

PERFORMANCE EVALUATION OF CONVOLUTIONAL NEURAL NETWORKS FOR CLASSIFICATION OF FLOWERS

Submitted in partial fulfillment of the requirements for the award of

**Bachelor of Engineering degree in
Electronics and Communication Engineering**

By



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This is to certify that this Project Report is the bonafide work of **DASARI REVANTH ROY (38130053)** and **MOGILI BHARATH KUMAR (38130136)** who carried out the project entitled **"PERFORMANCE EVALUATION OF CONVOLUTION NEURAL NETWORKS FOR CLASSIFICATION OF FLOWERS"** our supervision from November 2021 to April 2022.

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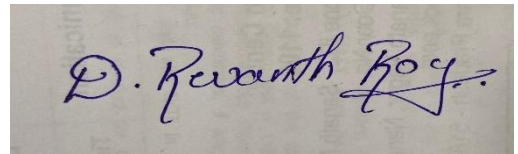
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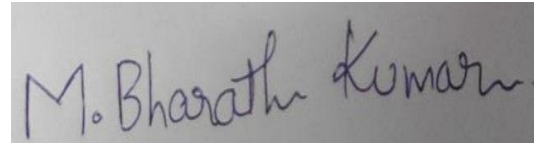
DECLARATION

We **DASARI REVANTH ROY (38130053)** and **MOGILI BHARATH KUMAR (38130136)**, hereby declare that the Project Report entitled **PERFORMANCE EVALUATION OF CONVOLUTION NEURAL NETWORKS FOR CLASSIFICATION OF FLOWERS** is done under the guidance of **Dr. N. M. NANDHITHA, M.E., Ph.D.** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in ELECTRONICS AND COMMUNICATION ENGINEERING.

DATE:

A photograph of a handwritten signature in blue ink on a light-colored paper. The signature reads "D. Revanth Roy" in a cursive script.

PLACE:

A photograph of a handwritten signature in blue ink on a light-colored paper. The signature reads "M. Bharath Kumar" in a cursive script.

SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

We are pleased to acknowledge our sincere thanks to Board of Management of **SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. We are grateful to them.

We convey our thanks to **Dr. N. M. NANDHITHA, M.E., Ph.D.** Dean, School of Electrical and Electronics Engineering and **Dr. T. RAVI, M.E., Ph.D.** Head of the Department, Department of Electronics and Communication Engineering for providing us necessary support and details at the right time during the progressive reviews.

We would like to express our sincere and deep sense of gratitude to our Project Guide **Dr. N. M. NANDHITHA, M.E., Ph.D.** Dean, School of Electrical and Electronics Engineering for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of the project work.

We wish to express our thanks to all teaching and Non-teaching staff members of the Department of Electronics and Communication Engineering who were helpful in many ways for the completion of the project.

We express our gratitude to our parents for their constant encouragement and support for the completion of the project.

ABSTRACT

Flower classification has never been an easy task due to the extensive and varied range of flower species. Traditional methods of classifying flowers requires lots of human efforts and also takes a lot of time to classify a single species of flowers. This method of classification often led to errors. Since Flowers in general have a similar background such as grass, leaves, trees , look similar in shape, hence it makes them tough to classify. In our work, we considered an existing model to classify the flower species i.e. Convolutional Neural Network (CNN) and proposed a new modified network architecture for the existing Network to distinguish flowers species with the better accuracy. Convolution Neural Networks are the recent paradigm which accepts images as input and performs both feature extraction and classification. First, the flower region is automatically segmented to allow localisation of the minimum bounding box around it. Second, the robust convolutional neural network classifier distinguishes the different flower types. Performance of the network highly depends on the extracted features. The performance of the proposed network is evaluated on the basis of accuracy, specificity and sensitivity. The classification process was performed using 102 categories of flower dataset prepared by Oxford university. The classification results were obtained as 89.902%.

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CHAPTER 1

INTRODUCTION

Flower image classification remains a challenge in the field of image processing because of variations in the viewpoint, occlusion, clutter, light variances, object deformations, small intra-class similarity and large inter class similarity. Therefore, to overcome this challenge a deep learning algorithm, Convolutional Neural Network (CNN), is used. Convolutional Neural Networks are continuously evolving over the years and has made a significant progress in image processing. The conventional techniques for the classification of flowers extract features from flower images to enhance the classification performance. Many image classification techniques rely on learning the features after segmentation of image for better accuracy. CNN use Content Based Image Retrieval (CBIR) technique to perform feature extraction and classification of image datasets. A pretrained neural network is fed with flower images and features are extracted for performance evaluation of the network. CNN architectures are pre-trained with a set of 1.3 million natural images from the ImageNet database. The pretrained network automatically detects the region around the flower and uses the cropped image alone to classify the image. However the architecture of conventional neural network is modified to enhance the accuracy and sensitivity of the flower classification. A flower image dataset consisting of 102 classes of flowers is considered for the processing and classification based on extracted features.

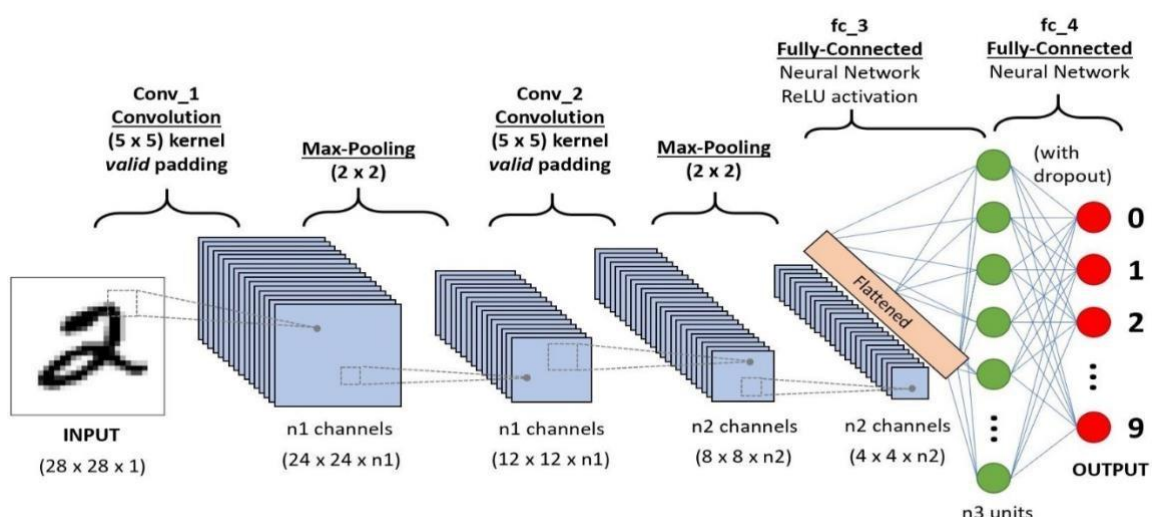
1.1 CONVOLUTIONAL NEURAL NETWORKS

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

They all use forward propagation to output calculated values and use back propagation to adjust weights and biases. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNet have the ability to learn these filters/characteristics. Different from the classical recognition algorithm, CNN repeatedly uses the convolution operation and pooling operation in the original input to obtain increasingly complex feature graphs, and finally directly outputs the results through the full connection. It mainly consists of five parts which are:

- (i) input layer,
- (ii) convolution layer,
- (iii) pooling layer,
- (iv) fully connected (FC) layer,
- (v) output layer

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.



A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting

to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.

1.2 BUILDING BLOCKS OF CONVOLUTIONAL NEURAL NETWORK

1.2.1 Convolutional layer

The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. This is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter ($M \times M$).

The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image

1.2.2 Pooling layer

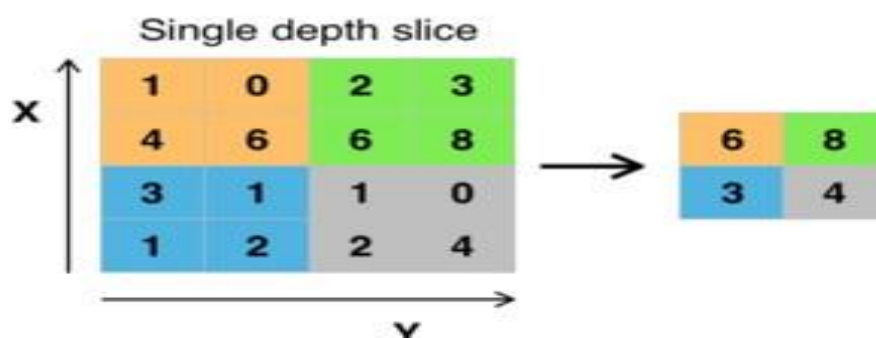


Fig:Max pooling with a 2x2 filter and stride

Another important concept of CNNs is pooling, which is a form of nonlinear down-sampling. There are several non-linear functions to implement pooling among which max pooling is the most common. It partitions the input image into a set of non-overlapping rectangles and, for each such sub-region, outputs the maximum. In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations.

In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer

1.2.3 ReLU layer

ReLU is the abbreviation of rectified linear unit, which applies the nonsaturating activation function .It effectively removes negative values from an activation map by setting them to zero. It increases the nonlinear properties of the decision function and of the overall network without affecting the receptive fields of the convolution layer.

one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network.

It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and

softmax functions are preferred an for a multi-class classification, generally softmax us used.

1.2.4 Fully connected layer

Finally, after several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular (non-convolutional) artificial neural networks. The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture.

