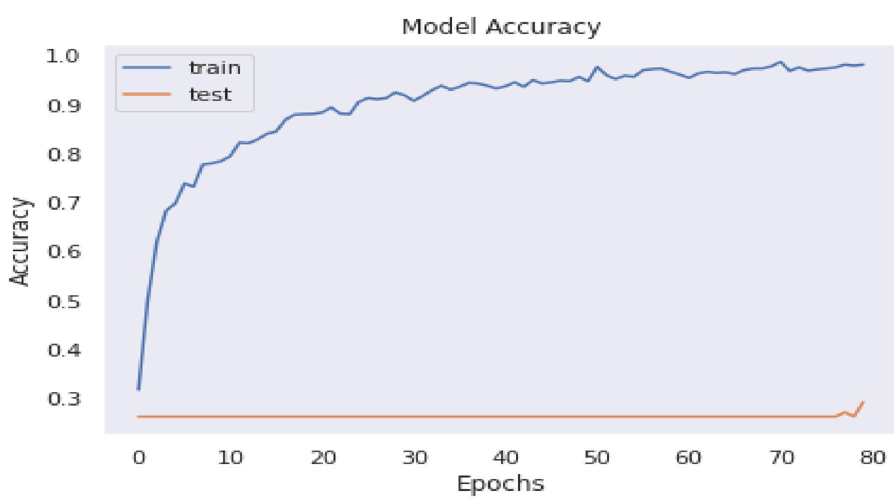


Fig 4.5.1.1: MobileNet Training and Validation Accuracy

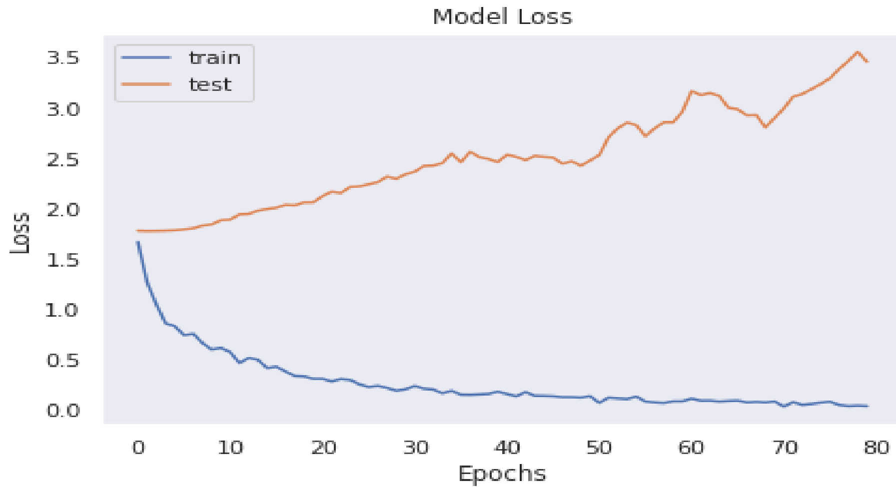


Fig 4.5.1.2: MobileNet Training and Validation Loss

4.5.2 InceptionV3

For our dataset, Inception3 gives a reasonable validation precision of 96 percent. But we can note in Fig 4.5.2.1 that training accuracy is good and that training accuracy and validation accuracy are slowly growing. Accuracy is not fulfilled slowly but according to the validation. Train loss is degreasing gently in 4.5.2.2.

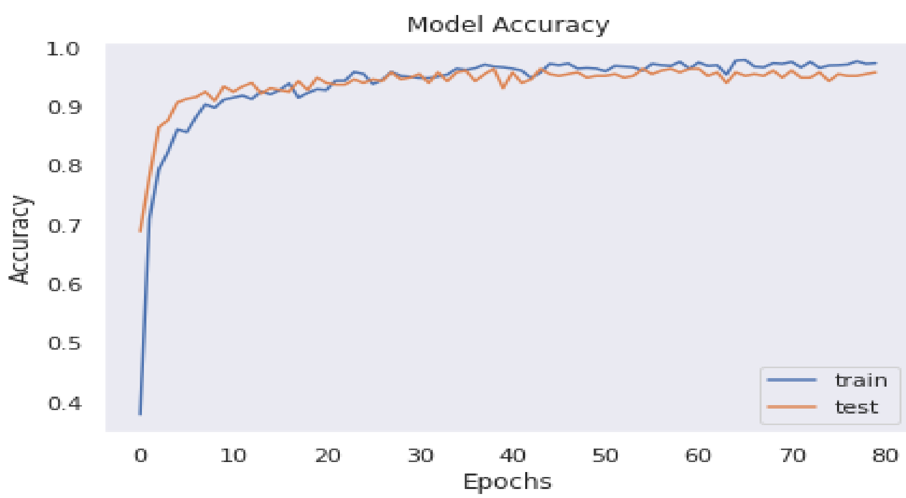


Fig 4.5.2.1: InceptionV3 Training and Validation Accuracy

Fig 4.5.2.2: InceptionV3 Training and Validation Loss

4.5.3 VGG16

For our dataset, VGG16 performed well and produced 94 percent validation accuracy. In Fig: 4.5.3.1, we see that there is a slight gap between the accuracy of training and the accuracy of validation. It makes low noise and smoother over training time. Fig: 4.5.3.2 indicates VGG16's training loss heading to the lower loss.

