MICROANEURYSMS DETECTION FOR DIABETIC RETINOPATHY USING PRETRAINED CONVOLUTIONAL NEURAL NETWORKS

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Dissertation submitted in partial fulfillment of the requirements for the degree of

BACHELOR OFTECHNOLOGY

Branch: INFORMATION TECHNOLOGY

of Anna University

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DEPARTMENT OF INFORMATION TECHNOLOGY

PSG COLLEGE OF TECHNOLOGY

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Bona fide record of work done by

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NOVEMBER 2022

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SYNOPSIS

In the field of ophthalmology, diabetic retinopathy (DR) is a major cause of blindness. DR is based on retinal lesions including microaneurysms. Microaneurysms have been found to be one of the signs and serious DR anomalies, so the proper detection of these lesions and the treatment should be done immediately to prevent loss of vision. In this paper, pretrained convolutional neural network- (CNN) based framework has been proposed for the detection of Microaneurysms. Recently, deep CNNs were individually applied to solve the specific problems. But, pre-trained CNN models with transfer learning can utilize the previous knowledge to solve the other related problems. In the proposed approach, initially data preprocessing is performed for standardization of microaneurysms patches. Furthermore, region of interest (ROI) localization is used to localize the features of exudates, and then transfer learning is performed for feature extraction using pre-trained CNN models (DenseNet, Residual Network-50, Nasnet and Efficientnet). Moreover, the fused features from fully connected (FC) layers are fed into the softmax classifier for microaneurysms classification. The performance of proposed framework has been analyzed using two well-known publicly available databases such as Aptos. The experimental results demonstrate that the proposed pretrained CNN-based framework outperforms the existing techniques for the detection of microaneurysms.

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CHAPTER 1

INTRODUCTION

Diabetes patients may develop the disease known as diabetic retinopathy. The retina, the light-sensitive lining in the back of the eye, suffers gradual damage as a result. A significant, sight-threatening consequence of diabetes is diabetic retinopathy. Diabetes affects how well the body uses and stores sugar (glucose).

The condition is characterized by an excess of blood sugar, which can harm the eyes as well as other parts of the body. Diabetes over time harms tiny blood vessels all across the body, including the retina. When these tiny blood vessels leak blood and other fluids, diabetic retinopathy develops. As a result, the retinal tissue swells, causing vision to become hazy or blurry. Usually, both eyes are affected by the illness. Longer diabetes duration increases the likelihood of complications:

- observing floaters or specks
- Blurred vision
- Having a shadowy or vacant area in the middle of your field of vision
- Difficulty seeing well at night

Long durations of high blood sugar levels can cause fluid to build up in the focusing lens inside the eye in diabetics. This alters the lens's curvature, which affects how you see. However, the lens normally returns to its former shape and eyesight improves once blood sugar levels are under control. Diabetes patients with improved blood sugar management skills will delay the start and progression of diabetic retinopathy. Nearly half of Americans did not aware whether diabetic eye problems produce visible symptoms, according to the 2018 American Eye-Q Survey carried out by the AOA (often which the early stages of diabetic retinopathy does not). More than one-third of Americans, according to the same survey. The American Optometric Association (AOA) advises that everyone with diabetes have a comprehensive dilated eye examination at least once a year because a similar survey revealed that more than one-third of Americans were unaware that the only way to determine whether a person's diabetes will cause blindness is through a comprehensive eye exam. The risk of diabetic retinopathy causing major vision loss can be reduced with early detection and treatment. Depending on the severity of the condition, there are many treatments for diabetic retinopathy. In order to stop blood vessels from leaking or to stop other blood vessels from leaking, people with diabetic retinopathy may require laser surgery. To reduce inflammation or inhibit the growth of new blood vessels, your optometrist may need to inject drugs into your eye. individuals with severe cases surgical treatment to remove and replace the vitreous, a gel-like fluid in the back of the eye, in cases of diabetic retinopathy. A retinal detachment may potentially require surgery to be repaired. This is a separation of the light-receiving lining in the back of the eye. If you are diabetic, you can help prevent or slow the development of diabetic retinopathy by:

- Taking your prescribed medication
- Sticking to your diet
- Exercising regularly
- Controlling high blood pressure
- Avoiding alcohol and smoking

1.1 What causes diabetic retinopathy?

The damage that diabetes does to the tiny blood vessels in the retina leads to diabetic retinopathy. Vision loss can result from these damaged blood vessels:

- The macula, the region of the retina responsible for sharp central vision, may experience fluid leakage. The macula, despite its diminutive size, is the area of the retina that gives humans the ability to see colour and fine detail. Vision blur is the effect of the fluid making the macula swell.
- New blood vessels may develop on the surface of the retina in an effort to increase blood flow there. These weak, aberrant blood vessels have the potential to rupture, leaking blood into the back of the eye and obstructing vision.

Diabetic retinopathy is classified into two types:

- **Non-proliferative diabetic retinopathy** (NPDR) In the early stage of the illness, when there won't be any or only minor symptoms. The blood vessels in the retina are compromised in NPDR. Microaneurysms, which are very small blood artery bulges, can let fluid into the retina. The macula may expand as a result of this leakage.
- **Proliferative diabetic retinopathy** (PDR) is the disease's most advanced version. Circulation issues are depriving the retina of oxygen at this point. As a result, the retina and the vitreous, the gel-like fluid that fills the back of the eye, can start to develop new, delicate blood vessels. The vitreous may become blood-stained due to the new blood vessels, impairing vision. The development of glaucoma and the detachment of the retina as a result of the creation of scar tissue are other PDR side effects. An eye condition known as glaucoma causes the optic nerve to progressively deteriorate. In PDR, new blood vessels develop in the region of the eye where the drainage of the eye's fluid occurs. This causes the eye pressure to significantly increase, which harms the optic nerve. PDR can result in serious vision loss and perhaps blindness if left untreated.

Risk factors for diabetic retinopathy include:

- **Diabetes.** A diabetic retinopathy diagnosis puts a person at risk for either type 1 or type 2 diabetes. The longer a person has diabetes, especially if it is not well controlled, the greater the risk of developing diabetic retinopathy.
- **Race.** African Americans and Hispanics are more likely to acquire diabetic retinopathy.
- **Medical conditions**. People who have other medical issues like high blood pressure or high cholesterol are more vulnerable.
- **Pregnancy.** Women who are pregnant are more likely to acquire diabetes and diabetic retinopathy. A woman is more likely to acquire diabetes later in life if she had gestational diabetes.

1.2 How is diabetic retinopathy diagnosed?

A thorough eye exam can be used to identify diabetic retinopathy. The following tests may be used to evaluate the retina and macula:

- Examining the patient's medical history to look for signs of diabetes, other general health issues, and visual problems.
- Measurements of visual acuity to assess how much central vision has been impacted.
- Refraction to assess whether a new prescription for eyeglasses is necessary
- Examining the retina with a dilated pupil and assessing the ocular components in general
- Determining the pressure inside the eye

Supplemental testing may include:

- Retinal imaging or tomography to record the retina's current condition
- Fluorescent angiography to evaluate abnormal blood vessel growth

1.3 How is diabetic retinopathy treated?

The flow of blood and fluid into the retina is stopped using a laser procedure called photocoagulation. In regions of the retina with aberrant blood vessels, a laser beam can be used to make tiny burns in an effort to stop the leaks.

Depending on the disease's stage, diabetic retinopathy is treated differently. Any form of treatment aims to halt or slow the disease's course.

Regular monitoring can be the only option for non-proliferative diabetic retinopathy in its early stages. Following your doctor's recommendations for exercise, food, and blood sugar management will help slow the disease's course.

Drugs are injected into the eye to prevent the growth of aberrant blood vessels and may help delay the harmful effects of diabetic retinopathy. Macular edoema can develop if the condition progresses and the aberrant blood vessels leak blood and fluid into the retina. The use of laser therapy (photocoagulation) halt this leak. In regions of the retina with aberrant blood vessels, a laser beam of light causes minor burns in an effort to stop the leaks. Proliferative diabetic retinopathy, which causes widespread blood vessel formation in the retina, can be cured by scattering laser burns throughout the retina. As a result, aberrant blood vessels constrict and vanish. Some side vision may be compromised during this operation to protect.

Transfer learning

The ability to transfer knowledge between jobs is innate in humans. We apply the knowledge we get while learning about one activity to solve related tasks in the same manner. We can transfer or use our knowledge across tasks more readily if they are closely related to one another. Simple illustrations include,

- Know how to ride a motorbike -> Learn how to ride a car
- Know how to play classic piano -> Learn how to play jazz piano
- Know math and statistics -> Learn machine learning

The first thing to keep in mind is that transfer learning, which is highly particular to deep learning, is not a new notion. The traditional way of creating and refining machine learning models and a methodology based on transfer learning principles are very different from one another.