In this, the input image from the previous layers are flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place.

1.2.5 Loss layer

The "loss layer" specifies how training penalizes the deviation between the predicted (output) and true labels and is normally the final layer of a neural network. Various loss functions appropriate for different tasks may be used.

There are various architectures of CNNs available which have been key in building algorithms which power and shall power AI as a whole in the foreseeable future. Some of them have been listed below:

1. LeNet
2. AlexNet
3. VGGNet
4. GoogLeNet
5. ResNet

6. ZFNet

7. DenseNet

These CNN architectures are trained, designed and developed by the following tools/frameworks.

TOOLS	FRAMEWORKS
Tensor flow	python, c, c++
Caffe	c++, python, matlab
Keras	python
Theano	python

Table ::Different designing, developing tools/frameworks

1.3 MATLAB

MATLAB, an abbreviation for ‘matrix laboratory,’ is a platform for solving mathematical and scientific problems. It is a proprietary programming language developed by [MathWorks](#), allowing matrix manipulations, functions and data plotting, algorithm implementation, user interface creation and interfacing with programs written in programming languages like [C](#), C++, Java and so on.

In MATLAB, the IPT is a collection of functions that extends the capability of the MATLAB numeric computing environment. It provides a comprehensive set of reference-standard algorithms and workflow applications for image processing, analysis, visualisation and algorithm development.

It can be used to perform image segmentation, image enhancement, noise reduction, geometric transformations, image registration and 3D image processing operations. Many of the IPT functions support C/C++ code generation for desktop prototyping and embedded vision system deployment.

We used MATLAB programming language for training the CNN's. We also worked on different types of clusters in MATLAB.

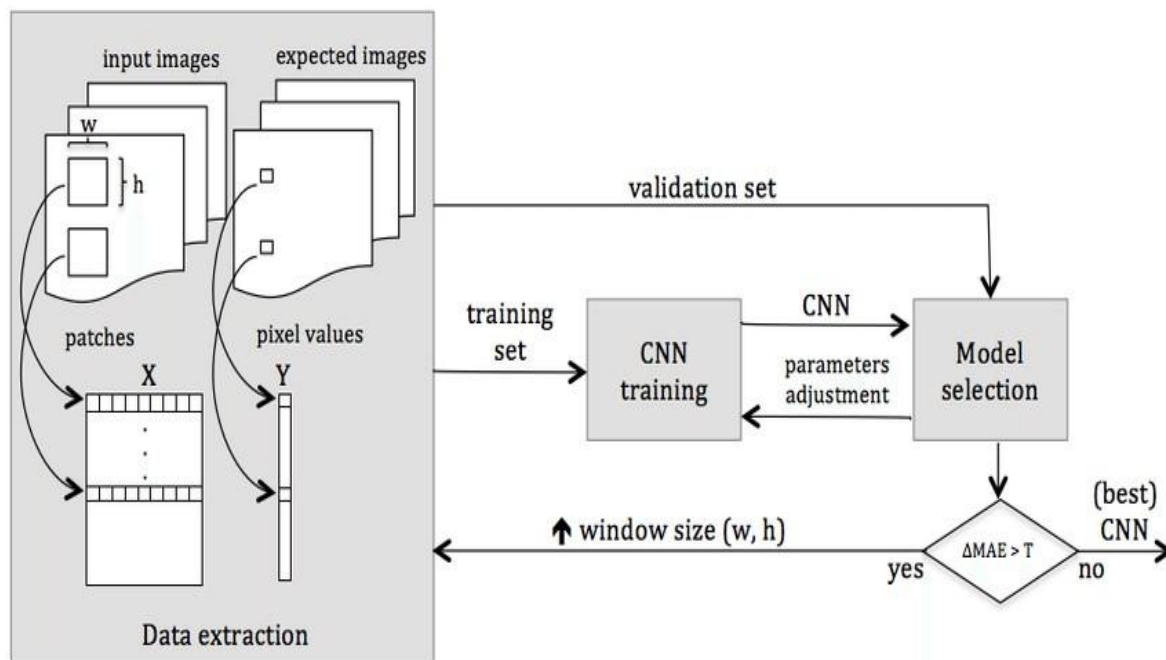


Fig : Processing of dataset

By using few CNN architectures and tools, we have to evaluate their complexity and performance and decide to train the dataset based on the output.

CHAPTER 2

LITERATURE SURVEY

Determining the freshness of fruits in the food industry by image classification using transfer learning: [Siba Prasada Panda](#), Aafreen kazi

Strength of transfer learning with respect to the CNN models in image classification of fruits rather than implementing the traditional CNN architectures was given an attempt of exploration in this study. Various architectures of CNNs and RNNs were used to classify different types of fruits its relative freshness was determined. The determination of freshness of fruits was found to be with high accuracy in the results. The accuracy in the suggested result was about 99 percent. This study is an attempt to select the best CNN that could be applied in the food industry in complementation with other computer vision techniques like background reduction, image augmentation methods.

Flower classification using deep convolutional neural networks: Hazem Hiary , Heba Saadeh , Maha Saadeh , Mohammad Yaqub

A two step deep learning classifier to classify flowers is proposed in this study. First, the flower region is automatically segmented to allow localisation of the minimum bounding box around it and a CNN classifier is built to classify different flowers. This study is successful in achieving an accuracy of 97%. In this study they have considered a three different flower datasets were used in to classify the flowers. The main aim of this work is to propose an accurate and robust classification method instead a binary segmentation method was developed.

An efficient classification of flower images with convolutional neural networks : M. V. D. Prasad, B. Jwala Lakshamma , A. Hari Chandana, K. Komali, M.V.N. Manoja, P. Rajesh Kumar, Ch. Raghava Prasad, Syed Inthiyaz , P. Sasi Kiran

A flower image database was considered to do the experimentation and the database is divided into 4 categories. Training is initiated with five different batch sizes. In Batch-I of training dataset 1 is used for training and the validation is carried out on four categories of datasets. Batch-II, III, IV of trainings are done using Dataset 2, 3, 4 respectively and Batch-V of training is implemented by considering all four datasets for training. The performance of proposed algorithm (CNN) is measured based on the accuracy in recall and recognition rates. The accuracy of the proposed model is 97.78%

Md Zahangir Alom , Tarek M. Taha , Chris Yakopcic , Stefan Westberg, Paheding Sidike , Mst Shamima Nasrin , Mahmudul Hasan , Brian C. Van Essen , Abdul A. S. Awwal and Vijayan K. Asari (2019) --A State-of-the-Art Survey on Deep Learning Theory and Architectures.

Different methods have been proposed based on different categories of learning, including supervised, semi-supervised, and un-supervised learning. Experimental results show state-of-the-art performance using deep learning when compared to traditional machine learning approaches in the fields of image processing, computer vision, speech recognition, machine translation, art, medical imaging, medical information processing, robotics and control, bioinformatics, natural language processing, cybersecurity, and many others. This survey presents a brief survey on the advances that have occurred in the area of Deep Learning (DL), starting with the Deep Neural Network (DNN). The survey goes on to cover Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), Auto-Encoder (AE), Deep Belief Network (DBN), Generative Adversarial Network (GAN), and Deep Reinforcement Learning (DRL) [12].

Justine Boulent, Samuel Foucher, Jerome Theau, and Pierre-Luc St-Charles (2019) Convolutional Neural Networks for the Automatic Identification of Plant Diseases.

Deep learning techniques, and in particular Convolutional Neural Networks (CNNs), have led to significant progress in image processing. Since 2016, many applications for the automatic identification of crop diseases have been developed. These applications could serve as a basis for the development of expertise assistance or automatic screening tools. Such tools could contribute to more sustainable agricultural practices and greater food production security. To assess the potential of these networks for such applications, we survey 19 studies that relied on CNNs to automatically identify crop diseases. We describe their profiles, their main implementation aspects and their performance. Our survey allows us to identify the major issues and shortcomings of works in this research area. We also provide guidelines to improve the use of CNNs in operational contexts as well as some directions for future research [5].

In this paper, some of the major issues and shortcomings of works that used CNNs to automatically identify crop diseases are identified. Many already-published

solutions based on CNNs are not currently operational for field use mostly due to a lack of conformity to several important concepts of machine learning. This lack of conformity may lead to poor generalization capabilities for unfamiliar data samples and/or imaging conditions, which lowers the practical use of the trained models. Nevertheless, the studied works show the potential of deep learning techniques for crop diseases identification.

Multiple Classification of Flower Images Using Transfer Learning: : [2019 International Artificial Intelligence and Data Processing Symposium \(IDAP\)](#)IEEE,2019, [10.1109/IDAP.2019.8875953](#):

Deep learning technologies have been successful in many fields in recent years. Image classification problem is one of the areas where the use of the results is successful. The study draws attention to the use of pretrained models in problem solving. With the approach called transfer learning, frequently used pretrained deep learning models such as Alexnet, Googlenet, VGG16, DenseNet and ResNet are used for image classification.

In this study, the importance of transfer learning approach is emphasized. Initialization of networks used for the classification task with pretrained networks rather than random weights is advantageous in terms of time and accuracy performance criteria. The results of the five CNN models, which are widely used in image classification processes, are shown. According to the results, multi-classification work showed acceptable accuracy performance for each model while highest accuracy was seen with VGG16 network.

