

AN EFFICIENT CLASSIFICATION OF FLOWER IMAGES USING CONVOLUTION NEURAL NETWORK

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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SCHOOL OF ELECTRICAL AND ELECTRONICS ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

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DEPARTMENT OF ELECTRONICS& COMMUNICATION ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **V.HEMASRI**(Reg. No. 37130432) and **ISWARYASRI.D.P.** (Reg. No. 37130162) carried out the project entitled **"AN EFFICIENT CLASSIFICATION OF FLOWER IMAGES USING CONVOLUTION NEURAL NETWORK"** under our supervision from December 2020 to April 2021.

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Head of the Department
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Submitted for Viva voce Examination held on_____

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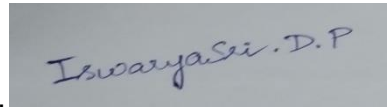
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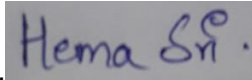
DECLARATION

We **V.HEMA SRI** (Reg.No.37130432) and **ISWARYASRI.D.P** (Reg.No.37130162) hereby declare that the Project Report entitled “**AN EFFICIENT CLASSIFICATION OF FLOWER IMAGES USING CONVOLUTION NEURAL NETWORK**” done by us under the guidance of **Mr.MUTHAIH.M.A** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electrical and Electronics Engineering.

1.

A rectangular box containing a handwritten signature in blue ink that reads "Iswarya Sri. D.P".

2.

A rectangular box containing a handwritten signature in blue ink that reads "Hema Sri.".

DATE:

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SIGNATURE OF THE CANDIDATES

ACKNOWLEDGEMENT

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

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ABSTRACT

Image processing plays an important role in extracting valuable information from images. Machine learning is entering much of the classification and recognition tasks performed by a computer. This project proposes the classification of flower images using a powerful artificial intelligence platform, convolutional neural networks (CNN) (CNN). A flower image database with 8500 images is considered for the experimentation. The entire database is sub classified the research is carried out on all the datasets. CNN architectures were developed and tested with our flower image data to obtain better accuracy in recognition. Various pooling systems are used to increase the classification rates. We achieved 95 percent recognition rate compared to other classifier models recorded on the same dataset. The various features are extracted and fed to the convolutional neural network (CNN) training portion. The CNN testing unit is used to identify the flower type productive and reliably. In this project, we used to classify flowers using the DenseNet 201. The proposed framework offers an interactive interface allowing each user to draw an appropriate bounding window that includes the interested flower field. Then, a flower boundary tracing method is designed to extract the flower area as accurately as possible. In addition to the colour and shape features of the entire flower field, the colour and shape features of area will also be used to reflect the flower characteristics more precisely.

TABLE OF CONTENT

CHAPTERS	TITLE	PAGENO
	LIST OF TABLES	VII
	LIST OF FIGURES	VIII
	ABSTRACT	V
1	INTRODUCTION	
	1.1.MOTIVATION	4
	1.2.OBJECTIVE	4
2	LITERATURE SURVEY	5
3	AIM	
	3.1 EXISITNG	9
4	MATERIALS AND METHODS	
	4.1. CONVOLUTION NEURAL NEYWORK	10
	4.1.1. CONVOLUTION LAYER	14
	4.1.2. POOLING LAYER	15
	4.1.3. NONLINEAR LAYER	15
	4.1.4. ReLU	15
	4.2. EXISTING DENSENET ARCHITECTURE	16
	4.2.1. DENSENET COMPOSITION LAYER	17
	4.2.2. DENSENET-B LAYER.	17
	4.2.3. MULTIPLE DENSE BLOCK WITH TRANSITION LAYER	18
	4.2.4. DENSENET BC LAYER	18
	4.3. PROPOSED DENSENET 201	19
	4.3.1. AUGMENTATION	20
	4.3.2. DATA SET	20
	4.3.3. TRANSFER LEARNING	21
	4.3.4. DATA NORMALIZATION	21
	4.3.5. PARAMETER EFFICIENCY	22
	4.3.6. MODEL COMPACTNESS	22
	4.3.7.IMPLICIT SUPERVISION	23
	4.3.8. OVERFITTING	23
	4.3.9. STOCHASTIC CONNECTION	23
	4.3.10. CONFUSION MATRIX	23
5	RESULTS AND DISCUSSIONS	31
6	CONCLUSION	32

7	REFERENCE	36
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LIST OF TABLES

TABLE	DESCRIPTION	PAGE NO
4.3.10.	SENSITIVITY AND SPECIFICITY	24

LIST OF FIGURES

FIG	DESCRIPTION	PAGE NO
4.1	ARCHITECTURE OF CONVOLUTION NEURAL NETWORK	12
4.1.1.	CONVOLUTION LAYER	14
4.2.	ARCHITECTURE OF DENSENET	16
4.2.1.	COMPOSITION LAYER	17
4.2.2	BOTTLE NECK LAYER	17
4.3	PROPOSED SYSTEM	19
4.3.10.	CONFUSION MATRIX	24

CHAPTER1

INTRODUCTION

In the universe there are a lot of flora. Some plants, including roses, have many colour. Both floral names and their details are difficult to recall. In addition, someone may be mistaken for related species of flora. White Champaka and Champak, for example, have identical names and petal forms, but have different colors and petal lengths. In this time, the identification of specific flora or species is almost impossible, but only details can be obtained from experts' personal knowledge and experience. Such experts may be available as a barrier to the search for such knowledge. The quest on the Internet is today very limited to the search for key word; text processing. In this case the search engineer has to include useful and inadequate keywords, which is the heart of the matter. This project offers a different approach to floral recognition and identification, focused on the processing of images. Those who would like to know information about the flora and species using image processing methods can do so by taking pictures, possibly using a smartphone and even a digital camera or using an Internet photo. The image processing method here proposed and defined by the system can then be entered in these images.

The identification of flowers has different applications. Personal photo organization is both the most common and influential among them. Who doesn't want to properly handle a large archive of picture memories, from individual items to large sceneries, according to the visual issues.

Flower identification supports the user experience in photo organization applications. In addition to photo storage, the apps also offer users much better discovery and search capabilities, which will take them one step further. You can achieve this by the abilities offered by machine learning for automated flower organizations. The integrated application programming interface for flora recognition classifies the flower according to known patterns. Other floral recognition applications include stocks and video websites, interactive and innovative ads, social networks facial and flower recognition and the flower classification of visually large websites.

Recognition of flowers is not a simple job. The use of metadata of unstructured data is a smart way to think about it. The hiring human experts to manually tag Music and film libraries is a daunting task, but it is highly impossible to distinguish pedestrians from other vehicles, through categorizing or tagging millions of videos and images uploaded by the users every day. When it comes to the problem of teaching driverless car sailing systems

The use of neural networks will be one way of solving this problem. We may take advantage of traditional neural networks to theoretically analyses images, but they are very costly from a computational perspective in practice.

The application of neural networks to flower recognition presents another problem: over fitting. Simply put, fitting occurs when a model closely matches the data on which it was educated. This produced added parameters (increasing further the costs of the computer) and results in a loss of overall output of the model's exposure to new data.