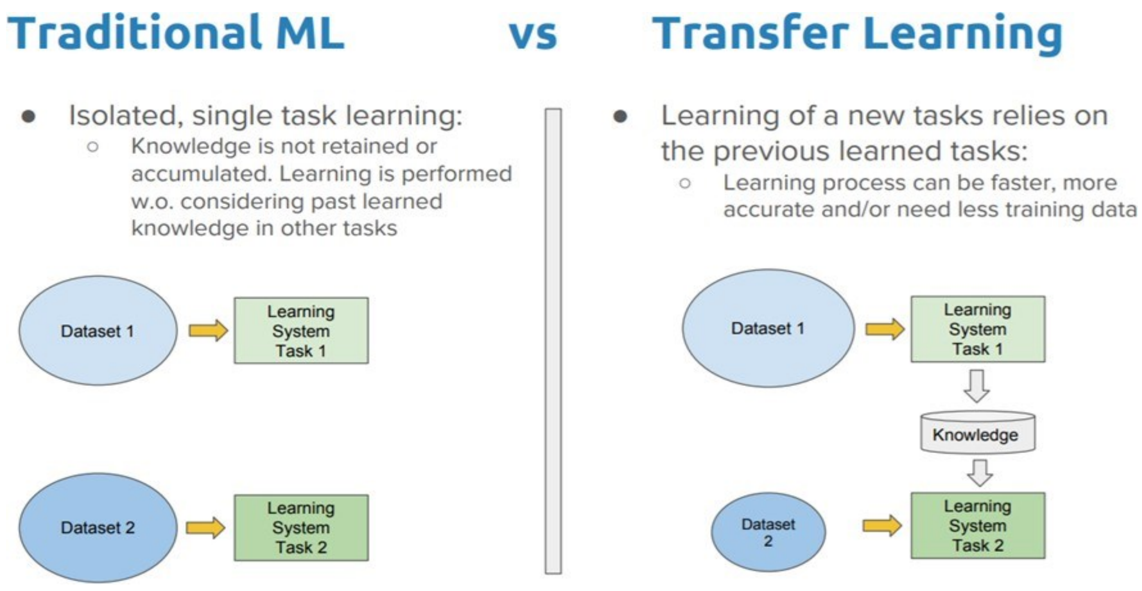


Fig 1.1 Differences between traditional Machine Learning and Transfer Learning

Traditional learning is solitary and relies only on a limited number of tasks, datasets, and the training of distinct, isolated models. No information that can be applied to another model is maintained. With transfer learning, you may train newer models using knowledge (features, weights, etc.) from older models that have already been trained, and even work around issues like the new task requiring less data.

Traditional learning is solitary and relies only on a limited number of tasks, datasets, and the training of distinct, isolated models. No information that can be applied to another model is maintained. With transfer learning, you may train newer models using knowledge (features, weights, etc.) from older models that have already been trained, and even work around issues like the new task requiring less data. not generalize well. This happens for a variety of reasons, which we can liberally and collectively term as the model's bias towards training data and domain.

We should be able to use the information from previously learned tasks and apply them to newer, related tasks as a result of transfer learning. If task T1 has considerably more data, we can use that learning to generalise the features and weights for task T2 (which has significantly less data). Certain low-level properties, like edges, forms, corners, and intensity, can be shared across tasks in the computer vision domain and help with knowledge transfer between jobs. Additionally, as shown in the earlier picture, prior experience with one activity serves as supplementary input while learning a new target task.

1.4 How to Use Transfer Learning?

You can use transfer learning to your own issues with predictive

modelling. The following are two typical methods:

1.5 Develop Model Approach

Select Source Task. You must choose an issue involving predictive modelling that is related, has a large amount of data, and where the input, output, and/or concepts discovered while mapping input to output data are all related in some way.

Develop Source Model. The next step is to create a proficient model for this initial assignment. To confirm that some feature learning has taken place, the model must be superior to a naive model.

Reuse Model. Then, a model on the second task of interest can be built from the model fit on the source task as a starting point. Depending on the modelling technique employed, this can include using the entire model or just a portion of it.

Tune Model. The model might need to be modified or improved depending on the input-output pair data provided for the relevant task.

1.6 Pre-trained Model Approach

- **Select Source Model**. One of the accessible models is a source model that has already been trained. Many research organisations publish models on sizable and difficult datasets, which may be part of the selection of potential models.Model for reuse. The model that has already been trained can then serve as the foundation for a model on the second task of interest. Depending on the modelling technique employed, this can include using the entire model or just a portion of it.
- **Tune Model**. The model might need to be modified or improved depending on the input-output pair data provided for the relevant task.

1.7 When to Use Transfer Learning?

Transfer learning is a time-saving, expedient method of improving performance. Generally speaking, it is not immediately apparent whether utilising transfer learning in the domain will be advantageous until after the model has been created and assessed.

When applying transfer learning, Lisa Torrey and Jude Shavlik outline three potential advantages to look for:

Higher start. The initial competence on the source model is higher than it otherwise would be (prior to model refinement).

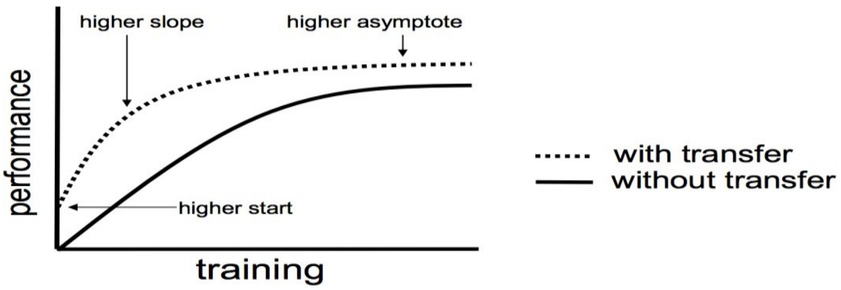


Fig 1.2 Graph Representation for transfer learning and without transfer learning

Higher slope. When the source model is trained, the rate of skill improvement is steeper than it otherwise would be.

Higher asymptote. The taught model's converged skill is superior to what it would be without training.

Transfer learning can help you create expert models on some situations when you may not have a lot of data, which is something you would not be able to do otherwise. The selection of the source model or data is still up for debate and may call for experience-based intuition or domain knowledge.

1.8 Motivation for problem

In 2014, the WHO (World Health Organization) estimated that 412 million individuals worldwide had diabetes mellitus. In 2010, 33 percent of those with diabetes were found to have diabetic retinopathy, and of those, 33 percent were adults.lost their vision as a result. In especially in America, it is predicted that the number of people with DR would treble by 2050.

The diagnosis of DR necessitates specialist expertise, which we can find using deep learning techniques, but it also takes a lot of time and requires a large amount of data, both of which are lacking in the healthcare industry

1.9Problem statement

Using the transfer learning method of the EfficientNet-B5 or any pretrained model to analyses images of fundus photographs to determine the stage of diabetic retinopathy. The project's primary goal is to find diabetic retinopathy early on to prevent blindness. We identify utilising Deep Transfer Learning and classification approaches, classifying the patient's retinal pictures into five labels ranging from 0 to 4, where each label, designated as Normal, Mild DR, Moderate DR, Severe DR, and Prolific DR, reflects a certain disease complication. For the provided input fundus image, one of these five steps is seen as an output label.

CHAPTER 2
LITERATURE SURVEY

2.1 Diabetic Retinopathy Detection and Classification using Pre-trained Convolutional Neural Networks.

In this study, the author used a very small dataset that contains 5 classes and 35,126 retinal fundus images to experiment with the pre-trained VGG16 and MobileNetV1 models using transfer learning and fine tuning. Based on their findings, it can be said that fine-tuning the pre-trained CNN model by replacing higher level layers resulted in greater accuracy than just replacing the final fully linked layer. Additionally, MobileNetV1 offered marginally greater accuracy compared to VGG16. MobileNetV1 is a CNN model that was created specifically for usage with embedded systems and is computationally less expensive. They have said that utilising MobileNetV1 as a pre-trained CNN model, it is conceivable to develop an automated embedded device for the diagnosis of diabetic retinopathy in the future.

2.2 Application of higher order spectra for the identification of diabetes retinopathy stages.

Include extraction based order and DL has been utilized to characterize DR. In Acharya et al. [18] higher request spectra procedure was utilized to extricate highlights from 300 fundus pictures and took care of to a help vector machine classifier; it grouped the pictures into 5 classes with responsiveness of 82% and particularity of 88%. Various calculations were created to separate DR sores like veins, exudates, and microaneurysms [19]. Exudates have been extricated for DR reviewing [20 - 24]. Support vector machine was utilized to order the DIABETDB1 dataset into positive and negative classes utilizing region and number of microaneurysms as elements [25].