Dhillon A., Verma G.K. Convolutional neural network: a review of models, methodologies and applications to object detection. *Prog Artif Intell* **9**, 85–112 (2020):

Deep learning has developed as an effective machine learning method that takes in numerous layers of features or representation of the data and provides state-of-the-art results. The application of deep learning has shown impressive performance in various application areas, particularly in image classification, segmentation and object detection. Recent advances of deep learning techniques bring encouraging performance to fine-grained image classification which aims to distinguish subordinate-level categories. This task is extremely challenging due to high intra-class and low inter-class variance.

In this paper, a detailed review of various deep architectures and model highlighting characteristics of particular model are provided. Firstly, the functioning of

CNN architectures and its components followed by detailed description of various CNN models starting with classical LeNet model to AlexNet, ZFNet, GoogleNet, VGGNet, ResNet, ResNeXt, SENet, DenseNet, Xception, PNAS/ENAS are described . We mainly focus on the application of deep learning architectures to three major applications, namely (i) wild animal detection, (ii) small arm detection and (iii) human being detection.

S. S. Shah and J. W. Sheppard, "Evaluating Explanations of Convolutional Neural Network Image Classifications," *2020 International Joint Conference on Neural Networks (IJCNN)*, 2020, pp. 1-8

In this paper, we seek to automate the evaluation of explanations of image classification decisions made by complex convolutional neural networks (CNN). Explanation frameworks like Local Interpretable Model-agnostic Explanations (LIME) treat complex machine learning models, such as deep neural networks, as black boxes and generate human-interpretable explanations of their decisions using linear proxy models. We propose a pair of experiments to quantitatively evaluate the quality of generated explanations by measuring their sufficiency and salience. To test if a generated explanation contains sufficient information for classification, we test the ability of a trained CNN to classify that explanation properly. We test explanations for salience by training two new CNNs, one using raw image data and the other using explanations as training data, and comparing their classification precision and recall on a common set of test data. We use our new evaluation framework to test our hypothesis that LIME is able to generate explanations that are both sufficient and salient. Our results show that the generated explanations have the potential to be sufficient and salient, provided that the complexity of the explanations is enough to describe the underlying classes.

B. R. Mete and T. Ensari, "Flower Classification with Deep CNN and Machine Learning Algorithms," *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 2019, pp. 1-5

Development of the recognition of rare plant species will be advantageous in the fields such as the pharmaceutical industry, botany, agricultural, and trade activities. It was also very challenging that there is diversity of flower species and it is very hard to classify them when they can be very similar to each other indeed. This paper presents a classification system for flower images by using Deep CNN and Data Augmentation. Recently, Deep CNN techniques have become the latest technology for such problems. However, the fact is that getting better performance for the flower classification is stuck due to the lack of labeled data. In the study, there are three primary contributions: First,

we proposed a classification model to cultivate the performance of classifying of flower images by using Deep CNN for extracting the features and various machine learning algorithms for classifying purposes. Second, we demonstrated the use of image augmentation for achieving better performance results. Last, we compared the performances of the machine-learning classifiers such as SVM, Random Forest, KNN, and Multi-Layer Perceptron(MLP). In the study, we evaluated our classification system using two datasets: Oxford-17 Flowers, and Oxford-102 Flowers. We divided each dataset into the training and test sets by 0.8 and 0.2, respectively. As a result, we obtained the best accuracy for Oxford 102-Flowers Dataset as 98.5% using SVM Classifier. For Oxford 17-Flowers Dataset, we found the best accuracy as 99.8% with MLP Classifier.

FatihahSahidan, Nurul & Juha, Ahmad & Mohammad, Norasiah & Ibrahim, Zaidah. (2019). Flower and leaf recognition for plant identification using convolutional neural network. Indonesian Journal of Electrical Engineering and Computer Science. 16. 737. 10.11591/ijeecs.v16.i2.pp737-743.

This paper presents flower and leaf recognition for plant identification using Convolutional Neural Network (CNN). In this study, the performance of CNN for plant identification using images of the leaves, flowers and a combination of both are investigated. Two publicly available datasets, namely Folio leaf dataset and 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 leaf images only arrive to the highest accuracy for plant identification compared to the images of flowers only or the combination of both, that are 98%, 85% and 74%, respectively.

This paper evaluates the performance of CNN for plant identification using the images of the leaves only, flowers only and a combination of both images. The experimental results show that the use of the images of the leaves only arrive to the best accuracy. This may be due to the fact that flowers have too many variations in terms of shapes and colours compared to the leaves.

Krishna, Sajja Tulasi and Hemantha Kumar Kalluri. "Deep learning and transfer learning approaches for image classification." International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7, Issue-5S4, February 2019

Deep Learning is one of the machine learning areas, applied in recent areas. Some of the experimental results proved that the deep learning systems are performed well compared to conventional machine learning systems in image processing, computer vision and pattern recognition. This paper provides a brief survey, beginning with Deep Neural Network (DNN) in Deep Learning area. The survey moves on to the Convolutional Neural Network (CNN) and its architectures, such as LeNet, AlexNet, GoogleNet, VGG16, VGG19, Resnet50 etc. We have included transfer learning by using the CNN's pre-trained architectures. These architectures are tested with large ImageNet data sets. The deep learning techniques are analyzed with the help of most popular data sets, which are freely available in web.

In this, we have provided a survey of deep learning and its network architectures. We have gone through the various state-of-the-art deep learning architectures. We explained about the pre-trained models, by applying transfer learning. Moreover, we discussed about some of the popular data sets with large volume of data. From this survey we concluded that the size of data may affect the accuracy and the number of epochs also. Based on this survey motivation we are going to implement face recognition system with accurate performance in minimum time.

Zhang, Meng & Chen, Tinghuan & Sun, Zhifei & Ma, Yuzhe & Yu, Bei. (2018). Recent Advances in Convolutional Neural Network Acceleration. *Neurocomputing*. 323. 10.1016/j.neucom.2018.09.038.

In recent years, convolutional neural networks (CNNs) have shown great performance in various fields such as image classification, pattern recognition, and multi-media compression. Two of the feature properties, local connectivity and weight sharing, can reduce the number of parameters and increase processing speed during training and inference. However, as the dimension of data becomes higher and the CNN architecture becomes more complicated, the end-to-end approach or the combined manner of CNN is computationally intensive, which becomes a limitation to CNN's further implementation. Therefore, it is necessary and urgent to implement CNN in a faster way. In this paper, we first summarize the acceleration methods that contribute to but not limited to CNN by reviewing a broad variety of research papers. We propose a taxonomy in terms of three levels, i.e. structure level, algorithm level, and implementation level, for acceleration methods. We also analyze the acceleration methods in terms of CNN architecture compression, algorithm optimization, and hardware-based improvement. At last, we give a discussion on different perspectives of these acceleration and optimization methods within each level. The discussion shows that the methods in each level still have large

exploration space. By incorporating such a wide range of disciplines, we expect to provide a comprehensive reference for researchers who are interested in CNN acceleration.

Alipour, Neda & Tarkhaneh, Omid & Awrangjeb, Mohammad & Tian, Hongda. (2021). Flower Image Classification Using Deep Convolutional Neural Network. 1-4.

These days deep learning methods play a pivotal role in complicated tasks, such as extracting useful features, segmentation, and semantic classification of images. we used the transfer learning approach employing DenseNet121 architecture to categorize various species of oxford-102 flowers dataset. In this regard, we have tried to fine-tune our model to achieve higher accuracy respect to other methods. We performed preprocessing by normalizing and resizing of our images and then fed them to our fine-tuned pretrained model. We divided our dataset to three sets of train, validation, and test. We could achieve the accuracy of 98.6% for 50 epochs which is better than other deep-learning based methods for the same dataset in the study.

Yadav, S.S., Jadhav, S.M. Deep convolutional neural network based medical image classification for disease diagnosis.

Medical image classification plays an essential role in clinical treatment and teaching tasks. The deep neural network is an emerging machine learning method that has proven its potential for different classification tasks. the convolutional neural network dominates with the best results on varying image classification tasks. However, medical image datasets are hard to collect because it needs a lot of professional expertise to label them. Therefore, this paper researches how to apply the convolutional neural network (CNN) based algorithm on a chest X-ray dataset to classify pneumonia. Three techniques are evaluated through experiments. These are linear support vector machine classifier with local rotation and orientation free features, transfer learning on two convolutional neural network models: Visual Geometry Group i.e., VGG16 and InceptionV3, and a capsule network training from scratch. Data augmentation is a data preprocessing method applied to all three methods. The results of the experiments show that data augmentation generally is an effective way for all three algorithms to improve performance. Also, Transfer learning is a more useful classification method on a small dataset compared to a support vector machine with oriented fast and rotated binary (ORB) robust independent elementary features and capsule network. In transfer learning, retraining specific features on a new target dataset is essential to improve performance. And, the second important factor is a proper network complexity that matches the scale of the dataset.