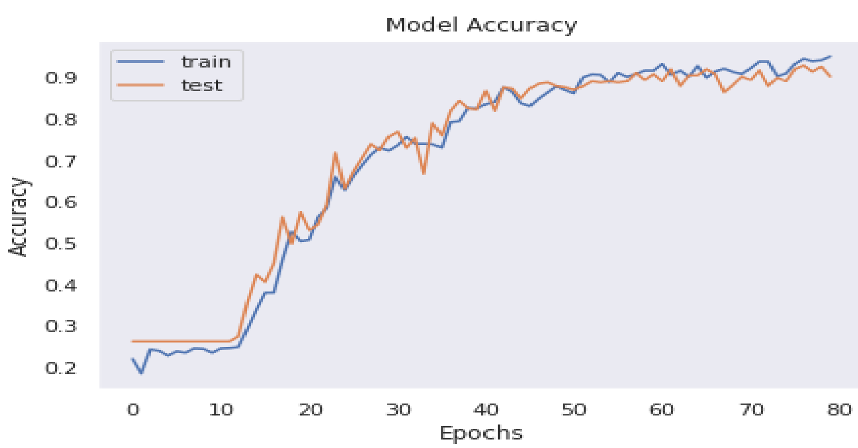


Fig 4.5.3.1: VGG16 Training and Validation Accuracy

Fig 4.5.3.2: VGG16 Training and Validation Loss

4.5.4 CNN

For our dataset, our CNN model offers the best validation precision of 97 percent. We show in Fig 4.5.4.1 that accuracy of training and accuracy of validation are satisfactory because it allows a little bit of noise and prevents overfitting successfully. Fig: 4.5.4.2 shows that the loss of training is significantly decreasing. From InceptionV3, VGG16, and MobileNet, our CNN offers high validation precision.

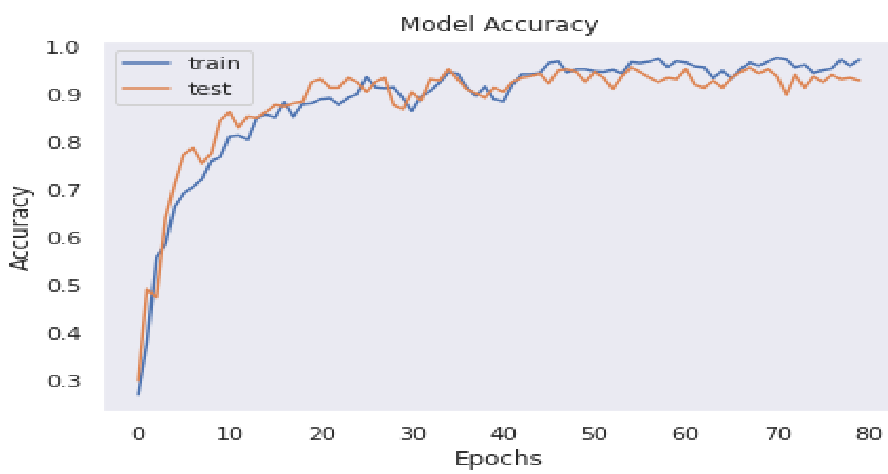


Fig 4.5.4.1: CNN Training and Validation Accuracy

Fig 4.5.4.2: CNN Training and Validation Loss

CHAPTER 5

Conclusion and Future Works

5.1 Conclusions

In this paper, CNN architecture and its competitive classification accuracy performance of up to 97 percent are used to construct a model. And we have defined the number of our model filters, the shape of the activation, the size of the activation, the total parameters and the number of convolution blocks. Our model is basic, but with high precision from another complex model, it performed much faster. Finally, we show that from the experiment, the approach proposed has high accuracy. Finally, we can claim that CNN can be used in a new and creative way to boost the object classification capabilities of different areas [16].

5.2 Future Work

For distinct rural flower classifications, our proposed CNN model shows better accuracy for classification against MobileNet, VGG16 and InceptionV3. But there are also ways to update our transfer learning model in the future. For all models, we will apply another different model such as AlexNet, ResNet to improve precision, efficient training and feature extraction, and GPU is the most relevant for training otherwise. However, for the highest accuracy, we propose a strong approach applying the ensemble method and we will test other advanced classification concepts, such as transfer learning [8].