2.3 Rethinking the inception architecture for computer vision

Highlight extraction based grouping techniques need master information to recognize the necessary elements, and they likewise include a tedious course of component choice, ID and extraction. Besides, DL based frameworks, for example, CNNs have been believed to outflank include extraction based strategies [26]. DL preparing for DR order have been acted in two significant classifications: gaining without any preparation and move learning.

2.4 Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs.

A convolutional neural network (CNN) was prepared to order a dataset of 128,175 fundus pictures into 2 classes, where the top of the line contains pictures with seriousness levels 0 and 1, and the inferior contains levels 2, 3 and 4 [27]. In a working cut point picked for high responsiveness, [27] had a responsiveness of 97.5% and explicitness of 93.4% on the EyePACS-1 dataset which comprises of 9963 pictures; it scored a responsiveness of 96.1% and a particularity of 93.9% on the Messidor-2 dataset; and in an assessment cut point chose for high particularity, the responsiveness and explicitness were 90.3% and 98.1% on the EyePACS-1, while 87% and 98.5% was scored on the Messidor-2, successively.

2.5 Convolutional neural networks for diabetic retinopathy

Utilizing a preparation dataset of north of 70,000 fundus pictures, Pratt et al. [28] prepared a CNN utilizing stochastic slope plunge calculation to group DR into 5 classes, and it accomplished 95% explicitness, 75% exactness and 30% responsiveness. A DL model was prepared without any preparation on the MESSIDOR-2 dataset for the programmed identification of DR in [29], and a 96.8% responsiveness and 87% explicitness were scored.

2.6 Automated identification of diabetic retinopathy using deep learning

A CNN was prepared without any preparation to order fundus pictures from the Kaggle dataset into referable and non-referable classes, and it scored a responsiveness of 96.2% and an explicitness of 66.6% [30]. A dataset of 71896 fundus pictures was utilized to prepare a CNN DR classifier and brought about a responsiveness of 90.5% and particularity of 91.6% [31]. A DL model was planned and prepared on a dataset of 75137 fundus pictures and brought about a responsiveness and particularity scores of 94% and 98%, separately [32].

2.7 Comparative Study of Fine-Tuning of Pre-Trained Convolutional Neural Networks for Diabetic Retinopathy Screening

To keep away from the time and asset consumed during DL, Mohammadian et al. [33] tweaked the Commencement V3 and Exemption pre-prepared models to group the Kaggle dataset into two classes. In the wake of utilizing information expansion to adjust the dataset,[33] came to at a precision score of 87.12% on the Beginning V3, and 74.49% on the Special case model.

2.8 Deep convolutional neural networks for diabetic retinopathy detection by image classification

Wan et al. [34] executed move learning and hyper boundary tuning on the pre-prepared models AlexNet, VggNet-s, VggNet-16, VggNet-19, GoogleNet and ResNet utilizing the Kaggle dataset and looked at their exhibitions. The most elevated precision score was that of VggNet-s model, which arrived at 95.68% while preparing with hyper-boundary tuning [34]. Move learning was utilized to take care of around the issue of deficient preparation dataset in [35] for retinal vessel division. A Beginning V4 [36] model-based DR order scored higher responsiveness when contrasted and human master graders on a 25,326 retinal pictures of patients with diabetes from Thailand [37].

2.9 Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy

Mansour [38] put to utilize the Kaggle dataset to prepare a profound convolutional brain network utilizing move learning for include extraction while building a PC supported conclusion for DR. In Dutta et al. [39] 2000 fundus pictures were chosen from the Kaggle dataset to prepare a shallow feed forward brain organization, profound brain organization and VggNet16 model. On a test dataset of 300 pictures, the shallow brain network scored a precision of 41%, and the profound brain network scored 86.3% whiles the VggNet-16 scored 78.3% exactness [39].

2.10 Diagnosis of Diabetic Retinopathy Using Deep Neural Networks

A preparation dataset of size 4476 was gathered and marked into 4 classes relying upon irregularities and required treatment [40]; they resized input pictures into 600x600 and cut each picture into four 300x300 pictures, and took care of these pictures into discrete pre-prepared Origin V3 models, which they called the Inception@4. After it was seen that precision consequence of the InceptionV4 outperformed the VggNet and ResNet models, it was conveyed on an electronic DR order framework.

2.11 Multi-Cell Multi-Task Convolutional Neural Networks for Diabetic Retinopathy Grading

A multi cell, perform various tasks convolutional brain network that utilizes a mix of cross entropy and mean square blunder was created to characterize pictures from the Kaggle dataset into 5 DR degrees [41]. A paired tree based multi-class VggNet classifier was prepared on the Kaggle dataset in Adly et al. [41], and it scored an exactness of 83.2%, responsiveness of 81.8% and particularity of 89.3% on an approval dataset of 6000 fundus pictures. Fundus Picture Characterization Utilizing VGG-19 Design with PCA and SVD

By utilizing SVMs with completely associated layers in view of the VggNet-19 model, Mateen et al. [43] came to at a precision of 98.34% while arranging DR on the Kaggle dataset. The Kaggle dataset [17], which contains 35126 marked fundus pictures, has been thoroughly utilized for DL based characterization of DR research purposes.

2.12 Existing system

In the study, they constructed a network with CNN architecture and data augmentation that can recognise the complex elements needed for the classification task, such as micro-aneurysms, exudate, and retinal haemorrhages, and as a result, automatically and without user input, deliver a diagnosis. On the publicly accessible Kaggle dataset, the network was trained using a powerful graphics processing unit (GPU), and the results are outstanding, especially for a difficult classification test. Our suggested CNN achieves a sensitivity of 95% and an accuracy of 75% on 5,000 validation images on the data set of 80,000 photos used. After reviewing the literature for other image identification challenges, we decided on the form of our neural network, which is illustrated below.

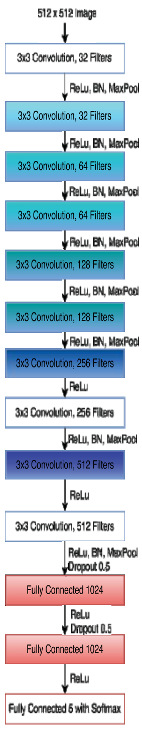


Fig 2.1 Structure of neural network for image recognition

It is believed that adding more convolution layers will enable the network to learn more detailed information. The initial layer of the network learns edges while the last convolutional layer, which is the deepest layer, should learn the characteristics of DR classification, such as hard exudate. After each convolution layer, the network does batch normalisation before beginning with convolution blocks with activation. As the number of feature maps grows, one batch normalisation is used for each block. The kernel size is 3x3 and the strides are 2x2 for all max pooling. The network is flattened to one dimension after the last convolutional block. It employs weighted class weights in relation to the number of photos in each class to prevent overfitting. To prevent overfitting, we similarly remove out thick layers until we reach the dense five-node classification layer, which utilises a SoftMax activation function to forecast our classification. To prevent over reliance on certain network nodes, the leaky rectified linear unit 13 activation function was utilised, applied with a value of 0.01. Similarly, L2 regularisation is used in the convolution layers. was employed for biases and weight. The commonly used categorical cross-entropy function was employed as the loss function to optimise.

The Kaggle coding website provided the testing dataset, which includes over 80,000 images with an average of 6 million pixels per and retinopathy scales. We were able to train on the entire dataset by resizing these images and using CNN on the powerful NVIDIA K40c GPU to process the data. The NVIDIA K40c comes with the NVIDIA CUDA Deep Neural Network library (cuDNN) and has 2880 CUDA cores for GPU learning. For validation reasons, 5,000 photos from the dataset were kept. It took 188 seconds to run the validation photos across the network. We define sensitivity as the number of patients correctly identified as having DR out of the genuine total amount of patients with DR and specificity as the number of patients correctly identified as not having DR out of the true total amount of patients with DR for this five class problem. The number of patients with a correct classification is how we define accuracy. The final trained network has a final specificity of 95%, an accuracy of 75%, and a sensitivity of 30%.

The network's classifications were listed numerically as follows: 0 - No DR (1) Mild DR DR of 2 is moderate. 3 - Extreme DR

True Label	0	1	2	3	4
0	**3456**	0	145	1	34
1	344	**0**	27	0	1
2	543	0	**179**	5	40
3	40	0	63	**10**	15
4	28	0	23	3	**43**

Predicted label

Fig 2.2 confusion matrix for the classification of the network

The confusion matrix for the five stages of diabetic retinopathy is displayed in the table above.

CHAPTER 3
SYSTEM REQUIREMENTS

This chapter system requirements is majorly divided into 2 parts as hardware and software requirements.