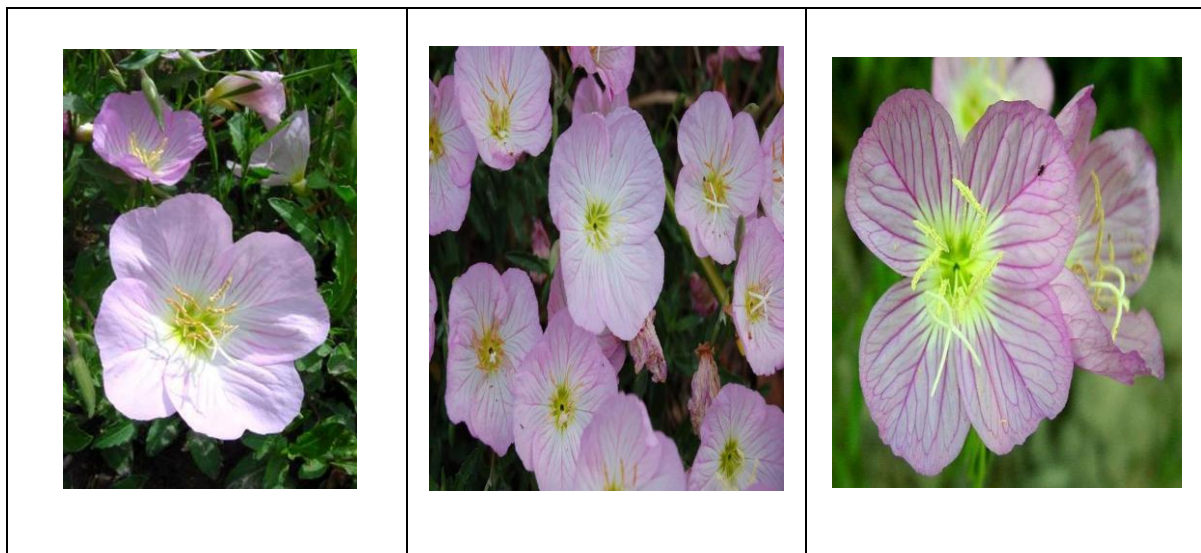
CHAPTER 3

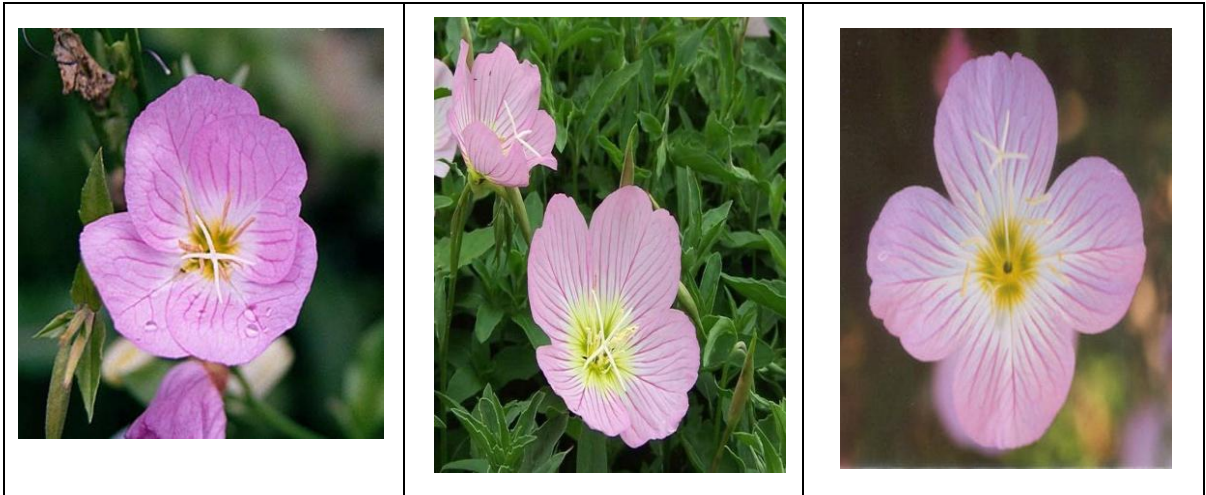
RESEARCH DATABASE

An extensive research database created by oxford university,consisting of 102 (one hundred and two)different flower categories used for processing and classification of flowers based on extracted features.The flowers chosen to be flower commonly occurring in the United Kingdom. Each class randomly consisted of between 40 and 258 images where each category is named as A1,A2,A3,..... and so on until A102. In total we have 8189 flower images with 102 categories. To train a model the dataset is divided equally into two parts i.e. training set for training and test set for testing. In our training models we have divided into two half's 50% for training and 50% for testing.this database in used in many types of researches. All the flower images are from the real world with the format of JPEG. The images of the dataset have large scale, pose and light variations. This is a competitive dataset that is used in many research studies.

Flowers from various categories of the dataset:

CLASS-A1





CLASS-A2

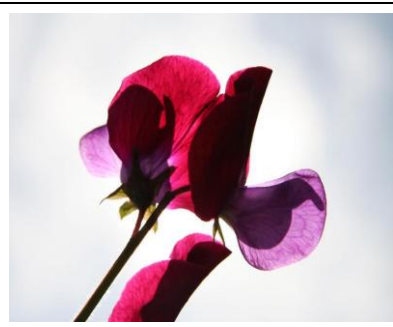


CLASS-A3

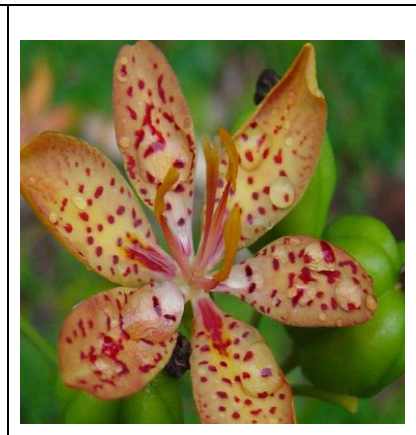


CLASS-A4





CLASS-A102



CHAPTER 4

CONVENTIONAL CONVOLUTIONAL NEURAL NETWORKS

4.1 VGG16:

- 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.
- VGG16, VGG19 architectures which is also called OxfordNet named after the Visual Geometry Group from Oxford, who developed it.
- There are total of 13 convolutional layers and 3 fully connected layers in VGG16 architecture. VGG has smaller filters (3*3) with more depth instead of having large filters.
- 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.
- During training, the input to the convnets is a fixed-size 224 x 224 RGB image

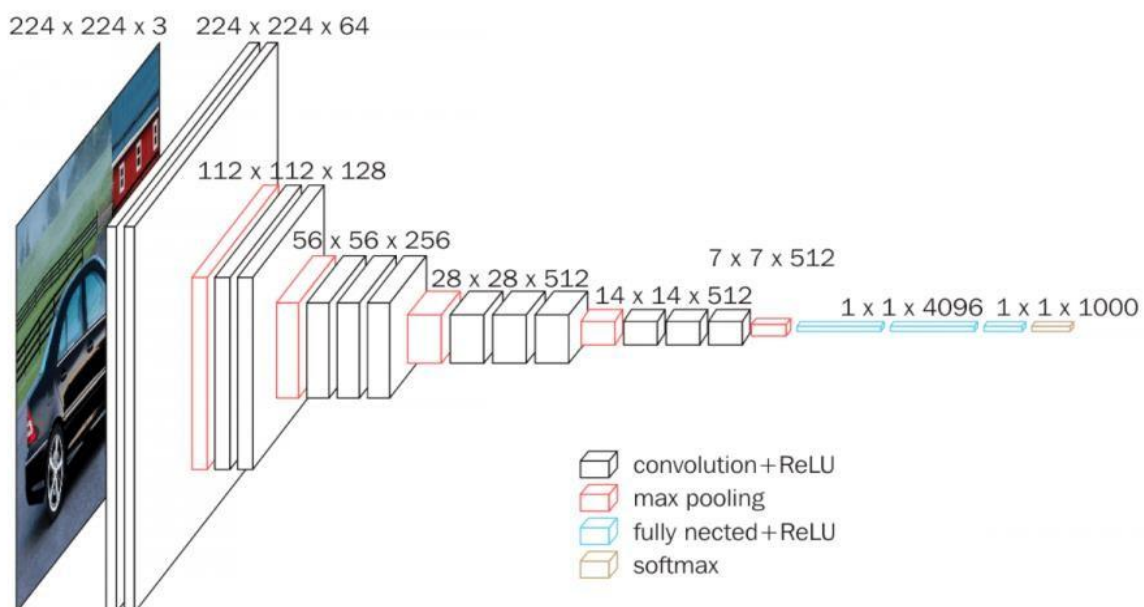


Fig:VGG16 Network Architecture

4.2 ALEXNET :

- AlexNet architecture consists of eight layers :five convolutional layers and three, some of which are followed by maximum pooling layers and then three fully-connected layers.
- The input for AlexNet is a 227x227x3 RGB image which passes through the first convolutional layer and the image dimensions changes to 55x55x96.
- The first two convolution layers are followed by an Overlapping Max pooling layer each.
- The third, fourth and fifth layers are convolutional layers with filter size 3x3 and a stride of one are directly connected with each other.
- The fifth convolutional layer output is flattened through a fully connected layer with 9216 feature maps each of size 1x1 followed by max pooling layer
- Next is again two fully connected layers with 4096 units.
- Finally, there is a softmax classifier having 1000 classes in which the output fully connect layer is fed into.