Human visual output is much higher than machine performance, possibly thanks to superior floral awareness, contextual information and large parallel processing. But after a prolonged surveillance time, human abilities deteriorate dramatically, some work environments becoming either inaccessible or harmful to people. Automatic recognition systems for various applications have therefore been developed. Computer vision imitation has recently gained ground in a variety of practical applications, driven by progress in IT capability and image processing technology. Flower recognition refers to technologies that identify digital images with locations, logos, human beings, artefacts, buildings and many other variables. For people like yourself and me it can be very easy to identify various images like animal images. We can easily identify a cat's image and distinguish it from a horse's image. But for a machine it may not be that simple.

A digital image is an image made up of pixels with a quantity of numeric representations in a finite quantity for their strength or grey level. The

programmer therefore considers the image to be numeric values of these pixels and must identify the patterns and regularities in this numerical data in order to recognize a certain image.

Flower identification with object detection should not be confused. We analyze an object and find different objects in the image during the object detection process to recognize the images and categories them. The task of recognizing images typically includes the construction of a neural network to process each image pixel. The networks are fed as many pre-label images as possible so that they can be "taught" to identify similar images.

So let me break the process for you in some simple steps:

1. We need an image-set with their labels. For instance, a dog's picture should be labeled as a dog or something we can understand.
2. Those pictures should then be fed into and trained in a Neural Network. We normally use convolutionary neural networks for the tasks involved with photos. In addition to multiperceptone layers, these systems include convolute layers and pooling layers (MLP). This explains the operation of convolutional and pooling strata.
3. We feed on the non-training picture and get predictions

In the coming sections, by following these simple steps we will make a classifier that can recognize RGB images of 10 different kinds of flowers. The capacity of software to recognize objects, locations, people, written and action in images in the sense of machine vision. In conjunction with the camera and the artificial intelligence programmed, computers may use machine vision technology to achieve image recognition.

Image recognition is used to perform many visual tasks on the computer, including the marking of the contents of images with meta-tags, the searching of image contents and the guiding of autonomous robots, cars and accident prevention systems. Although people and animals can easily identify objects, the task is difficult for computers. Image recognition software involves profound learning by the

machine. Performance is better with convolutionary neural network processors, as otherwise massive power for its computer-intensive design is needed for the specific task. Image recognition algorithms can work with comparative 3D models, edge detection and materials, from various angles. Image reconnaissance algorithms are also trained with directed machine learning in millions of pre-marked images. Current and potential image recognition technologies include smart picture library applications, focused ads, media interaction, accessibility of improved testing capabilities for visually impaired. Many companies that invest substantial resources and study in image recognition and associated applications include Google, Facebook, Microsoft, Apple and Pinterest. Privacy issues around image recognition and related technologies are problematic because these businesses will draw a significant amount to their social media sites of data from user images.

1.2 MOTIVATION

We will establish the classification system for flowering in this project. This scheme uses floral images' edge and colour properties to categories flowers. For the classification of flowers, image processing is a key phase in the identification of computerised plant species. The classification of the floral images is based on the low-level functionality, such as colour, texture and the content of the image.

1.3 OBJECTIVE

This project aims to establish an efficient approach to the rating of flowers with the help of algorithms from the Convolutional Neural Network (CNN).

CHAPTER 2

LITERATURE SURVEY

For human beings, plants become the main source of food, fuel, etc. Therefore, researchers and agriculture-related sectors work hard to carry on agriculture without any breach for a long time. Plant phenotyping without restriction addresses rural requirements. The increase in crop yield, which needs an extraordinary amount of study, is a significant rural requirement. Plant phenotyping is used for plant traits analysis to predict crop yield. Image analysis. Analyze image representations on plants by examining pictures of various plant organs, such as leaves, anatomy, form and surface. Various approaches and specific acquisition scenarios were suggested for managed experimental design. Some try to create software applications to automatically analyses the flower images. Various computer vision and imaging techniques have been proposed in order to achieve the aim to increase the yield of non-destructive flower phenotyping. Vital research was conducted in the area of phenotyping of plants, including research into the identification of plants, the number of leaves, the segmentation of the leaves and the analysis of the plant's images for production and growth. Plant phenotyping in the regulated laboratory setting, green house or on-site has been carried out in recent days. A lot has been done to plant phenotyping by researchers and academics. Huang has all suggested an automated system for plant species identification. Manuel Grand-Brochede painted the studies by applying several segmentation methods to remove the tree leaves from natural photographs. In order to extract the leaf area of the complicated pictures, Tangent proposed an algorithm. Infrasond or depth information is used by many segmentation systems for segmentation.

Hyper spectral Image Classification Using Convolutional Neural Networks and Multiple Feature Learning, IEEE 2018

Samsung Lin

Due to its better functional representation and high accuracy, revolutionary neural networks (CNNs) have been expanded into hyperspectral (HSI) classification whereas multiple feature learning has proven its efficacy in machine viewing areas. This paper provides a new method to better predict class labels of HSI pixels using

both CNN and multiple feature learning. We have created a new CNN architecture with different characteristics derived as an input from raw imagery. The network generates the appropriate feature maps for the input and the generated feature map forms a joint feature map in a concatenating layer. The joint feature map is then entered into the following layers for each pixel to predict the final labels.

Comparative Study of First Order Optimizers for Image Classification Using Convolutional Neural Networks on Histopathology Images, IEEE 2019

Ibrahim Kandel,

A experienced doctor with years of experience is needed for the classification of images to properly identify histopathological images. An algorithm was created in this study to assist doctors in classifying images of histopathology, the algorithm is given an image of histopathology as input to it, which produces the proportion of cancer. A neural network is the primary classification used in this algorithm and is a state-of-the-art classifier used to classify images without having to rely on a manual selection of the images features. The main goal of this research is to boost the strength of the classifier by comparing six different stochastic gradient-based optimizers in the first order to choose the best for this data set.

A Novel Architecture to Classify Histopathology Images Using Convolutional Neural Networks, IEEE 2019

Mauro Castell.
Histopathology studies are performed to assess if the cells are normal or abdominal. Tissue structure under a microscope Histopathology is a very critical examination for determining the care plan of patients. Even an experienced pathologist has difficulty classifying histopathology picture and also needs a second opinion. A specific form of deep learning architecture, Convolutionary Neural Networks (CNN), has achieved remarkable results on computer vision tasks such as image classification. We suggest a new CNN architecture in this document to identify photographs of histopathology. There are 15 converting layers and two completely connected layers in the proposed model. To detect the most effective, two different optimizers were compared to the different activation functions.

Dual and Single Polarized SAR Image Classification Using Compact Convolutional Neural Networks

Precise land use/land cover classification of images with synthetic opening radar (SAR) plays a major role in research fields and applications in environmental, economic and nature areas. In the case of the absence of completely polar metric SAR data, single or dual SAR data may also be used, with some difficulties. Traditional machine learning approaches, for example, typically concentrate on discovering more discriminatory characteristics to solve the lack of knowledge due to single or double polarimetry. In addition to traditional ML methods, studies that propose deep convolutionary neural networks (CNNs), such as specifications of large volumes of training data and special hardware for complex deep networking, have also been limited and disadvantaged. In this report, we suggest that the classification of sliding windows with compact and adaptive CNNs should be based on a systematic approach which could overwhelm such disadvantages while achieving the latest performance standards for land use.