3.1 HARDWARE REQUIREMENTS

- 4GB ram laptop

3.2 SOFTWARE REQUIREMENTS

- Operating system used - Windows
- Programing language used- Python

3.2.1 Libraries used

Various libraries are in microaneurysms detection for diabetic retinopathy using pertained convolutional neural networks are:

- Tf Learn
- Tqdm
- Open Cv
- NumPY
- TensorFlow
- SymPy

3.2.1.1 TF learn

TFLearn is a transparent and flexible deep learning component of the TensorFlow framework. The primary goal of TFLearn is to give TensorFlow a higher level API for facilitating and displaying new experiments. It may adopt best practices for data automation, model tracking, performance monitoring, and model retraining with the help of the TensorFlow platform. Success depends on the use of production-level technologies to automate and monitor model training throughout the lifespan of a good, service, or business procedure.

3.2.1.2 Tqdm

Python's tqdm module is used to build progress metres and progress bars. The word "tqdm" is an acronym for the Arabic word "taqaddum," which signifies "progress." It can easily implement tqdm in our loops, functions, and even Pandas. The tqdm Python package offers functions that wrap around the requested iterable and output a clever progress bar. Python is a popular language for carrying out lengthy, computationally heavy tasks. The progress of these tasks is shown by a tqdm progress metre.

3.1.2.3 Open Cv

An Open Source Computer Vision Library called OpenCV is available for free use. A standard infrastructure for computer vision applications was created with OpenCV in order to speed up the incorporation of artificial intelligence into products. On the other side, OpenCV is a computer vision framework that enables various image and video processing. It has been a widely used tool for image processing jobs ever since its release.

3.1.2.4 NumPY

The Python package NumPy is used to manipulate arrays. Additionally, it has matrices, Fourier transform, and functions for working in the area of linear algebra. The cornerstone Python module for scientific computing is called NumPy. It is a Python library that offers a multidimensional array object, various derived objects, and a variety of routines for quick operations on arrays, including discrete Fourier transforms, basic linear algebra, basic statistical operations, shape manipulation, sorting, selecting, I/O, random simulation, and much more.

3.1.2.5 TensorFlow

It can adopt best practices for data automation, model tracking, performance monitoring, and model retraining with the help of the TensorFlow platform. Success depends on the use of production-level technologies to automate and monitor model training over the course of a good, service, or business process. A complete open source machine learning platform is called TensorFlow. Both novices and experts may easily develop machine learning models thanks to TensorFlow.

3.1.2.6 SymPy

A Python library for working with mathematics is called SymPy, which stands for Symbolic Mathematics in Python. The SciPy Ecosystem includes other colossal software packages like NumPy, Pandas, and Matplotlib as well as this one as a core library. You can work with mathematical expressions with SymPy. A Symbolic Mathematics in Python is called SymPy. Its goal is to develop into a fully-fledged computer algebra system (CAS) while keeping the code as straightforward as possible to make it understandable and simple to extend. All of SymPy's code is written in Python.

CHAPTER 4
IMPLEMENTATION

4.1 MICROANNEURYSM DETECTION FOR DIABETIC RETINOPATHY DATASET USED:

A large set of retina images taken using fundus photography under a variety of imaging conditions. A clinician has rated each image for the severity of diabetic retinopathy on a scale of 0 to 4:

- 0 - No DR
- 1 - Mild
- 2 - Moderate
- 3 - Severe
- 4 - Proliferative DR

4.1.1 DATASET DESCRIPTION

The dataset being used for the study of micorannuerysm detection for diabetic retinopathy is Aptos2019. The dataset time corresponds to the year 2019. The dataset consists of a total of 5590 images. Among them 3662 correspond to the Training data and 1928 images belong to the testing data. Thus a 80-20 split is being used for the training and testing phase in the dataset.

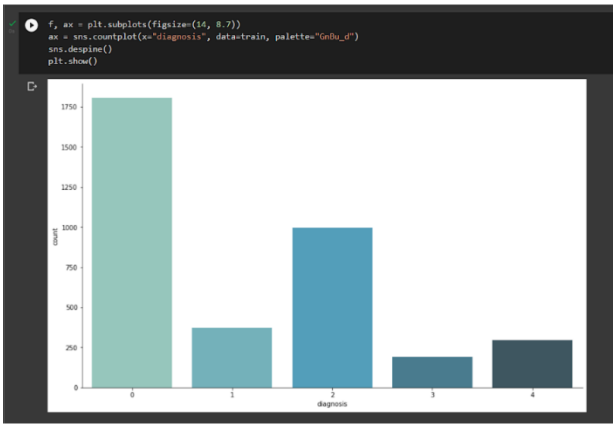


Fig 4.1 Dataset Split

4.2 PREPROCESSING

A preliminary processing of data in order to prepare it for the primary processing or for further analysis. The term can be applied to any first or preparatory processing stage when there are several steps required to prepare data for the user.

4.2.1 NEED FOR PREPROCESSING

Like any real-world data set, we will encounter noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed or overexposed. The images were gathered from multiple clinics using a variety of cameras over an extended period of time, which will introduce further variation.

Thus, there are various problems associated with the original Image such as some images are very dark and sometimes different color illumination is confusing. We can get the uninformative dark areas for some pictures. So, we have to reduce the picture size, crop the uninformative areas out.

Thus, there arises a great need for preprocessing the raw images which will help for future analysis and also in the efficient performance of the model. We can also try gray scale to feel and understand better for some pictures, as color distraction is gone.

4.2.2 PREPROCESSING METHODS

One of the methods being used for preprocessing is the Ben Graham's preprocessing method where we make use of an insightful way to improve lighting condition. Here, we apply his idea, and can see many important details in the eyes much better.

4.2.3 PREPROCESSING BY AUTO CROPPING

To crop out the uninformative black areas which are evident on the source images, we can try auto cropping. Ultimately one method works perfectly for a gray scale image, but none works on a color image. In this method, we modify the method working on gray-scale a bit to make it suitable for a color image.

Color Version of Cropping & Ben's Preprocessing - Initially,the gray scale was a better representation. Now its found that the color version is better and thus it’s better to use color cropping. For color version, note that I use argument sigmaX = 30 of cv2.GaussianBlur, where Ben actually used sigmaX = 10 which may have better performance. It is found that that this sigmaX = 30 or sigmaX = 50 make beautiful yellow moon pictures.