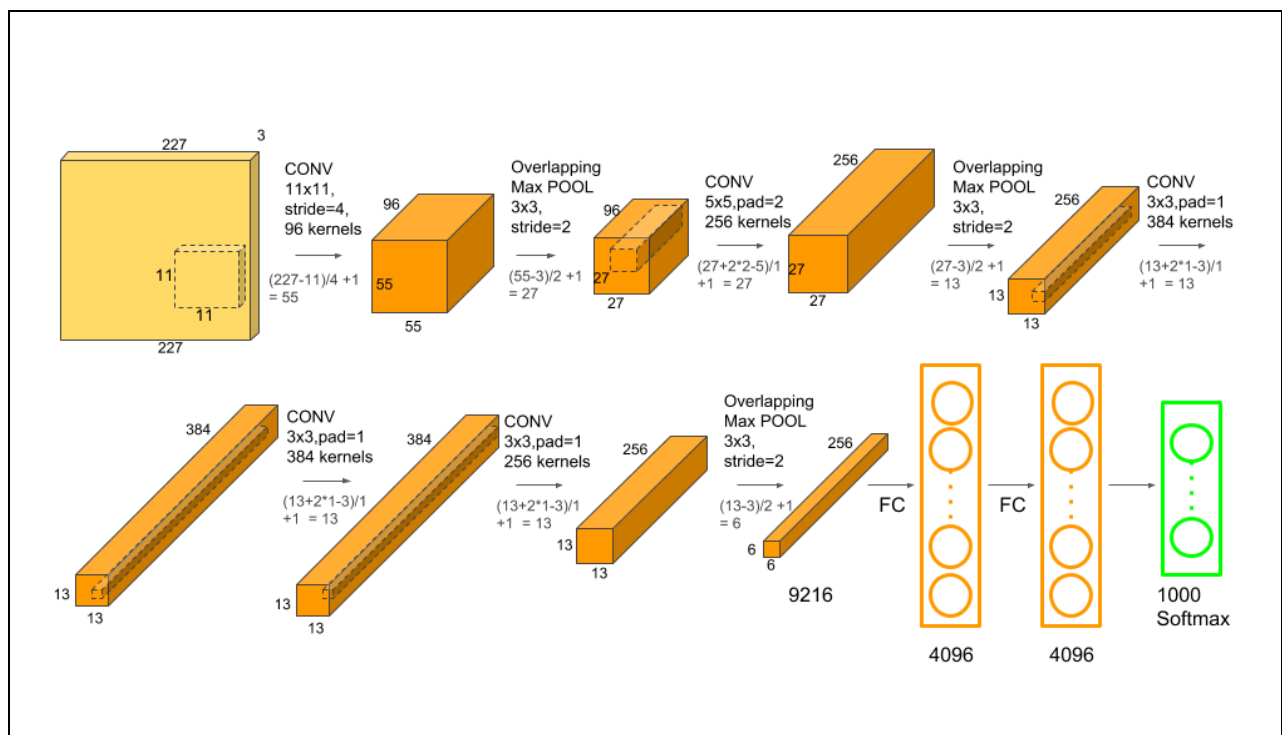
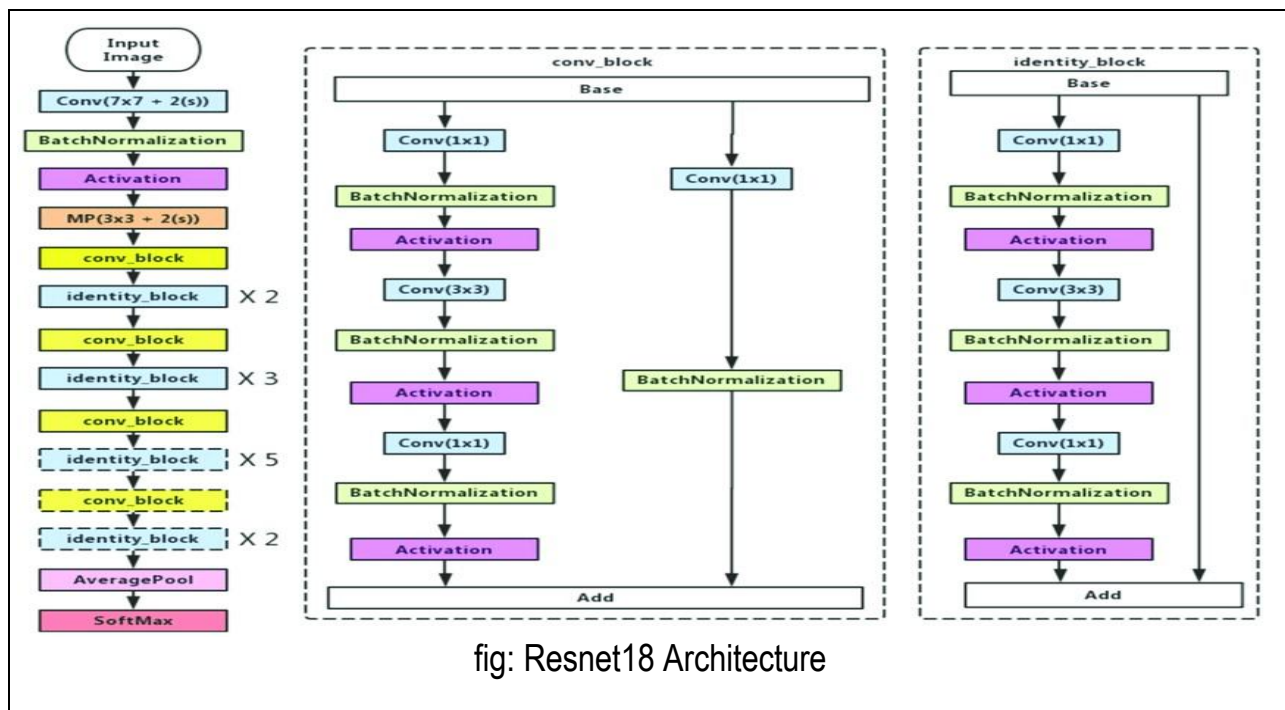


Fig:Alexnet Architecture

4.3 RESNET18:

- ResNet-18 is a convolutional neural network that is trained on more than a million images from the ImageNet database.
- The network is a total of eighteen layers in the network: 17 convolutional layers, a fully-connected layer and an additional softmax layer to perform classification task.
- The network can classify images into 1000 object categories.
- 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.



4.4 DENSENET201:

- Densenet architecture focuses on making deep learning networks go even more deeper by connecting all the preceeding layers to the current layer.
- DenseNet is a convolutional neural network that is trained on more than a million images from the ImageNet database.
- The network has 201 layers deep and can classify images into 1000 object categories.
- 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.
- DenseNet focuses on making deep networks go even more deeper and making them more efficient.
- It requires fewer parametrs than traditional convolutional networks as it does not require unimportant feature maps.
- DenseNet consists of two important blocks other than the basic convolutional and pooling layers. they are the Dense Blocks and the Transition layers.

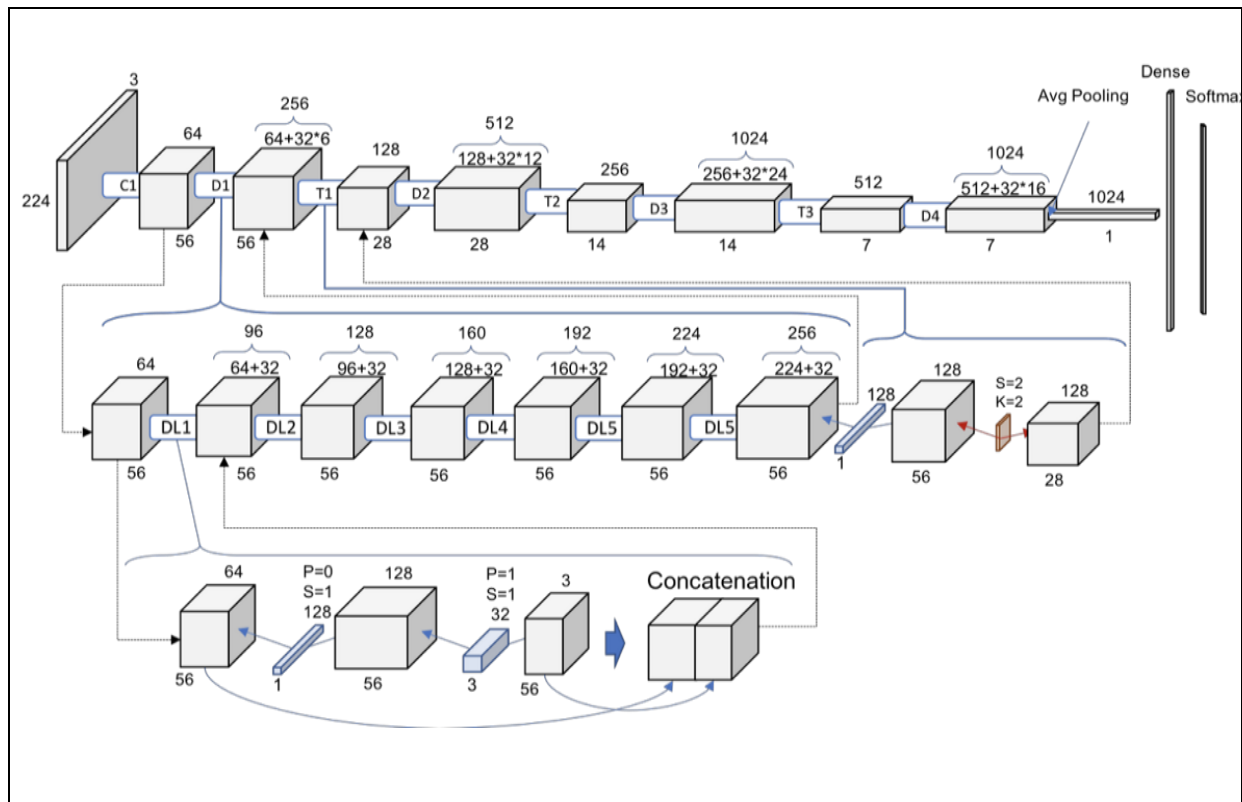


Fig: Densenet201 Network Architecture

CHAPTER 5

RESULTS AND DISCUSSION

5.1 CLASIFICATION OF FLOWER DATA SET USING VGG 16:

In this work, flower images are trained using VGG16 architecture which is also called OxfordNet named after the Visual Geometry Group from Oxford, who developed it. We have used 102 different categories of flower images which is already mentioned above chapters. Here we have divided the total images into two halves , where the first half is used for testing and the second half is used for training purpose. After training we have analysed the results by comparing the test data set with output data. The performance of the neural networks in terms of accuracy and sensitivity.