Cotton Leaf Disease Identification using Pattern Recognition Techniques, P. R. Rote, Department of Electronics Engineering, priya darshini College of Engineering, Nagpur, India

Early, accurate identification of leaf diseases on the cotton plant is essential as they can damage yield. The proposed work includes a pattern detection and classification scheme for three diseases of cotton leaves: Bacterial blight, Myrothecium and Alternaria. The photos for the work are taken at Nagpur Cotton Research Central Institute and in Buldana and Wardha districts. The images are collected from the fields. For image segmentation, the active contour model is used, and Hu moments are extracted as trains for adaptive neuropathic inference scheme. The accuracy of classification is 85%. The systems proposed are designed to process images from different distances obtained in natural conditions. This makes the device stable under various climates. Figure 6 displays the flowchart of Alternaria, bacterial leaf blight, and cotton leaf diseases suggested for identification. Figure 6 shows. The imaging processing techniques are used to flatter photographs by means of a digital camera. Photos are then segmented using methods to separate the disease spot from the context. These segmented sections draw on the features and use the

important features to train the classification network. The systems proposed are designed to process images taken from different distances under natural conditions. This strengthens the mechanism in various climatic conditions. Pictures are obtained by a digital camera and the preprocessing of images is used for smoothing pictures. Images are then segmented to separate the disease spot from the background. These segmented sections draw on the features and use the important features to train the classification network.

CHAPTER 3

AIM

With an efficient classification we have to achieve high precision for image classification by using a convolution neural network, without losing the resolution of the pixel we have to extract the floral image features for implementing the deep CNN model of the floral classification. The learned features are considered as the highest abstract representation of low-level floral images through the deep architecture. Here, we used to achieve a high efficiency by using adjusted DenseNet 201 of more than 90%.

3.1. EXISTING SYSTEM

Recent years people using the pretrained models to make the model to learn effectively and to get efficient outcomes, classification of images is one of the problem faced by the researchers in the existing model densenet is used where we used to get the 89% as outcome, when the image is passed through several layers of the convolution network then the level of feature extraction will be high, in DenseNeteach layer used to pass the features of the present layer to the next preceding layers here the number of channel is fewer compared to the DenseNet 201, in DenseNet we will be using the fewer layers for feature extraction whereas densenet 201 has very deeper layers which will collect the very small information in the every layer of dense block it is not possible in the DenseNet, in DenseNet we can reuse the features here N is the no of layers then the Nth layer will have N layers, features of present layer is passed to preceding layer through the concatenation of features, whereas transition layer consists of convolution layer and pooling layers.

CHAPTER 4

4.1. CONVOLUTION NEURAL NETWORK(CNN)

Neural network is a machine learning subset and is the core of profound learning they are inspired by the human brain, their name and structure, which mimeticises the way biological neurons signal each other. ANNs are composed of node layers, which include an input layer, one or more cached layers, and an output layer. Each node, or artificial neuron, is connected and has a weight and threshold associated with it. If the performance of any node exceeds the threshold, this node is enabled and data is sent to the next network layer. No data is otherwise transferred to the next network layer. The general rationale for neural networks as an AI approach is close to that for logical approaches. In the latter case, the idea was to simulate higher thinking processes and, in particular, to manipulate symbols representing certain concrete or abstract notions using logical rules to obtain a knowledge on the human level. The rationale for neural networks is that knowledge can emerge by simulating subsymbolic data processing at the neural levels and neural networks. All this sounds very fair, but remember that we do not make aircraft with wings or bones, muscles and father to build flying machines. Also, the internal mechanism of the neurons is generally neglected in artificial neural networks and the artificial neurons are also considerably simpler than their natural counterparts. In artificial models too, the dynamics of electro-chemical signals between natural neurons are generally overlooked when it comes to building AI-systems instead of simulating organic systems. The interchangeable use of deep learning and neural networks is sometimes confusing. It is important to note that the depth of the neural network is just the depth of the layers of the profound learning. A neural network of over three layers – including the inputs and the output – can be called a profound learning algorithm. A neural network with just two or three layers is just a fundamental neural network.

A distributed system of artificial 'neurons' exchanging messages is the revolutionaries neural net. The links have numerical weights that are modified during the training process to allow a properly trained network to respond properly with an image. The network includes several layers of the feature detection "neurons." Each layer has multiple neurons that respond to different input layer combinations. The

layers are intended to detect a variety of primitive layer input designs, second layer pattern patterns, patterns from the third layer patterns, etc. The typical patterns of 5 to 25 layers are recognized by typical CNNs.

Training takes place in a wide range of representative input models, with the "labeled" input dataset characterized by the desired output response. Training uses general methods to measure mid- and last-neuron weight. Clearly. Evidence. Evidence. The training is a block exercise. A neuron receives input signals from its dendrites and emits output signals along its axon from a real animal neural system. The axon branches and connects through synapses with other neurons. The neuron is activated and transmitted to succeeding neurons when certain threshold conditions between their input dendrites is exceeded by the combination of input signals. The machine neural model depends on the interacting signal that passes through axons (for example, x_0) multiplying (for example, w_0x_0) on the synaptic power of the other neuron dendrites (e.g., w_0). Synaptic weights can be acquired and neuronal impacts can be regulated. The dendrites convey the signal throughout the body of the cell. If the ultimate level exceeds the threshold, the neuron fires a spike along the axon. The computing model assumes that exact firing times are irrelevant and only the frequency of firing provides information. The firing rate of the neuron is modeled on an activation function f which describes the spike rate on the axon. Based on the interpretation of the rate code. Sigmoid is a common activation feature. In brief, the input and weight point result are calculated in each neuron, the partition is added and the nonlinear function is a trigger (for example, following a sigmoid response function).

A CNN is a special case of the above-mentioned neural network. A CNN consists of one or more convolutionary layers often accompanied by one or more completely connected layers, such as in a regular neural network, using a subsampling layer. A sensory mechanism, the visual cortex, in the brain motivates the design of a CNN. The visual cortex contains several cells which are responsible for the light detection in small, overlapping visual field sub-regions, known as receptive fields. These cells serve as local filters throughout the input space, and larger receptive areas exist in the more complex cells. The convolution layer in the

visual cortex in a CNN fulfils the role of the cells. Each feature of a layer receives inputs from a number of features in a small neighborhood called a local receptive field on the previous level. Features that can extract basic visual features, including the directed edges, endpoints, corners, etc, can then be combined in the higher layers with local receptive fields. A hand-designed extractor collects relevant information from the input and removes non-relevant uncertainty in the conventional pattern / image recognition model. A workable classifier, a regular neural network, classifying the functional vectors into groups, follows the extractor. The role of extractor in a CNN is the function of convolution layers. They're not crafted, though. In the training process, weights of the convolution filter kernel are determined. Convolutionary layers may extract the local characteristics because they limit the secret layers' reception areas to local ones.