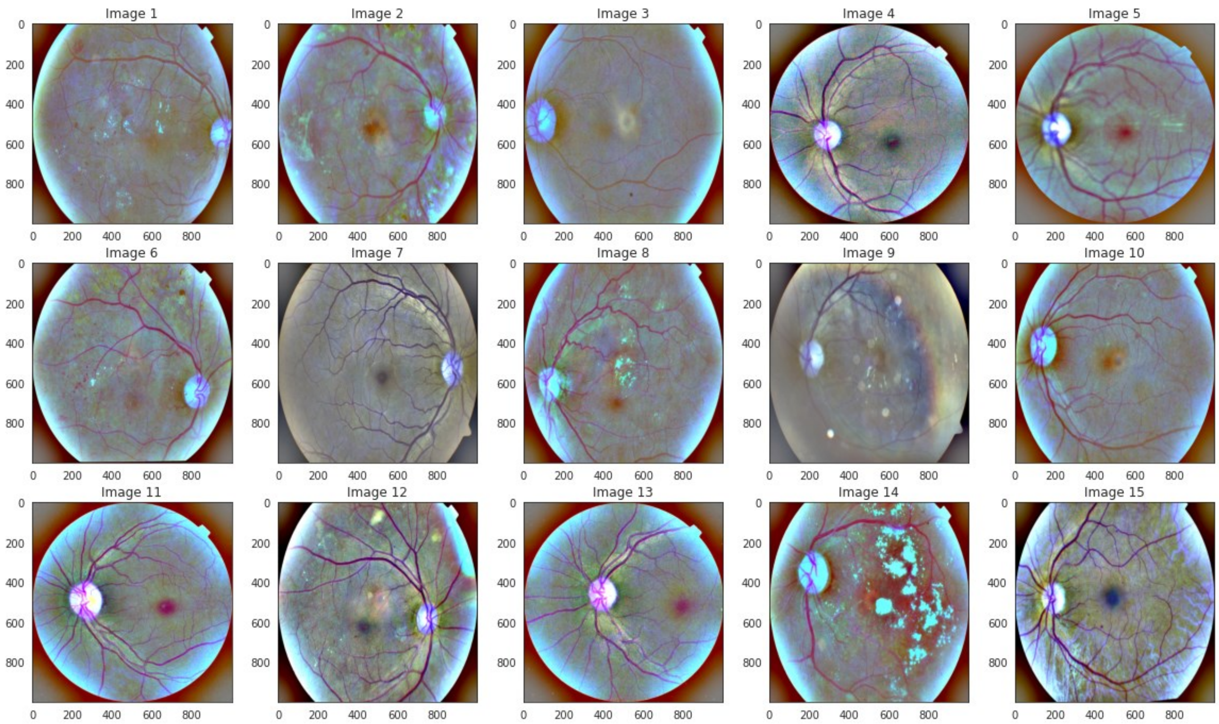


Fig 4.2 Pictorial representation of scanned retinal images

4.3 PRETRAINED MODELS

Thus we have made use of 3 models for training the dataset

- RESNET
- DENSENET
- EFFICENTNET
- NASNET

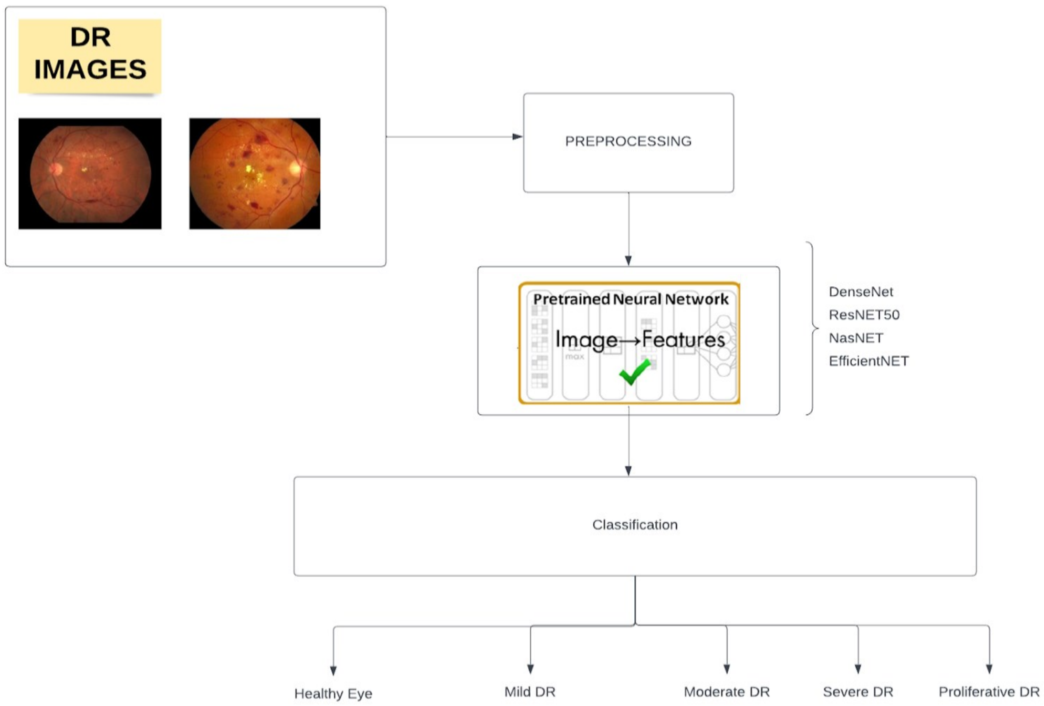


Fig 4.3 Pictorial representation of the Proposed System

4.3.1 RESNET50

ResNet-50 is a convolutional neural network that is 50 layers deep. We 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, such as keyboard, mouse, pencil, and many animals. Residual Network-50 is a deep convolutional neural network to achieve significant results in the classification of ImageNet database. ResNet-50 is composed of numerous sizes of convolutional filters to reduce the training time and manage the degradation issue that happens because of deep structures.

In our project, ResNet-50 is applied, which is already trained on the standard ImageNet database except fully connected softmax layer associated with this model.

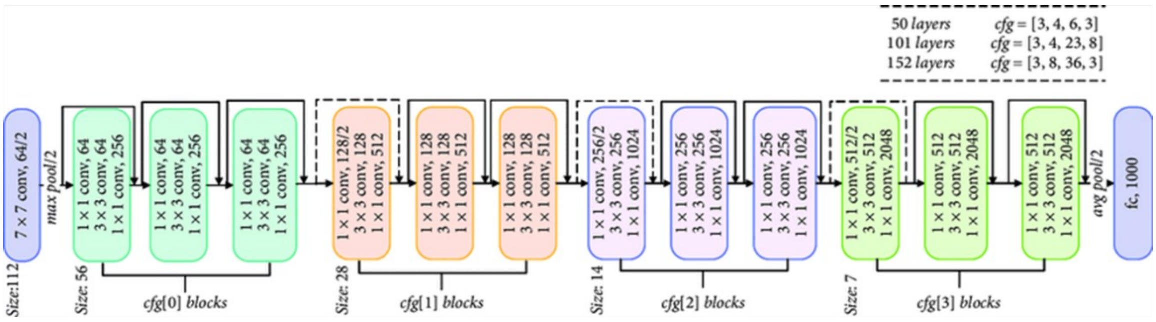


Fig 4.4 Layers of RESNET 50

```
Epoch 1/20
366/366 [==============================] - 629s 2s/step - loss: 0.2760 - accuracy: 0.7163 - val_loss: 0.3047 - val_accuracy: 0.6923 - lr: 5.0000e-05
Epoch 2/20
366/366 [==============================] - 635s 2s/step - loss: 0.2723 - accuracy: 0.7132 - val_loss: 0.3382 - val_accuracy: 0.6360 - lr: 5.0000e-05
Epoch 3/20
366/366 [==============================] - 635s 2s/step - loss: 0.2754 - accuracy: 0.7136 - val_loss: 0.3060 - val_accuracy: 0.6923 - lr: 5.0000e-05
Epoch 4/20
366/366 [==============================] - 640s 2s/step - loss: 0.2658 - accuracy: 0.7190 - val_loss: 0.2692 - val_accuracy: 0.7074 - lr: 5.0000e-05
Epoch 5/20
366/366 [==============================] - 638s 2s/step - loss: 0.2604 - accuracy: 0.7252 - val_loss: 0.3149 - val_accuracy: 0.6745 - lr: 5.0000e-05
Epoch 6/20
366/366 [==============================] - 632s 2s/step - loss: 0.2702 - accuracy: 0.7259 - val_loss: 0.3511 - val_accuracy: 0.6841 - lr: 5.0000e-05
Epoch 7/20
366/366 [==============================] - 636s 2s/step - loss: 0.2653 - accuracy: 0.7159 - val_loss: 0.2663 - val_accuracy: 0.7102 - lr: 5.0000e-05
Epoch 8/20
366/366 [==============================] - 650s 2s/step - loss: 0.2572 - accuracy: 0.7242 - val_loss: 0.2952 - val_accuracy: 0.6745 - lr: 5.0000e-05
Epoch 9/20
366/366 [==============================] - 651s 2s/step - loss: 0.2617 - accuracy: 0.7235 - val_loss: 0.2522 - val_accuracy: 0.7129 - lr: 5.0000e-05
Epoch 10/20
366/366 [==============================] - 665s 2s/step - loss: 0.2517 - accuracy: 0.7211 - val_loss: 0.2670 - val_accuracy: 0.7115 - lr: 5.0000e-05
Epoch 11/20
366/366 [==============================] - 710s 2s/step - loss: 0.2512 - accuracy: 0.7317 - val_loss: 0.2791 - val_accuracy: 0.6992 - lr: 5.0000e-05
Epoch 12/20
366/366 [==============================] - ETA: 0s - loss: 0.2471 - accuracy: 0.7276
Epoch 12: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
366/366 [==============================] - 704s 2s/step - loss: 0.2471 - accuracy: 0.7276 - val_loss: 0.2587 - val_accuracy: 0.6978 - lr: 5.0000e-05
Epoch 13/20
366/366 [==============================] - 706s 2s/step - loss: 0.2410 - accuracy: 0.7392 - val_loss: 0.2496 - val_accuracy: 0.7170 - lr: 2.5000e-05
Epoch 14/20
366/366 [==============================] - 704s 2s/step - loss: 0.2356 - accuracy: 0.7423 - val_loss: 0.2526 - val_accuracy: 0.7129 - lr: 2.5000e-05
Epoch 15/20
366/366 [==============================] - 673s 2s/step - loss: 0.2324 - accuracy: 0.7467 - val_loss: 0.2577 - val_accuracy: 0.7198 - lr: 2.5000e-05
Epoch 16/20
366/366 [==============================] - ETA: 0s - loss: 0.2278 - accuracy: 0.7498
Epoch 16: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05.
366/366 [==============================] - 690s 2s/step - loss: 0.2278 - accuracy: 0.7498 - val_loss: 0.2561 - val_accuracy: 0.7212 - lr: 2.5000e-05
Epoch 17/20
366/366 [==============================] - 674s 2s/step - loss: 0.2217 - accuracy: 0.7615 - val_loss: 0.2503 - val_accuracy: 0.7157 - lr: 1.2500e-05
Epoch 18/20
366/366 [==============================] - 713s 2s/step - loss: 0.2126 - accuracy: 0.7632 - val_loss: 0.2492 - val_accuracy: 0.7308 - lr: 1.2500e-05
```

\ **Fig 4.5 Accuracy Performances of RESNET50**

4.3.2 DENSENET

- A DenseNet is a type of convolutional neural network that utilises dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other.