Desired	Actual	True/False
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1

Table 5.1 few results of vgg16 trained model.

Table 5.1 shows few results that obtained after the training of the image dataset. The actual output is compared with the desired result and evaluated as true '1' for a match and '0' for a mismatch.

Class	Match	Sensitivity
A1	10	100
A2	10	100
A3	1	10
A4	5	50
A5	6	60
A6	3	30
A7	2	20
A8	10	100
A9	8	80
A10	10	100
A11	1	10
A12	5	50
A13	7	70
A14	10	100
A15	5	50
A16	10	100
A17	5	50
A18	6	60
A19	7	70
A20	5	50
A21	7	70
A22	3	30

A23	10	100
A24	9	90
A25	8	80
A26	8	80
A27	8	80
A28	7	70
A29	0	0
A30	3	30

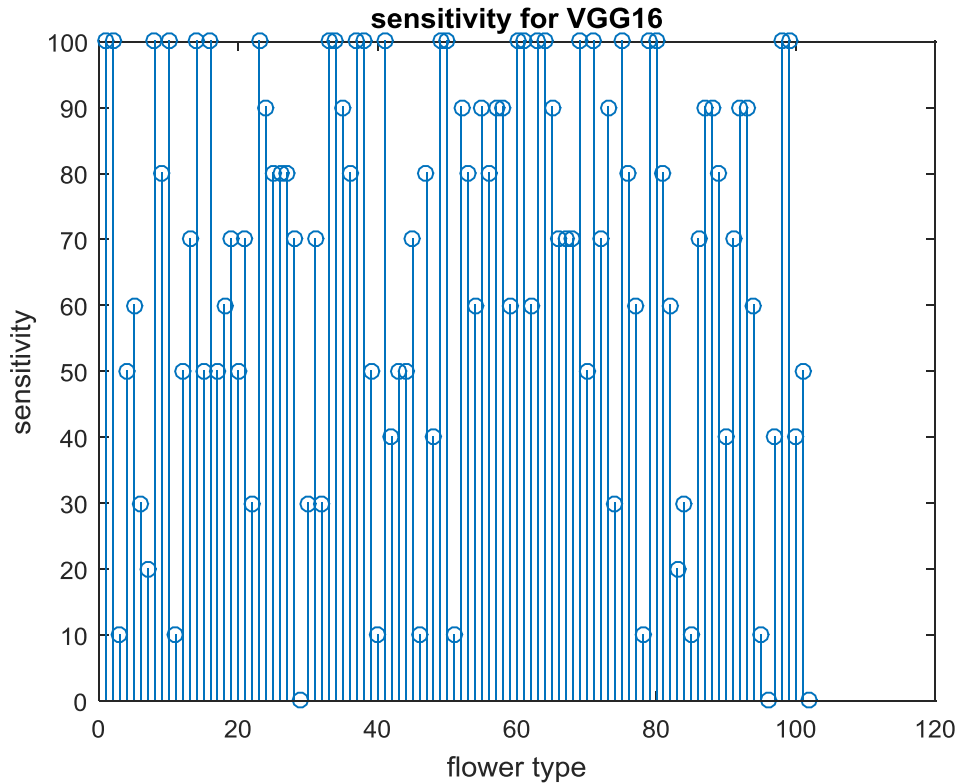
Table 5.2 Sensitivity of vgg16 trained model.

Table 5.2 shows the detailed Sensitivity of few classes of flowers from the image dataset when trained using VGG16 network architecture.

Matched	2694
Mismatch	1376
Total	4070
Percentage	66.47%

Table 5.3 results of VGG16 model

Table 5.3 shows the total number of images used for testing, number of images matched, number of images mismatch and percentage of images matched for vgg16 model. To this day is it still considered to be an excellent vision model, although it has been somewhat outperformed by more recent advances such as Inception and ResNet that's why we are going to use ResNet also.



Graph 5.1 Sensitivity analysis of VGG16

Graph 5.1. The graph above is the sensitivity with respect to each class i.e. tested and trained using the VGG16 architecture. The graph depicts each class of 102 classes of flowers on X-axis plotted against the sensitivity on Y-axis on scale of 100.

Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions.

Here in VGG16 model the accuracy is 66.47% which is too low than the existing models. Therefore the dataset needs to trained using the other architecture for the better accuracy.

5.2 CLASIFICATION OF FLOWER DATA SET USING RESNET18

To improve the specificity and accuracy flower images are trained using RESNET18, ResNet makes it possible to train up to hundreds or even thousands of layers and still achieves compelling performance. Taking advantage of its powerful representational

ability, the performance of many computer vision applications other than image classification have been boosted, such as object detection and face recognition. Because of its high features, layers and capability we are using it for our flower classification. In this work we are using 102 different categories of flowers. From total images we are dividing them into half for testing and training.

Actual	Desired	True/Flase
A101	A101	1
A101	A101	1
A101	A101	1
A101	A101	1
A74	A101	0
A8	A101	0
A90	A101	0
A101	A101	1
A101	A101	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1
A102	A102	1

Table 5.4 few results of resnet18 trained model.

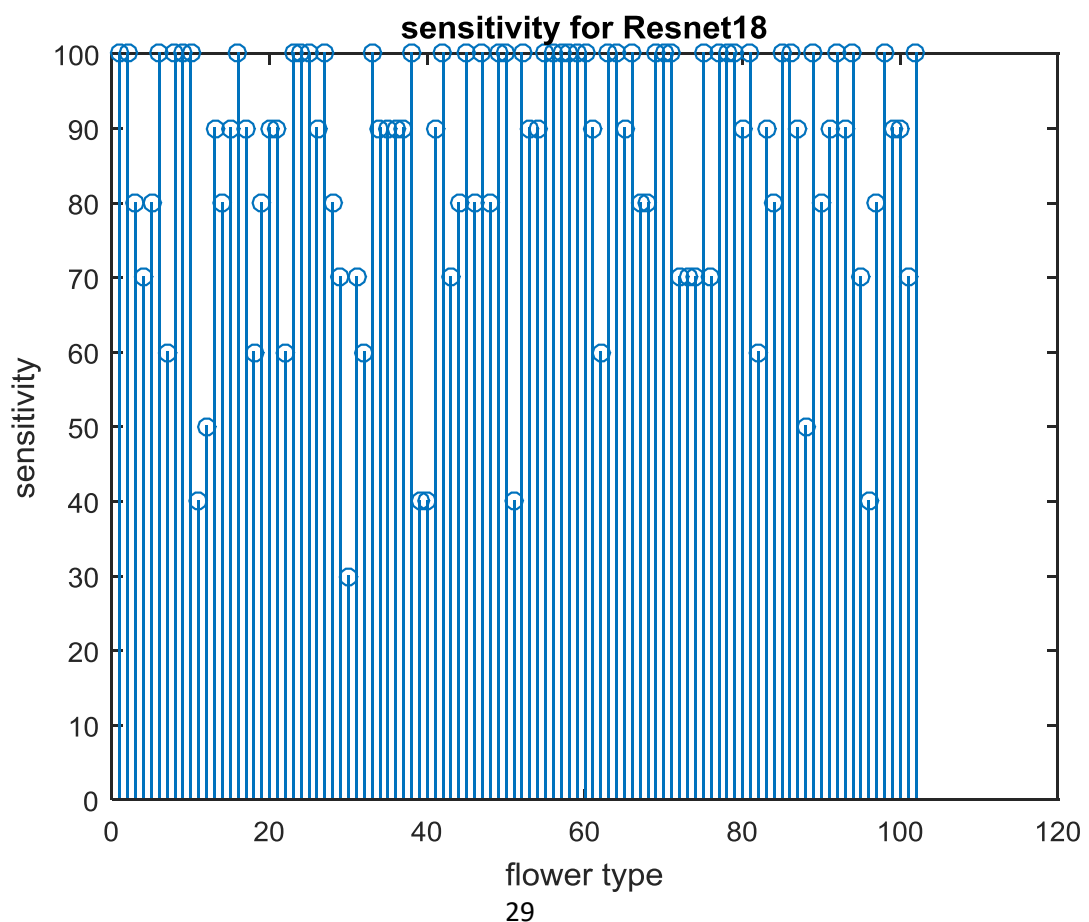
Table 5.4 shows few results that are actual required category with respect to current category obtained after training. We have compared the desired and actual outputs with true or false to evaluate the matching images.

Class	Match	Sensitivity
A1	10	100
A2	10	100
A3	8	80
A4	7	70
A5	8	80
A6	10	100
A7	6	60
A8	10	100
A9	10	100
A10	10	100
A11	4	40
A12	5	50
A13	9	90
A14	8	80
A15	9	90
A16	10	100
A17	9	90
A18	6	60
A19	8	80
A20	9	90
A21	9	90

A22	6	60
A23	10	100
A24	10	100
A25	10	100
A26	9	90
A27	10	100
A28	8	80
A29	7	70
A30	3	30

Table 5.5 Sensitivity of ResNet18 architecture

Table 5.5 is the detailed sensitivity list of few classes of flower dataset when it is trained and tested on ResNet18 architecture, it shows the sensitivity achieved by each class, also the number of matches per class are listed. For the better understanding a graph is plotted between class and sensitivity corresponding to it.