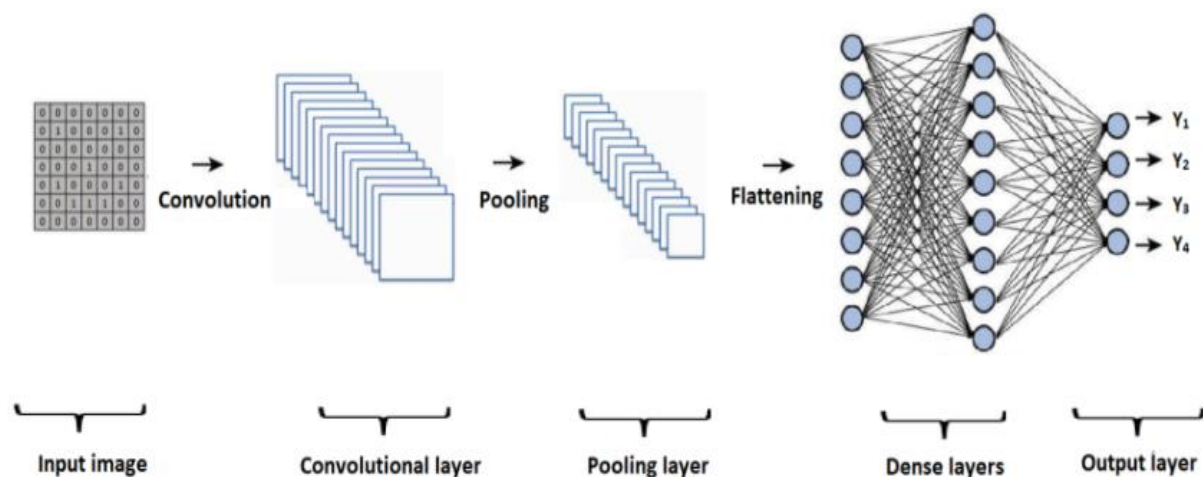


Figure 4.1: Architecture of CNN

In a number of fields, CNNs include recognition of the image and pattern, voice recognition, linguistics processing, video analysis. There are a variety of causes for the importance of convolutionary neural networks. Function extractors are hand crafted in conventional pattern recognition models. During the training phase the weights of the convolutionary layer for the extraction of functions are calculated and the completely connected layer used for classification. The better network architectures of CNNs reduce memory requirements and computational complexity and provide better performance for applications with a local correlation between the data entered and the input (e.g., image and speech). Many computer resources requirements for the training and evaluation of CNN are met by graphics processing unit (GPUs), DSPs or another, high-performance and energy-efficient silicone architecture when the CNN calculation's peculiar patterns are performed. The best possible accurate detection rates (CDRs) were achieved with CNNs in pattern and image recognition applications. The pre-processing phase is usually dependent on input information, particularly the camera system, and is often used outside of the visual subsystem on a hardwired device. Decisions are usually made on known items at the end of the pipeline. It can make complex decisions, but it operates on far less data and thus usually these decisions are not computationally complicated or intensive in storage. The biggest challenge is to identify and recognize artifacts in which CNNs play a large role.

4.1.1. CONVOLUTION LAYER

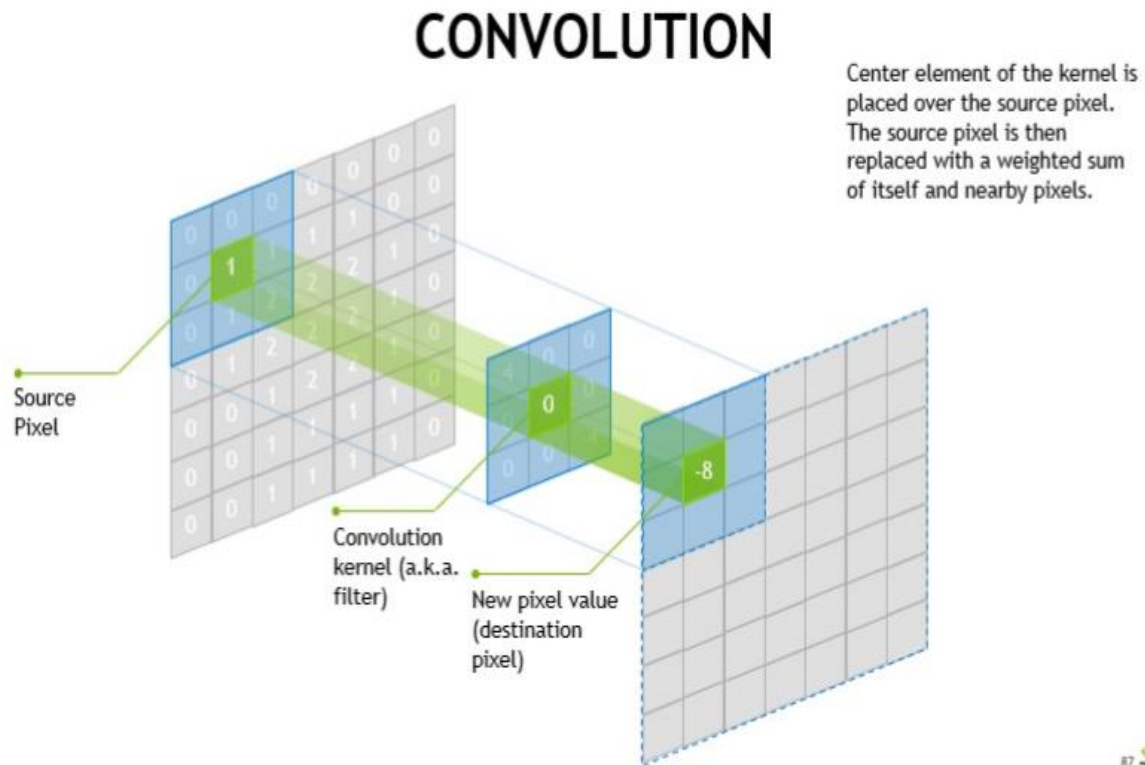


Fig 4.1.1 convolution layer

The convolution process extracts various input characteristics. The first layer extracts features such as borders, lines and corners. Top-level layers extract higher-level capabilities. The entry is $N \times N \times D$ and has H kernels each separately, which are $k \times k \times D$. Convolutioning one kernel input generates one output function and H features with H kernels. Any kernel is moved from the top left corner of the input, one element at a time. The kernel will move one item downward until the top-right corner is arrived. Once again, from left to right, the kernel will be shifted one element at a time. This is done before the kernel reaches the lower right corner. There are 28 singular positions where $N = 32$ and $k = 5$ can be selected from the left to the right. In accordance with these positions, every function of the output consists of 28×28 (ie $(N-k+1) \times (N-k+1)$). In the sliding window process $k \times k \times D$ input elements and $k \times k \times D$ kernel elements, element by element, elements are multiplied and accumulated on each kernel position. To build a single element of the output function, Multiple-accumulative $K \times k \times D$ activities are required.

4.1.2.POOLING LAYER

The sampling layer pooling/sub lowers functionality resolution. It robustly controls noise and distortion. Pooling is possible in two ways: maximum pooling and average pooling. In each case, the input is separated into two-dimensional spaces that do not overlap. The pooling layer is layer 2. Each input is 28x28 and is divided into 14x14 size 2x2 regions. The entrance is 4x4 in dimension. A 4x4-image is divided into four matrices of size 2x2 that are not overlapped. In the case of max pooling, the maximum sum of four values in the 2x2 matrix is the contribution. In case of average pooling, the average score is four. Please note that the average product is a fraction of the indexed output to the nearest integer (2,2).

4.1.3. NON-LINEAR LAYER

Neural and CNN in general depend on a non-linear "start" function to signalize the identification of probable characteristics of each hidden layer. In order to efficiently enforce this non-linear trigger, A number of specific functions such as rectified linear (Re-LU) units and continuous (nonlinear) trigger functions are available to CNNs.