- 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.

- Also, DenseNet has been shown to have better feature use efficiency, output- forming ResNet with fewer parameters.

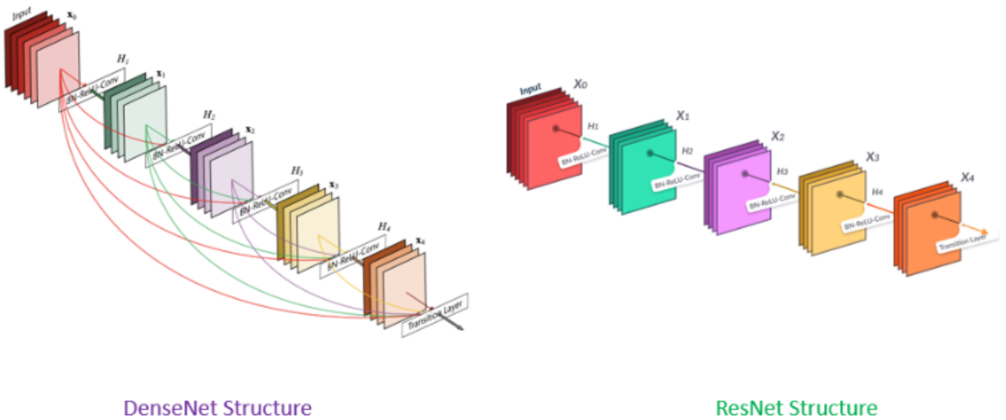


Fig 4.6 Comparison of DenseNet and ResNet Structure

```
Epoch 1/20
91/91 [==============================] - 231s 3s/step - loss: 0.2988 - accuracy: 0.8942 - val_loss: 0.4852 - val_accuracy: 0.8255
Epoch 2/20
91/91 [==============================] - 223s 2s/step - loss: 0.2815 - accuracy: 0.8942 - val_loss: 0.4882 - val_accuracy: 0.8214
Epoch 3/20
91/91 [==============================] - 223s 2s/step - loss: 0.2963 - accuracy: 0.8956 - val_loss: 0.4649 - val_accuracy: 0.8407
Epoch 4/20
91/91 [==============================] - 230s 3s/step - loss: 0.2962 - accuracy: 0.8878 - val_loss: 0.4700 - val_accuracy: 0.8297
Epoch 5/20
91/91 [==============================] - 225s 2s/step - loss: 0.2655 - accuracy: 0.9017 - val_loss: 0.4548 - val_accuracy: 0.8365
Epoch 6/20
91/91 [==============================] - 262s 3s/step - loss: 0.2715 - accuracy: 0.9038 - val_loss: 0.5072 - val_accuracy: 0.8379
Epoch 7/20
91/91 [==============================] - 226s 2s/step - loss: 0.2852 - accuracy: 0.8915 - val_loss: 0.5500 - val_accuracy: 0.8091
Epoch 8/20
91/91 [==============================] - 225s 2s/step - loss: 0.2140 - accuracy: 0.9135 - val_loss: 0.5430 - val_accuracy: 0.8324
Epoch 9/20
91/91 [==============================] - 228s 3s/step - loss: 0.2755 - accuracy: 0.9052 - val_loss: 0.4957 - val_accuracy: 0.8159
Epoch 10/20
91/91 [==============================] - 233s 3s/step - loss: 0.2189 - accuracy: 0.9231 - val_loss: 0.5350 - val_accuracy: 0.7967
Epoch 11/20
91/91 [==============================] - 223s 2s/step - loss: 0.2312 - accuracy: 0.9203 - val_loss: 0.6492 - val_accuracy: 0.7898
Epoch 12/20
91/91 [==============================] - 220s 2s/step - loss: 0.2459 - accuracy: 0.9176 - val_loss: 0.5754 - val_accuracy: 0.8393
Epoch 13/20
91/91 [==============================] - 224s 2s/step - loss: 0.1994 - accuracy: 0.9299 - val_loss: 0.4957 - val_accuracy: 0.8104
Epoch 14/20
91/91 [==============================] - 227s 3s/step - loss: 0.1986 - accuracy: 0.9341 - val_loss: 0.4793 - val_accuracy: 0.8283
Epoch 15/20
91/91 [==============================] - 222s 2s/step - loss: 0.1654 - accuracy: 0.9396 - val_loss: 0.6079 - val_accuracy: 0.8118
Epoch 16/20
91/91 [==============================] - 224s 2s/step - loss: 0.1749 - accuracy: 0.9515 - val_loss: 0.5612 - val_accuracy: 0.8187
Epoch 17/20
91/91 [==============================] - 225s 2s/step - loss: 0.1737 - accuracy: 0.9451 - val_loss: 0.5584 - val_accuracy: 0.8571
Epoch 18/20
91/91 [==============================] - 227s 3s/step - loss: 0.1942 - accuracy: 0.9404 - val_loss: 0.4904 - val_accuracy: 0.8297
Epoch 19/20
91/91 [==============================] - 227s 3s/step - loss: 0.1706 - accuracy: 0.9451 - val_loss: 0.6067 - val_accuracy: 0.8338
Epoch 20/20
91/91 [==============================] - 224s 2s/step - loss: 0.2029 - accuracy: 0.9299 - val_loss: 0.6437 - val_accuracy: 0.8255
```

Fig 4.7 Accuracy Performances of DenseNet

4.3.3 EFFICIENTNET

- EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient.
- EfficientNet uses a technique called compound coefficient to scale up models in a simple but effective manner.
- Instead of randomly scaling up width, depth or resolution, compound scaling uniformly scales each dimension with a certain fixed set of scaling coefficients.
- Using the scaling method and AutoML, the authors of efficient developed seven models of various dimensions, which surpassed the state-of-the-art accuracy of most convolutional neural networks, and with much better efficiency.
- Thus the EfficientNet models achieve both higher accuracy and better efficiency over existing CNNs, reducing parameter size and FLOPS by an order of magnitude.

4.3.4 NASNET

- NASNet stands for Neural Search Architecture (NAS) Network and is a Machine Learning model.
- NASNet-Large is a convolutional neural network that is trained on more than a million images from the ImageNet database.

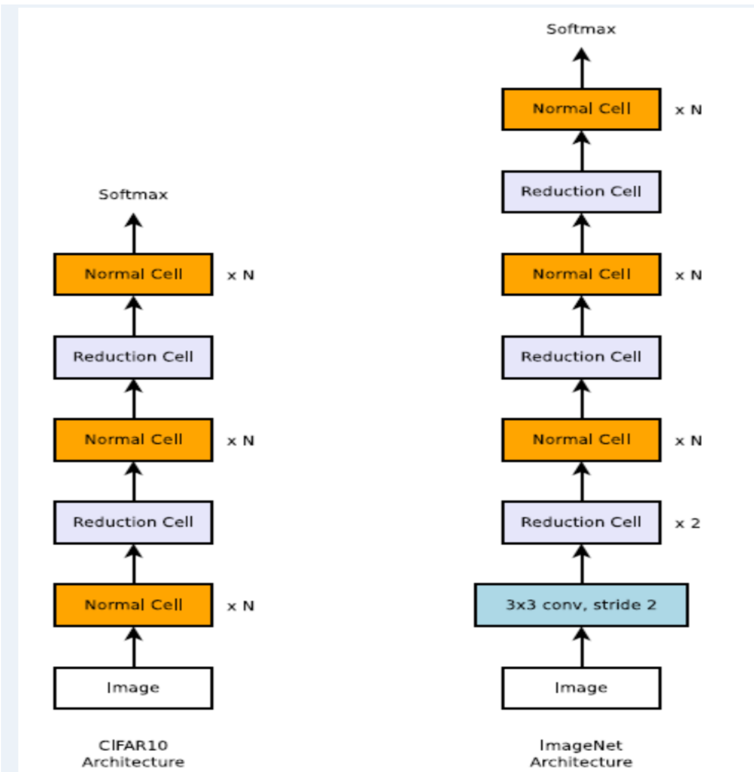


Fig 4.8 Structural Layers of NASNET

```
[ ] model.fit_generator(train_generator,
                        steps_per_epoch=train_generator.samples // BATCH_SIZE,
                        epochs=5,
                        validation_data=valid_generator,
                        validation_steps = valid_generator.samples // BATCH_SIZE)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: UserWarning: `Model.fit_generator` is deprecated and will be removed in a
  """
Epoch 1/5
366/366 [==============================] - 1556s 4s/step - loss: 0.6559 - accuracy: 0.7598 - val_loss: 0.8442 - val_accuracy: 0.7418
Epoch 2/5
366/366 [==============================] - 570s 2s/step - loss: 0.4526 - accuracy: 0.8374 - val_loss: 0.8876 - val_accuracy: 0.7404
Epoch 3/5
366/366 [==============================] - 573s 2s/step - loss: 0.3164 - accuracy: 0.8809 - val_loss: 0.9638 - val_accuracy: 0.7706
Epoch 4/5
366/366 [==============================] - 572s 2s/step - loss: 0.2109 - accuracy: 0.9281 - val_loss: 1.1631 - val_accuracy: 0.7418
Epoch 5/5
366/366 [==============================] - 570s 2s/step - loss: 0.1504 - accuracy: 0.9483 - val_loss: 1.1247 - val_accuracy: 0.7761
<keras.callbacks.History at 0x7f3e94609b10>
```