Graph 5.2 Sensitivity Analysis of ResNet18

The sensitivity achieved by each of the 102 classes is shown using the graph 5.2. The classes from A1 to A102 are taken on the X-axis and the sensitivity is taken on the corresponding Y-axis the graph respectively.

Accuracy of the Resnet18 architecture for the classification of flower database is 85.39%. This accuracy is obtained when percentage is calculated between the sum of all the classes sensitivity to the sum of total possible sensitivity that can achieved.

5.3 Classification of flower dataset using AlexNet:

AlexNet is a convolutional neural network that is 8 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories. AlexNet is a leading architecture for any object-detection task and may have huge applications in the computer vision sector of artificial intelligence problems. In the future, AlexNet may be adopted more than CNNs for image tasks. AlexNet was first utilized in the public setting when it won the ImageNet Large Scale Visual Recognition Challenge (ILSSVRC 2012 contest). AlexNet showed that deep convolutional neural network can be used for solving image classification. AlexNet uses the ReLU activation function which doesn't suffer from the VG problem. AlexNet was the first CNN to use ReLU as activation function, instead of Sigmoid function. The introduction of ReLU as activation function greatly improved the training speed of deep-learning networks. AlexNet when trained and tested on a flower dataset has produced the following results,

Actual	Desired	True/False
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A97	A1	0
A1	A1	1
A86	A1	0
A1	A1	1

A33	A10	0
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1

Table 5.6 Few Results of AlexNet Model

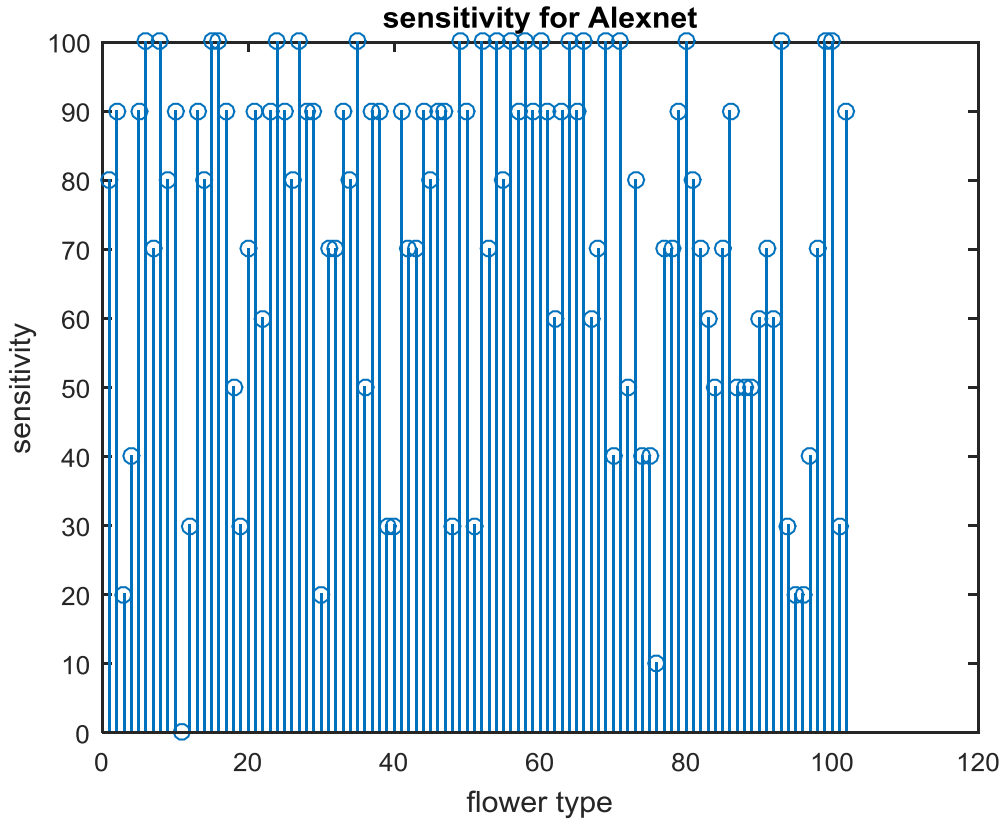
Table 5.4 shows few results that are actual required category with respect to current category obtained after training. We have compared the desired and actual outputs with true or false to evaluate the matching images.

Class	Match	Sensitivity
A1	8	80
A2	9	90
A3	2	20
A4	4	40
A5	9	90
A6	10	100
A7	7	70
A8	10	100
A9	8	80
A10	9	90
A11	0	0
A12	3	30
A13	9	90
A14	8	80
A15	10	100
A16	10	100
A17	9	90
A18	5	50
A19	3	30

A20	7	70
A21	9	90
A22	6	60
A23	9	90
A24	10	100
A25	9	90
A26	8	80
A27	10	100
A28	9	90
A29	9	90
A30	2	20

Table 5.7 Sensitivity Analysis of few Classes of flower Dataset

Sensitivity analysis is a necessary approach for understanding the relationship and the influence of each input parameter on the outputs of a problem. Table 5.7 has the sensitivity analysis of few classes from the flower image dataset when trained under



AlexNet.

Graph 5.3 Sensitivity Analysis of AlexNet

The Sensitivity Graph tool is designed to allow you to review the results of sensitivity simulations. Project sensitivity is a holistic evaluation of how likely it is that a project will succeed through data-driven forecasting. Graph 5.3 has the sensitivity analysis of all the 102 categories of flower.

The accuracy of the AlexNet architecture is 72.35%. Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions.

5.4 CLASIFICATION OF FLOWER DATA SET USING DENSENET201

DenseNet is more efficient on some image classification benchmarks. DenseNet was developed specifically to improve the declined accuracy caused by the vanishing gradient in high-level neural networks. In simpler terms, due to the longer path between the input layer and the output layer, the information vanishes before reaching its destination. From the following charts, we can see densenet is much more efficient in terms of parameters and computation for the same level of accuracy, compared with Resnet. For this reason we also wanted to try our dataset with this model. For this model also we are using the same 102 different categories of flowers. From total images we are dividing them into half for testing and training. We have used matlab as frame work and we used latest R2021b version of matlab.

Actual	Desired	True/False
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1

A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A14	A10	0
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1

Table 5.8 few results of densenet201 trained model.

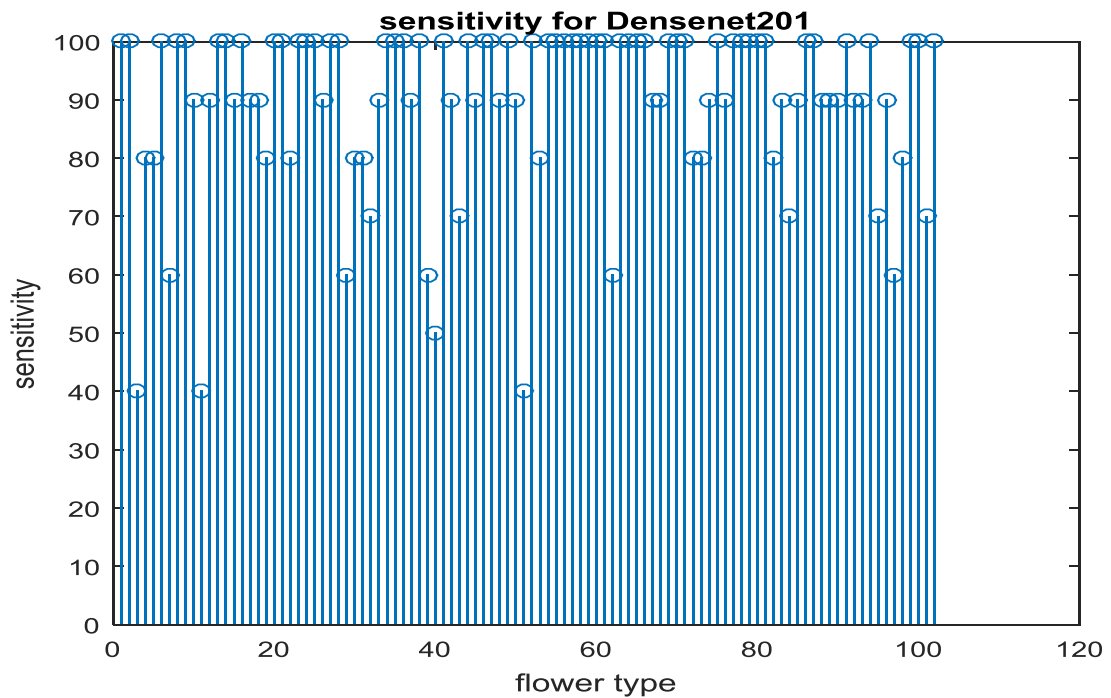
Table 5.8 shows few results that are actual required category with respect to current category obtained after training. We have compared the desired and actual outputs with true or false to evaluate the matching images.