4.1.4. ReLU

$Y = \max(x, 0)$ is implemented by A ReLU for the input and output size of this layer. It increases the nonlinear characteristics of the decision and the entire network and does not affect its receptive areas. The advantage of ReLU, compared to other CNN nonlinear functions, is that the network trains are much faster (e.g. hyperbolic tangent, absolute hyperbolic tangent, and sigmoid).

EXISTING SYSTEM

4.2. DENSENET ARCHITECTURE

DenseNet is a network architecture in which each layer is feed-forward directly connected to each other (within each dense block). The charts of all previous layers are handled for each layer with different inputs, while their characteristics are handed over to all layers as inputs. DenseNet has various persuasive benefit: it alleviates the issue of disappearance, reinforces the propagation of features, encourages reuse of features and greatly reduces the number of parameters.

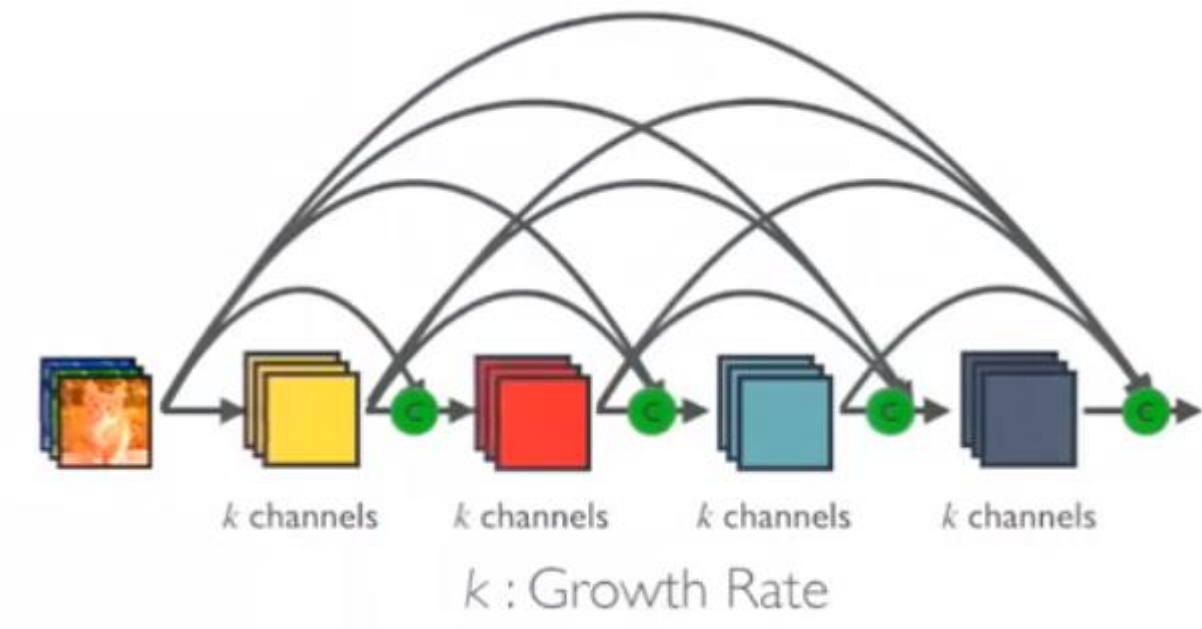


Fig 4.2. architecture of densenet

The network can be thinner and compact no.of channels for every layer received from all previous layers and can have a high calculative efficiency and memory efficiency.

4.2.1. DENSENET COMPOSITION LAYER

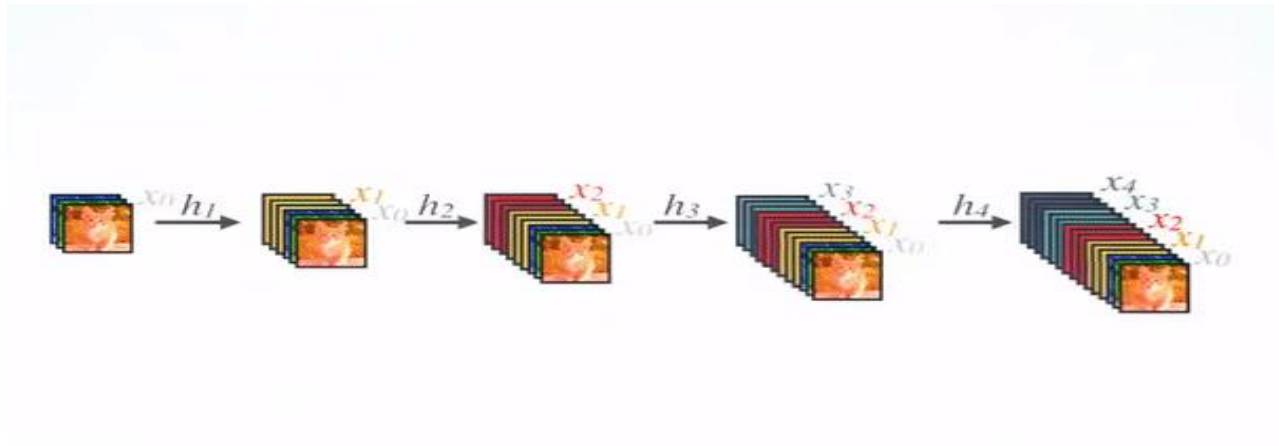


Fig 4.2.1.composition layer

For each composition layer, pre-activation batch norm, ReLU, then 3x3 convolution are done with output features maps of k channels.

4.2.2. DENSENET-B (BOTTLENECK LAYER)

To reduce the model complexity and size BottleNeck-ReLU-1x1 convolution is done before BottleNeck-ReLU-3X3 CONV.

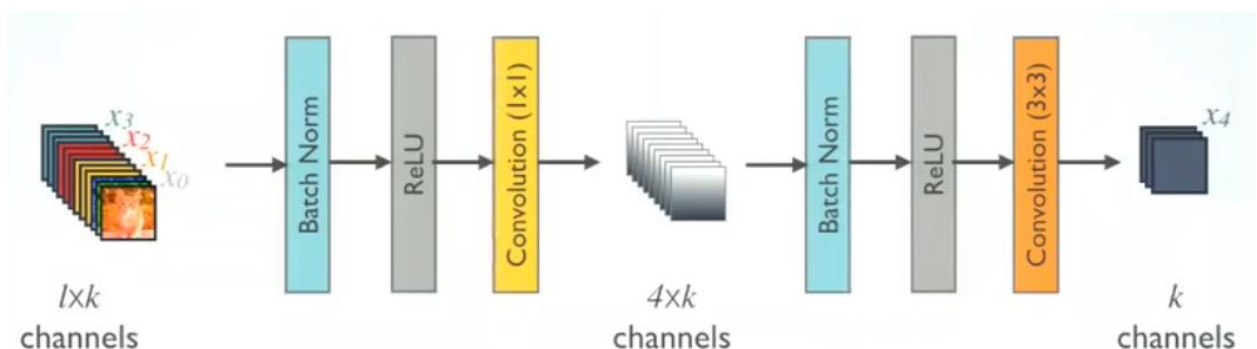


Fig 4.2.2.