Fig 4.9 Accuracy Performances of NASNET

4.3.5 ENSEMBLE MODEL

In the ENSEMBLE model, we have ensembled two of our models which have been trained and produced efficient results namely the DenseNet and NASNet

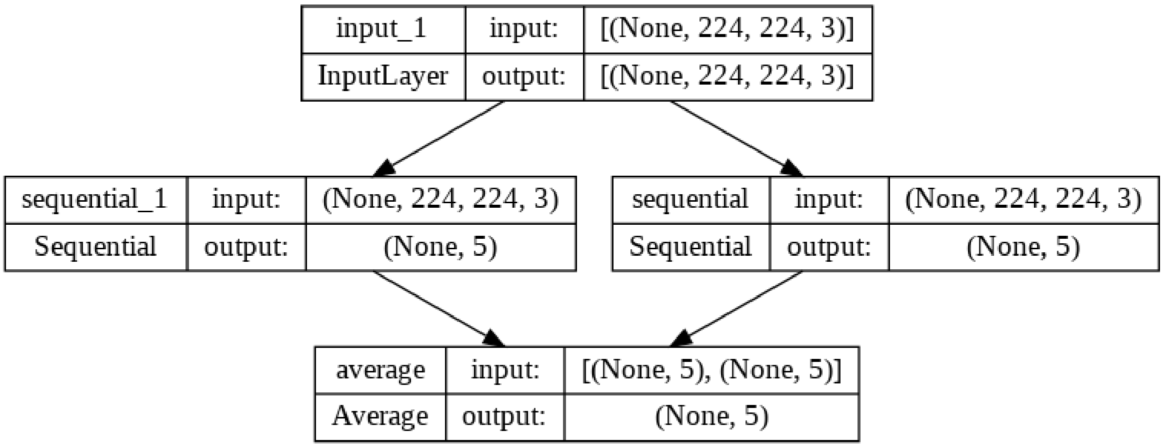


Fig 4.10 Architecture of Ensemble Model

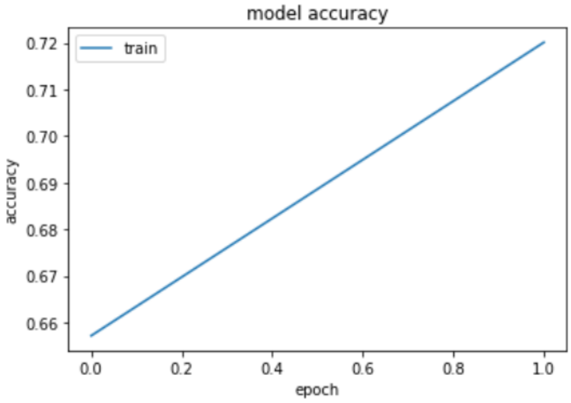
```
[ ] ensemble_model.fit_generator(train_generator,
                        steps_per_epoch=train_generator.samples // BATCH_SIZE,
                        epochs=5,
                        validation_data=valid_generator,
                        validation_steps = test_generator.samples // BATCH_SIZE)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: UserWarning: `Model.fit_generator` is deprecated and will be removed in a
  """
Epoch 1/5
60/60 [==============================] - 145s 2s/step - loss: 0.6578 - accuracy: 0.8109 - val_loss: 0.4865 - val_accuracy: 0.8438
Epoch 2/5
60/60 [==============================] - 142s 2s/step - loss: 0.3962 - accuracy: 0.8655 - val_loss: 0.3896 - val_accuracy: 0.8562
Epoch 3/5
60/60 [==============================] - 140s 2s/step - loss: 0.3691 - accuracy: 0.8445 - val_loss: 0.3764 - val_accuracy: 0.8708
Epoch 4/5
60/60 [==============================] - 137s 2s/step - loss: 0.2611 - accuracy: 0.9160 - val_loss: 0.2559 - val_accuracy: 0.9104
Epoch 5/5
60/60 [==============================] - 138s 2s/step - loss: 0.2171 - accuracy: 0.9265 - val_loss: 0.2333 - val_accuracy: 0.9187
```

Fig 4.11 Accuracy Performances of Ensemble Model

CHAPTER 5
RESULTS

5.1 RESNET PERFORMANCE

The above graph represents the performance efficiency of the RESNET model which is being employed. The graph corresponds to the Epoch Vs the model accuracy. On studying the below graph, we can note that as the epoch value increases, the model accuracy also increases correspondingly. Thus the RESNET model performance accuracy graph is a linear graph.

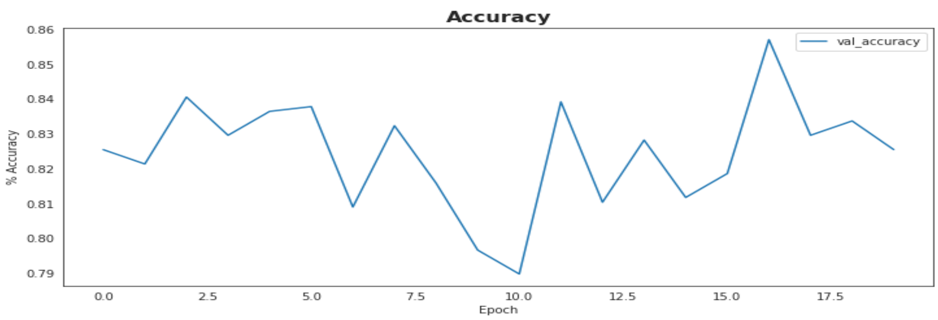


5.1 Restnet Performance Graph

5.2 DENSENET PERFORMANCE

The below graph represents the DENSENT model performance accuracy graph. The values represented in the X-axis represents the Epoch values and the Y-axis represents the model performance accuracy in percentage.

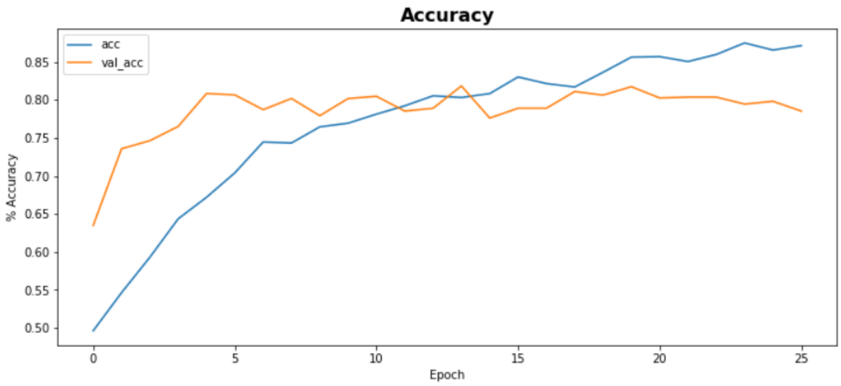
We can see that the performance graph seems to be increasing as the epoch value increases, but at a particular point when the epoch value reaches 10, the densenet model performance accuracy seems to be dipping majorly, and then the value accuracy.



5.2. Densenet Performance Graph

5.3 EFFICIENTNET PERFORMANCE

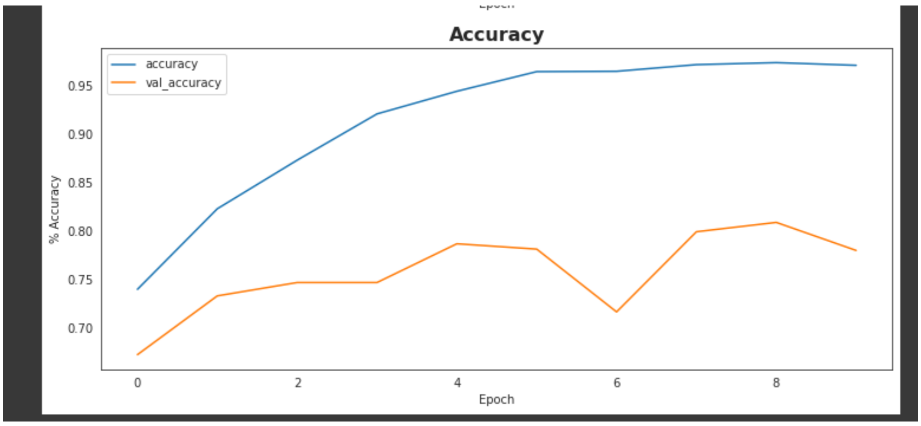
The below graph represents the EFFICIENTNET model performance accuracy graph. The values represented in the X-axis represents the Epoch values and the Y-axis represents the model performance accuracy in percentage. There is are steady increase in the validation accuracy of this model.