Class	match	sensitivity
A1	10	100
A2	10	100
A3	4	40
A4	8	80
A5	8	80
A6	10	100
A7	6	60
A8	10	100
A9	10	100
A10	9	90
A11	4	40
A12	9	90
A13	10	100

A14	10	100
A15	9	90
A16	10	100
A17	9	90
A18	9	90
A19	8	80
A20	10	100
A21	10	100
A22	8	80
A23	10	100
A24	10	100
A25	10	100
A26	9	90
A27	10	100
A28	10	100
A29	6	60
A30	8	80
A31	8	80
A32	7	70
A33	9	90
A34	10	100
A35	10	100
A36	10	100
A37	9	90
A38	10	100
A39	6	60
A40	5	50

Table 5.9 Sensitivity Analysis using DenseNet201 model.

Sensitivity analysis, also referred to as what-if analysis, is a mathematical tool used in scientific and financial modeling to study how uncertainties in a model affect that model's overall uncertainty. sensitivity is a holistic evaluation of how likely it is that a project will succeed through data-driven forecasting.



Graph 5.4 Sensitivity Analysis of DenseNet201 model

Out of all the trained architectures (VGG16, AlexNet, ResNet18, DenseNet201) DenseNet 201 has given the highest sensitivity as well as accuracy. DenseNet201 architecture accuracy is 89.80% which is the highest among our trained datasets.

In our work the DenseNet architecture was not able to improve or maintain the consistency in performance with the growing number of parameters, it is observed there has been a degradation in the performance when the parameters are increased. Hence the DenseNet201 model is modified and the modified DenseNet architecture is successful in maintain the consistency with the changing parameters.

CHAPTER 6

MODIFIED DENSENET201

Convolutional Neural Network (CNN) is one the best known methods to classify flowers based on feature extraction. In our work we modified dense convolutional network (DenseNet) for the classification of flower images. DenseNet improves gradient propagation by connecting the all the layers with each other. In General a network with 'L' number of layers has 'L' number of connection whereas in DenseNet we have $L(L+1)/2$ number of connections. DenseNet utilises dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other. DenseNet201 has 201 layers is deep, increase in the number of layers increases the number of the connections The increase in the number of layers in the network increases the number of connections, deeper models doesn't perform up to their ability as well as the shallow ones. Modified DenseNet201 architecture the number of connections are reduced to 797 while the conventional DenseNet201 architecture consisted of 805 connections. DenseNet works on the idea neural networks can be substantially deeper, more accurate and more efficient to train if they have short connections between layer close to the input and to those to the output. Hence In our work we reduced the number of connections between layers and thus improved the accuracy as well as the specificity. The connections reduced in the modified DenseNet201 model is from the concatenation block. The results of our are discussed below

Actual	Desired	True/False
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1

A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A1	A1	1
A92	A10	0
A10	A10	1
A10	A10	1
A10	A10	1
A14	A10	0
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1
A10	A10	1

Table 5.10 Results of Modified DenseNet model

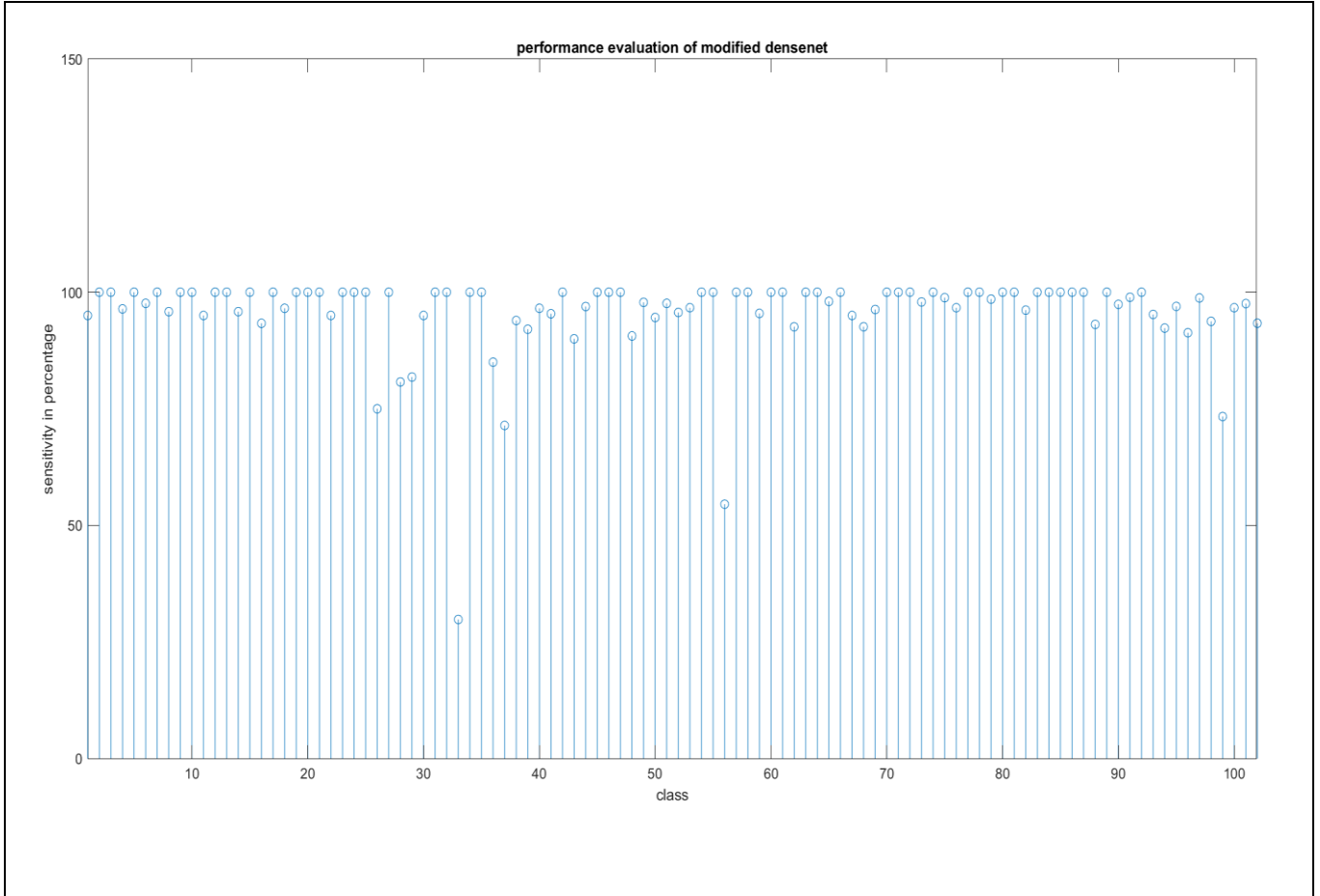
Table 5.10 shows a few results from the elaborated analysis. The actual and desired results are the comparison, deviation of the desired result can be evaluated from the above table. True is used for a match and is represented with '1' and a mismatch is false represented with '0'.

Category	Match	Sensitivity
A1	10	100
A2	10	100
A3	7	70
A4	8	80
A5	8	80
A6	10	100
A7	7	70
A8	10	100

A9	10	100
A10	8	80
A11	7	70
A12	9	90
A13	9	90
A14	10	100
A15	10	100
A16	10	100
A17	9	90
A18	9	90
A19	9	90
A20	10	100
A21	10	100
A22	6	60
A23	10	100
A24	10	100
A25	9	90
A26	8	80
A27	10	100
A28	10	100
A29	9	90
A30	6	60
A31	8	80
A32	8	80
A33	10	100
A34	10	100
A35	10	100

Table 5.11 Category wise Sensitivity of Modified DenseNet201 Model

Sensitivity of all the 102 categories of flower in the image dataset is evaluated and analysed, it is inferred that the modified model has differentiated the flowers in almost all the cases except for a few mismatches. The detailed analysis is shown in the following graph.



Graph 5.5 Sensitivity Analysis of Modified DenseNet201

Graph 5.5 shows the Performance of modified DenseNet201, it shows the total number of categories of flowers used for testing on the X-axis, sensitivity of each and every category/class of flowers on the Y-axis on the scale of 100.

In our work, modified densenet yielded an accuracy of 89.902% which is the highest among all the trained models. Modified DenseNet201 is consistent with the growing number of parameters without any performance degradation. The proposed model is able to maintain all the major advantages of conventional DenseNet architecture i.e. alleviating the vanishing-gradient and feature reusability.

Chapter 7

CONCLUSION

In this work, a deep learning technique along with Matlab is used to evaluate the performance of Convolutional Neural Networks (CNN) when tested on Oxford 102-category flower dataset. The data set is divided into two equal test and train subsets which are completely different from each other without any overlapping of data. The dataset is divided into epochs for testing. The roles of epochs in CNN was able to control accuracy and also prevent any problems such as overfitting. A Modified version of an existing architecture is proposed since the conventional models could not achieve a good accuracy. The conventional networks considered for testing are VGG16, RESNET18, ALEXNET, DENSENET201, while the DENSENET201 is modified to achieve a higher accuracy. The performance of the networks is evaluated on the basis of specificity and accuracy achieved by the respective networks. The results have shown that of all the architecture models the proposed model has produced the highest accuracy. The accuracy of the tested Convolutional Neural Networks architectures is as 66.47% in the case of VGG16, 72.35% for AlexNet model, 85.39% for ResNet18 model, DenseNet201 has an efficiency and accuracy of 89.80% respectively and finally the proposed model has the best among all the model architectures i.e. 89.902%. Though the proposed model has achieved highest accuracy on the tested dataset the performance results may vary when tested on large image dataset. The project has stopped at simulation level.

In the future this model can be used in real time applications after performing testing on more dataset, also modification of remaining networks can be performed and their results can analysed and studied for a robust model. The future enhancement will focus on classifying the colored images of large size, varying parameters and its very useful for image segmentation process.

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