4.2.3. MULTIPLE DENSE BLOCK WITH TRANSITION LAYERS

The transition layers between contiguous dense blocks 1 to 1 Conv, followed by 2 to 2 average bundles are used as transition layers. The map sizes within the dense block are identical to allow them to be easily combined. A global average pooling is done at the end of the last dense block, and a softmax classification is attached.

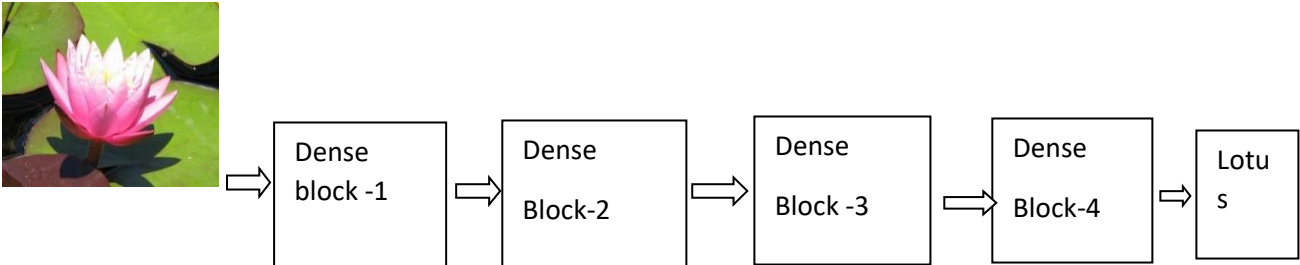
4.2.4. DENSENET-BC (FURTHER COMPRESSION)

If a block contains m character maps, then γ is called the compression factor in a transition layer, generating γm the output character maps. When $\gamma=1$, there is no difference in the number of feature-maps over transition layers. DenseNet is referred to $\gamma=1$ for $\gamma=0.5$ for experiment, DenseNet is referred to as DenseNet-C. The model is called DENSENET-BC if it is used both in the bottleneck and in the transition layers with a value $\gamma=1$.

4.2.5. DENSENET TRAINING AND RESULTS

The DenseNet architecture defined in the original research paper is applied to three datasets: CIFAR, SVHN, and ImageNet. All the architectures used a stochastic gradient descent optimizer for training.

4.3.PROPOSED DENSENET 201



4.3. Proposed system

The DenseNet 201 was a dense network type, and the input blob DenseNet 201 was made up of a single frame with an order of $1 \times 3 \times 224 \times 224$ RGB in 201 layers with a size of 77MB. The first input we use for training is an image, which typically contains a matrix for pixels after resizing 128 to 128 pixels. While we flatten the image into a list of row pixels for certain machine learning methods (RF, SVM). The outcome is influenced not only by model parameters, but also by the quality of training data. We perform data increase methods so that images are rotated, shifted and zoomed and ZCA is used. This increase is useful for extracting functional weights. Our training dataset is very thin, but it is important for good results to have a large dataset. Random samples are produced using illustrated approaches and plugged into training datasets. It creates more valid information, offers additional information and thus avoids overfitting. We first pre-proceed to change the calculated values on various scales in a notionally typical manner, rather than using raw data. We also brought the data value closer together by subtracting each data by average, by standard deviation. However, we did not change the outcome of this optimization in SVM. The cause may be the strength of non-linear models dealing with complex datasets and pixel changes often distorting the original images. Increased neural network depth resulted in the disappearance of information about the input or gradient across several layers. To resolve this, authors implemented a single communication pattern architecture to ensure optimal information flow between layers in both forward and rearward calculations. This network links all layers in such

a way that each layer receives additional inputs from all layers and transfers its own function maps to all layers. L -Layers are in the network. A non-linear transformation $H_l([x_0, x_1 \dots x_{l-1}])$ is carried out in each layer. $H_l([x_0, x_1, \dots, x_{l-1}])$ where the layer is l -indexed. $H_l(.)H_l(.)$ is a composite function for batch normalization (BN) operations, linear corrected unit (ReLU), pooling and convolution operations (Conv). The feature maps created in layers $0, l-10, \dots, l-1$, here $[x_0, x_1, \dots, x_{l-1}]$ are concatenated. If the function maps are variable in size, the above stated concatenation operation is not viable. As we know, down sampling layers are the central component of the image recognition networks. The authors divided the entire architecture into a number of densely linked dense blocks to facilitate the down sampling in the architecture. The layers between these dense blocks are layers of conversion and pooling efficiency. The concept of the dense convolutionary neural network for the classification of images, developed by densenet model 201, is that the feed forward mode combined feature maps learned in different layers link each layer to each other, increasing the input variation of subsequent layers and improving it.

4.3.1. AUGMENTATION:

Increased Data enhancement is a method which allows practitioners to improve the range of data on training models significantly without actually collecting new data. Techniques for data increase such as cropping, horizontal, rotation, etc. are commonly used in training models. In this project, the image augmentation has been used to increase training benefits and decrease the use of network regularization.

4.3.2. DATA SET

We have created a 102 category dataset, consisting of 102 flower categories. The flowers chosen to be flower commonly occurring in the United Kingdom. Each class consists of between 20 to 40 images total 4051 images.



4.3.3. TRANSFER LEARNING

Transfer learning is usually a method in which a pretrained model is used again.

There is a weight initialization, feature extraction, and two key approaches to applying transfer learning.

As a starting point for the training phase the weights of reused layers may be used and adapted in response to new problems. This application addresses transfer learning as a form of weight initialization system. This may be useful if the first associated problem has far more data than the interest problem and the resemblance of the problem's structure can be useful in both contexts.

To support the transition, three attributes are important:

1. Pretrained model performance helps the consumer remove the hyper parameter tuning;
2. The early layers can be considered to remove low levels of elements, such as edges, tints, blobs, shades and textures, in a pretrained model;
3. Only the past several layers of a pretrained model will need to be retrained by the goal model, as we assume that the final several layers perform complex recognition tasks.

4.3.4. DATA NORMALIZATION

Data standardization shall scale the data down to a certain short interval. It is also used to eliminate the unit limit of the data for the processing of specific comparison and measurement indicators and transform it into a pure dimensionless value so as to allow comparisons and weighing of indicators of different units and magnitudes. One of the advantages of standardization is the rise in model convergence another advantage of normalization is the increased precision, which is important when calculating distance algorithms such as euclidean distances. Standardization is also required, so that each function can contribute the same to the performance.

4.3.5. PARAMETER EFFICIENCY

Parameters are more robust than other architectures for DenseNets (in particular, ResNets). Especially parameters-efficient is the DenseNet BC with its bottleneck structure and dimension reduction. As an example, our model 250 layer has only 15.3M, but always exceeds Net and Wide ResNets with more than 30M parameters; this dense communication pattern can have a counterintuitive impact, since it needs less parameters than conventional networks since redundant feature maps do not need relearning. Traditional feed-forward architectures can be interpreted as algorithms with a layer-to-layer transmission. Each layer reads the preceding layer status and writes to the next layer. It modifies the state but also provides preserved details. ResNets explicitly preserve this knowledge through the transformation of additive identity. Recent ResNets variations show that several layers contribute very little and can actually be dropped randomly during training. This makes the condition of ResNets similar to recurring (unrolling) neural networks, but the number of ResNets parameters is much greater since each layer is weighted by its own. Our proposed DenseNet architecture distinguishes specifically between network added information and maintained information. The layers of DenseNet (e.g. 12 function maps per layer) are very narrow, adding only a small number of function maps to the 'collective awareness' of a network and maintaining the remaining feature maps unchanged, such that the final classification decides on all network function maps.