APPENDIX

To complete our project, we have faced so many problems and the first was the selection of methodology. This project was so difficult because of different databases and different ways, only some work was done before. We have to collect and manipulate data from various online platforms to train our model. We developed a new CNN model with a higher accuracy rate for classification and successfully trained it. We have also trained and contrasted several other conventional CNN models with our winning model. The best classification result from other models is successfully obtained by our model. Our task was very difficult to develop, but our work on the thesis was very interesting.

REFERENCE

[1] Prasad, M. V. D., B. Jwala Lakshmamma, A. Hari Chandana, K. Komali, M. V. N. Manoja, P. Rajesh Kumar, and P. Sasi Kiran. "An efficient classification of flower images with convolutional neural networks." International Journal of Engineering & Technology 7, no. 11 (2018): 384-391.
[2] Tiay, Tanakorn, Pipimphorn Benyaphaichit, and Panomkhawn Riyamongkol. "Flower recognition system based on image processing." In 2014 Third ICT International Student Project Conference (ICT-ISPC), pp. 99-102. IEEE, 2014.
[3] M. Das, R. Manmatha, and E. M. Riseman, "Indexing flower patent images using domain knowledge", IEEE Intell. Syst., vol 14, pp. 24-33, 1999.
[4] Nilsback, M. E., & Zisserman, A. (2006). A visual vocabulary for flower classification. Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference, Vol. 2, 1447-1454. IEEE.
[5] Hong, An-xiang, Gang Chen, Jun-li Li, Zhe-ru Chi, and Dan Zhang. "A flower image retrieval method based on ROI feature." Journal of Zhejiang University-Science A 5, no. 7 (2004): 764-772. https://doi.org/10.1631/jzus.2004.0764.
[6] Almogdady, Huthaifa, Saher Manaseer, and Hazem Hiary. "A Flower Recognition System Based On Image Processing And Neural Networks." *International Journal Of Scientific & Technology Research* 7, no. 11 (2018).
[7] Pardee, Warisara, Prawaran Yusungnern, and Peeraya Sripian. "Flower Identification System by Image Processing." In 3rd International Conference on Creative Technology CRETECH. 2015.
[8] Zhang, Yu-Dong, Zhengchao Dong, Xianqing Chen, Wenjuan Jia, Sidan Du, Khan Muhammad, and Shui-Hua Wang. "Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation." Multimedia Tools and Applications 78, no. 3 (2019): 3613-3632.
[9] Kesim, Ege, Zumray Dokur, and Tamer Olmez. "X-ray chest image classification by a small-sized convolutional neural network." In 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), pp. 1-5. IEEE, 2019.
[10] Zheng, Shuai, Sadeep Jayasumana, Bernardino Romera-Paredes, Vibhav Vineet, Zhizhong Su, Dalong Du, Chang Huang, and Philip HS Torr. "Conditional random fields as recurrent neural networks." In Proceedings of the IEEE international conference on computer vision, pp. 1529-1537. 2015.
[11] Zaid, Gabriel, Lilian Bossuet, Amaury Habrard, and Alexandre Venelli. "Methodology for efficient CNN architectures in profiling attacks." IACR Transactions on Cryptographic Hardware and Embedded Systems (2020): 1-36.
[12] Haque, Sadeka, AKM Shahariar Azad Rabby, Monira Akter Laboni, Nafis Neehal, and Syed Akhter Hossain. "ExNET: Deep Neural Network for Exercise Pose Detection." In International Conference on Recent Trends in Image Processing and Pattern Recognition, pp. 186-193. Springer, Singapore, 2018.
[13] Dropout in (Deep) Machine learning. <<https://medium.com/@amarbudhiraja/httpsmedium-com-amarbudhiraja-learning-less-to learn-better-dropout-in-deep-machinelearning-74334da4bfc5>> Last accessed on 11-09-2019 at 03.06 AM.
[14] Islam, Mohammad Shakirul, Ferdouse Ahmed Foysal, Nafis Neehal, Enamul Karim, and Syed Akhter Hossain. "InceptB: a CNN based classification approach for recognizing traditional bengali games." Procedia computer science 143 (2018): 595-602.
[15] Maron, Roman C., Michael Weichenthal, Jochen S. Utikal, Achim Hekler, Carola Berking, Axel Hauschild, Alexander H. Enk et al. "Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks." European Journal of Cancer 119 (2019): 57-65.
[16] Vaibhav, Kumar, Jagdish Prasad, and Baldev Singh. "Convolutional Neural Network for Classification for Indian Jewellery." In Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur-India. 2019.

[17] Nagpal, Chaitanya, and Shiv Ram Dubey. "A performance evaluation of convolutional neural networks for face anti spoofing." In 2019 International Joint Conference on Neural Networks (IJCNN), pp. 1-8. IEEE, 2019.

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