5.3 Efficient Net Performance Graph

5.4 NASNET PERFORMANCE

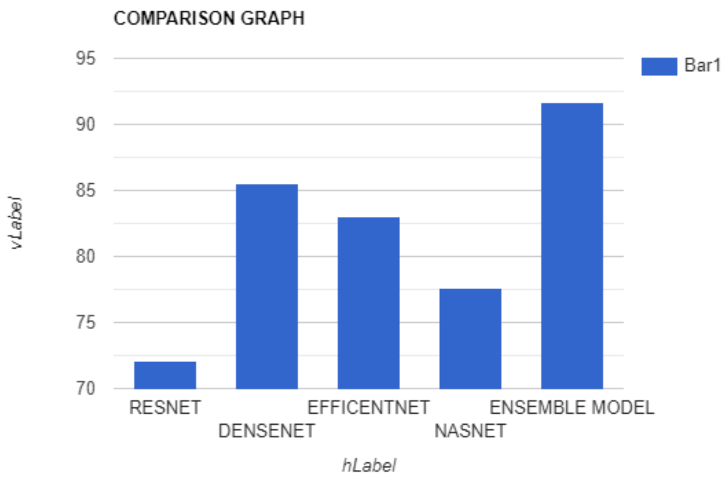
The below graph represents the NASNET model performance accuracy graph. The values represented in the X-axis represents the Epoch values and the Y-axis represents the model performance accuracy in percentage. The validation accuracy of this model is revolves around 78%.



5.4 NasNet Performance Graph

5.5 COMPARISON

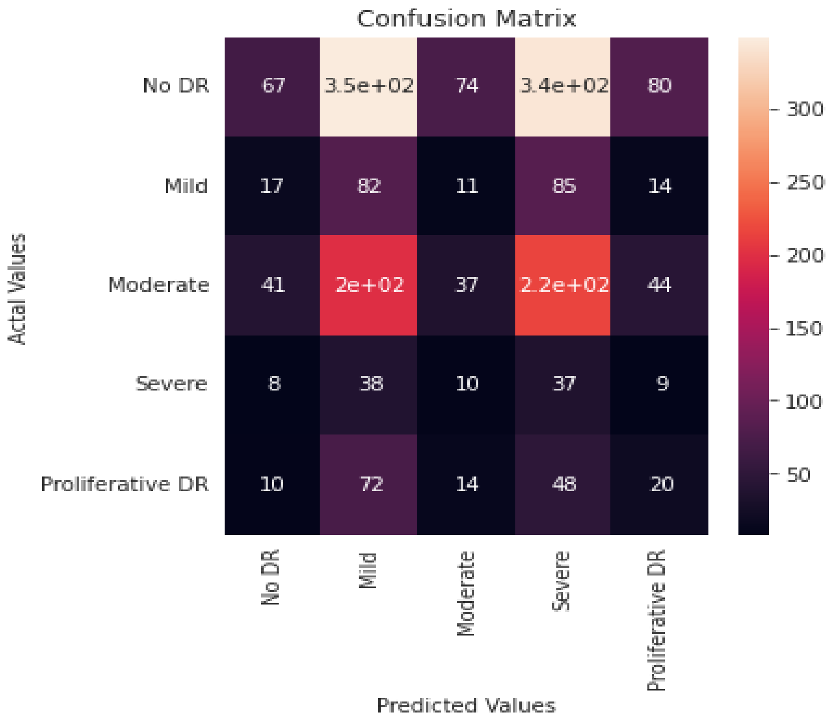
The below fig 5.5 shows that comparison bar graphs of all pre-trained models and our ensemble model, our model performance quite better than comparing other models.



5.5 Comparison Graph

5.6 CONFUSION MATRIX

A confusion matrix is a table that is used to define the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of a classification algorithm.



5.6 Confusion Matrix

5.7 KAPPA SCORE

Generally, a kappa of less than 0.4 is considered poor (a Kappa of 0 means there is no difference between the observers and chance alone). Kappa values of 0.4 to 0.75 are considered moderate to good and a kappa of >0.75 represents excellent agreement.

```
[ ] from sklearn.metrics import cohen_kappa_score
    val = cohen_kappa_score(act_d, y, labels=None, weights=None)
    print(val)

    0.9379088604121397
```

5.7 Kappa Score Results

CONCLUSION AND FUTURE WORK

In this article, a pretrained convolutional neural network (CNN) based framework is proposed for the detection of retinal exudates in fundus images using ensemble learning. In the proposed framework, pretrained models, namely DenseNet, Residual Network-50, Nasnet and Efficient Net, are used to extract the features from fundus images, based on transfer learning for the improvement of classification accuracy. Finally, the classification accuracy of the proposed model is compared with various DCNN models separately and with the existing techniques. The proposed transfer learning-based framework has been evaluated and outstanding results in terms of accuracy are obtained, instead of training from scratch. Hence, the accuracy of the proposed approach outperforms the other existing techniques for detecting diabetic retinopathy using the Aptos dataset. In future work, the proposed framework can also be extended to diagnose hemorrhages for diabetic retinopathy.

BIBLIOGRAPHY

1. Patel, Sanskruti. "Diabetic retinopathy detection and classification using pre-trained convolutional neural networks." International Journal on Emerging Technologies 11.3 (2020): 1082-1087.
2. Mateen, Muhammad, et al. "Exudate detection for diabetic retinopathy using pretrained convolutional neural networks." Complexity 2020 (2020).
3. Wynne Hsu, P MD S Pallawala, Mong Li Lee, KahGuan Au Eong, "The Role of Domain Knowledge in the Detection of Retinal Hard Exudates", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Kauai Marriott, Hawaii, vol. 12, pp. 533-548(2001).
4. T. Walter, J.Klein, P.Massin and A.Erginary, "A Contribution of image processing to the diagnosis of Diabetic Retinopathy detection of exudates in color fundus images of the human retina", IEEE Trans. Ón Med. images, vol. 21, no. 10, pp. 1236-1243(2002).
5. Bhatkar, Amol Prataprao, and G. U. Kharat. "Detection of diabetic retinopathy in retinal images using MLP classifier." 2015 IEEE international symposium on nanoelectronic and information systems. IEEE, 2015.
6. S.Roychowdhury, D.D.Koozekanani, Keshab K.Parhi, <DREAM: Diabetic Retinopathy Analysis Using Machine Learning=, IEEE Journal of BioMedical and Health Informatics, Vol.18, No 5, September (2014)
7. J.Lachure, A.V.Deorankar, S.Lachure, S.Gupta, R.Jadhav, <Diabetic Retinopathy using Morphological operations and Machine Learning=, IEEE International Advance Computing Conference(IACC), (2015)
8. Shahin, T E Taha, W Al-Nuaimy, S.El Raaie, O F Zahran, F E Abd El-Samie, <Automated Detection of Diabetic Retinopathy in Blurred Digital Fundus Images=, IEEE International Computer Engineering Conference , pages-20- 25,(2012).
9. P Kulkarni, J Zepeda, F Jurie, P Perez, L Chevallier, <Hybrid Multi-layer Deep CNN/Aggregator feature for Image Classification=, Computer Vision and pattern recognition, ICASSP conference, (2015).
10. Kaggle Dataset:https://www.kaggle.com/c/diabetic-retinopathydetection/data
11. Xiang chen et al, <A novel method for automatic hard exudates detection in color retinal images=, Proceedings of the 2012 International Conference on Machine Learning and Cybernetics, Xian (2012).
12. G.Gardner,D.Keating, T.H.Willamson, A.T.Elliott, <Automatic detection of diabetic retinopathy using an artificial neural network: a screening Tool=, Brithish Journal of Opthalmology,(1996);80:940-944.
13. S.Roychowdhury, D.D.Koozekanani, Keshab K.Parhi, <DREAM: Diabetic Retinopathy Analysis Using Machine Learning=, IEEE Journal of BioMedical and Health Informatics, Vol.18, No 5, September (2014).
14. G.Lim, M.L.Lee, W.hsu, <Transformed Representations for Convolutional Neural Networks in Diabetic Retinopathy Screening=, Modern Artificial Intelligence for Health Analytic Papers from the AAAI(2014).
15. J.J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, B. van Ginneken, "Ridge based vessel segmentation in color images of the retina", IEEE Transactions on Medical Imaging, 2004, vol. 23, pp. 501-509