4.3.6. MODEL COMPACTNESS

The function maps learned by any layer of DenseNet can be accessed across all subsequent layers as a direct consequence of the input concatenation. This promotes reuse of features across the network and contributes to more compact models

4.3.7. IMPLICIT DEEP SUPERVISION

Similar depth of control is implicitly carried out by DenseNets: a single classifier above the network directly monitors all strata across two or three transfer strata at most. DenseNets have a much less complicated loss and gradient function, since all layers share the same loss function.

4.3.8. OVERFITTING

One positive side-effect of the more efficient use of parameters is a tendency of DenseNets to be less prone to overfitting.

4.3.9. STOCHASTIC CONNECTION

Interesting links are established between dense convolutionary networks and stochastic regularization of residual networks at stochastic level, layers are randomly dropped in residual networks creating direct links between the surrounding layers. The network results in a communication design close to that of DenseNet, since its pooling layers are never lowered: for two layers between the same pooling layers, there is no chance of being directly linked – if all intermediate layers are loosed allegedly. Although the approaches are ultimately quite different, the interpretation of stochastic depth by DenseNet can provide insights into the effectiveness of this regularizer.

4.3.10. CONFUSION MATRIX

A confusion matrix is a $N \times N$ matrix used to estimate the classification model's output, where N is the number of target groups. The matrix contrasts the true goal values with the machine learning model's predictions. This gives us a holistic view of how well and what kind of errors our classification model works. In the supervised category of machine learning with a marked dataset, an uncertainty matrix is helpful.

It is represented by a table as shown below. This is an example of a binary classification confusion matrix (i.e. 0-Negative or 1-Positive).

		ACTUAL VALUES	
		POSITIVE	NEGATIVE
PREDICTED VALUES	POSITIVE	TP	FP
	NEGATIVE	FN	TN

Fig 4.3.10. CONFUSION MATRIX

SENSITIVITY

Sensitivity is also called as true positive it is ratio of correct positive to the total positives

Sensitivity=true positive/true positive + false negative.

Sensitivity for each class of the flower is calculated

SPECIFICITY

Specificity is also called as true negative rate.

Specificity=true negative/true negative +false positive.

Table 4.3.10 specificity and sensitivity

SENSITIVITY	SPECIFICITY
A1=95	A1=99.99
A2=100	A2=100
A3=85	A3=99.96
A4=72	A4=100
A5=95.23	A5=99.99
A6=95	A6=99.99
A7=100	A7=99.98
A8=100	A8=99.99
A9=100	A9=99.96
A10=100	A10=99.99
A11=97.61	A11=99.94
A12=100	A12=100
A13=100	A13=99.96
A14=100	A14=99.99
A15=100	A15=99.99
A16=94.44	A16=99.99
A17=100	A17=99.99

A18=100	A18=99.84
A19=100	A19=99.96
A20=100	A20=99.99
A21=100	A21=99.67
A22=96.55	A22=99.91
A23=100	A23=99.69
A24=100	A24=99.95
A25=100	A25=100
A26=89.47	A26=100
A27=100	A27=100
A28=100	A28=99.97
A29=97.43	A29=100
A30=95.34	A30=99.99
A31=100	A31=99.99
A32=90.90	A32=99.97
A33=100	A33=100
A34=100	A34=100
A35=100	A35=100
A36=54.65	A36=100

A37=100	A37=99.99
A38=100	A38=99.97
A39=75	A39=99.82
A40=87.87	A40=100
A4=96.32	A41=100
A42=96.55	A42=100
A43=95.38	A43=99.99
A44=100	A44=99.96
A45=90	A45=99.99
A46=98.97	A46=99.97
A47=100	A47=100
A48=100	A48=99.96
A49=100	A49=100
A50=100	A50=99.97
A51=82.94	A51=99.71
A52=92.85	A52=99.99
A53=93.47	A53=100
A54=100	A54=99.99
A55=100	A55=99.97

A56=100	A56=100
A57=63.64	A57=100
A58=100	A58=100
A59=100	A59=100
A60=100	A60=100
A61=100	A61=100
A62=92.30	A62=100
A63=100	A63=100
A64=100	A64=100
A65=100	A65=100
A66=100	A66=99.99
A67=100	A67=99.99
A68=88.46	A68=100
A69=100	A69=100
A70=100	A70=99.99
A71=100	A71=99.97
A72=100	A72=99.95
A73=98.97	A73=100
A74=100	A74=99.96

A75=100	A75=99.97
A76=100	A76=99.99
A77=100	A77=99.99
A78=100	A78=100
A79=100	A79=100
A80=100	A80=99.99
A81=100	A81=100
A82=100	A82=99.99
A83=96.875	A83=99.99
A84=100	A84=100
A85=100	A85=100
A86=100	A86=99.93
A87=96.6	A87=100
A88=97.36	A88=99.95
A89=100	A89=99.97
A90=90.90	A90=99.99
A91=92.30	A91=99.99
A92=100	A92=99.99
A93=95.45	A93=100

A94=100	A94=99.99
A95=98.36	A95=99.99
A96=75.5	A96=99.95
A97=100	A97=99.99
A98=100	A98=99.97
A99=93.10	A99=99.96
A100=100	A100=100
A101=96.55	A101=99.99
A102=95.83	A102=99.99

Above tabulation is the calculated values of sensitivity and specificity of the dataset.

CHAPTER 5

RESULTS AND DISCUSSION

This paper proposes an effective classification of 102 flower images using DenseNet 102 and the composite learning factor. Every phase of our procedure has been expanded and findings have been evaluated. Our DenseNet-201 approach is superior to the current DenseNet network in the experiments. We developed a 95.23% accuracy DenseNet-102 model. DenseNet reduces our research scientist's disappearing gradient problem. This amended Densenet 201 decreases the complexity and performance without any modifications. Thanks to our dense connectivity pattern, our proposed method results in a better flow than the previous best unattended approach and reduces the output gap for supervised approaches.

The dataset collected from

<https://www.robots.ox.ac.uk/~vgg/data/flowers/102/>

~~https://www.robots.ox.ac.uk/~vgg/data/flowers/102/~~ **transfer**

CONFUSION MATRIX

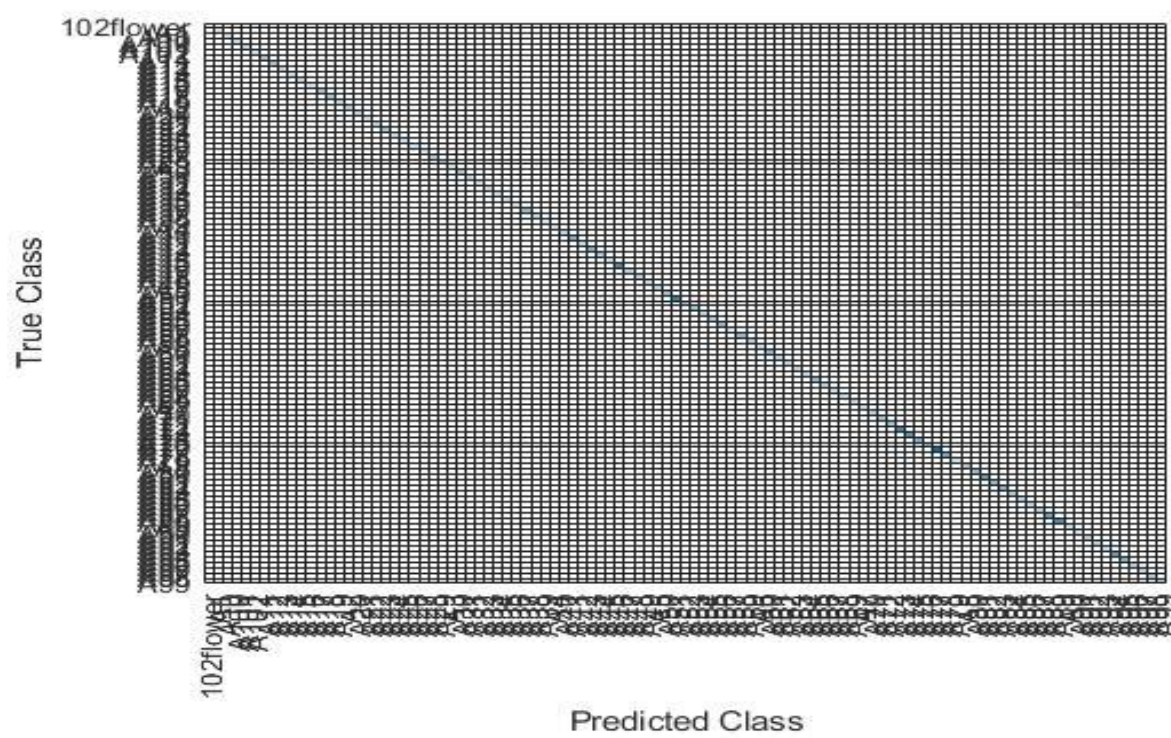


Fig:5.1 confusion matrix

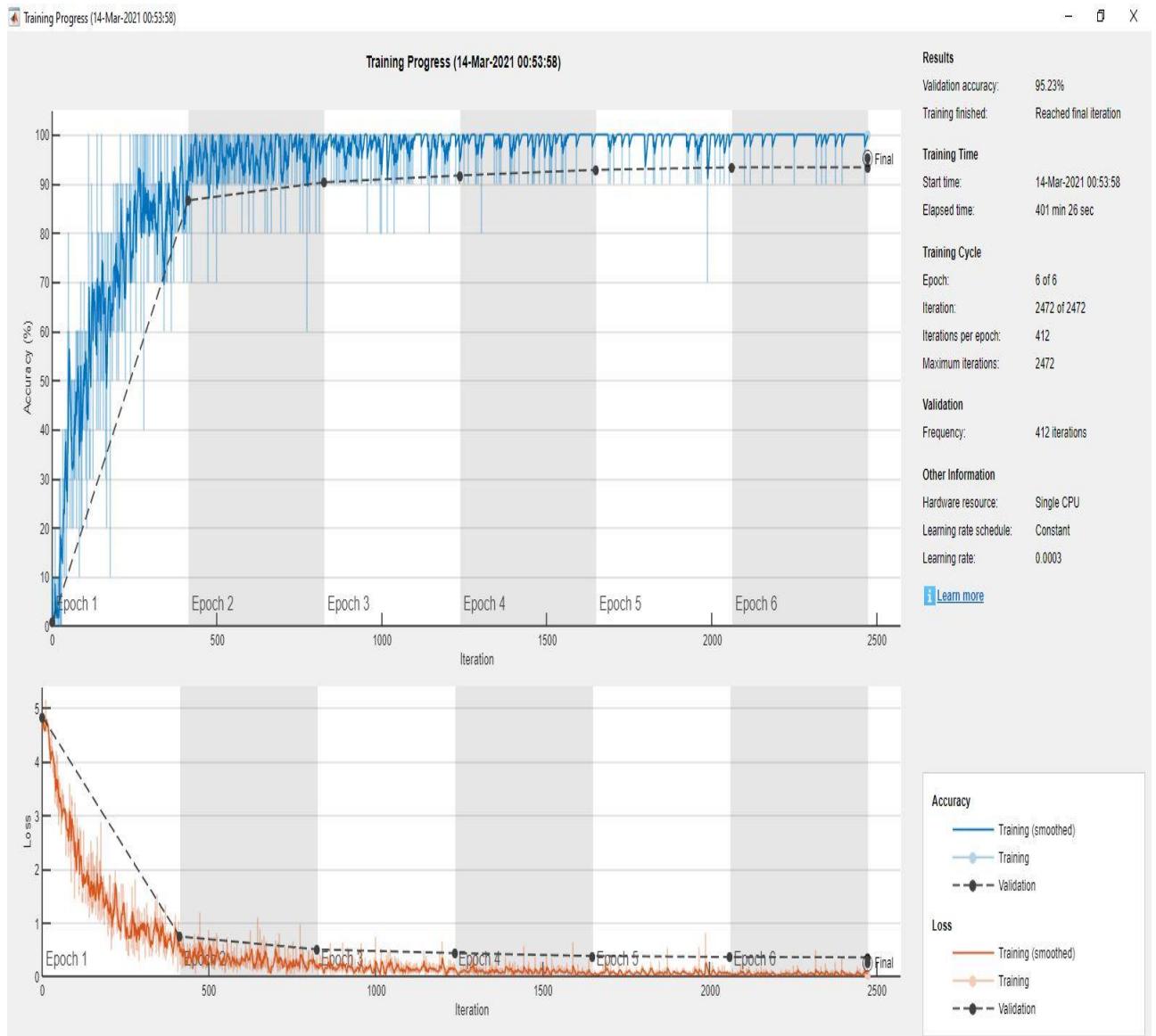


Fig 5.2 output graph.

CHAPTER 6

CONCLUSION AND FUTURE WORK

We introduced a new network architecture, known as the Dense Convolutionary Network (DenseNet). It provides direct links between two layers of the same functionality map size. We have shown that DenseNets 201 naturally scale to hundreds of layers without difficulties with optimization. DenseNets 201 seems to produce consistent accuracy improvements without evidence of any loss of efficiency or overfitting in increasing numbers of parameters. It obtained the most cutting-edge performance in many highly competitive datasets under various configurations. Furthermore, in order to achieve state of the art efficiency, DenseNets need considerably less parameters and less calculation. As we adopted hyperparameter settings which are tailored in our study for residual networks, we feel more accuracy gains can be achieved through more precise tuning of hyperparameters and schedules of learning rates

The results of the study show that the number of images generated to reflect each flower form affects the accuracy of the training results. This means that any research involving image processing must take account of those parameters. One fascinating point is that a replication of photos that are very difficult to learn helps CNN increase its ranking precision. This is also a field where the actions of the photographs can be better grasped if used in the CNN grouping. While more studies will enhance the results presented, this study is essential for future work as a guideline. Shapes may be viewed as attributes in the dataset to further increase the accuracy of classification. Thus it is possible to combine colour, texture and form characteristics in flora with a proposed floral classification model. As a content-based image recovery problem is still in its infancy, there are plenty of scenarios. Consequently, the results of this research contribute to a long journey of research on image recovery.

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