Retinal Diseases Detection using Deep Learning

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Retina is an important aspect of human vision because it converts light rays into images and sends messages to the brain. We run the danger of suffering long-term harm to the eyesight if we have a problem with our retina that might lead to vision loss or blindness which can be caused by eye illness, ocular trauma, or other problems. Retinal based diseases such as diabetic retinopathy, age-related macular degeneration (AMD) and retinal detachment . However, if someone can take care of his/her retinal health by eye-checkup annually it might help. Moreover, human civilization is now way advanced by the blessings of modern technology. Furthermore, we came up with an idea which will lead us to the success door of retinal disease detection in a very easy and cheap way. In this modern world, a large amount of people use smartphones and high resolution cameras and that is the main fact. Detecting retinal diseases with computer vision based image processing will help a lot of people in the world to be healthy in terms of their eyesight. We are planning to apply Convolutional Neural Network (CNN) to identify and classify retinal diseases with high accuracy. However,we will go through some methodologies such as data pre-processing, segmentation, analyzing etc. For Large-Scale Image Recognition we are using our customized Convolutional Network that we have proposed in this paper. Here, we started our data segmentation from Kaggle. We have used 28972 images from Kaggle as our data-set. Then we segmented it in three parts: Test, training and validation. And here we will detect a total of four different retinal pictures.. They are: CNV, DME, DRUSEN and NORMAL. We have trained our proposed CNN model with these dataset and gained 98.97% validation accuracy. Moreover, we also run some pre-trained models. They are: Resnet50, Inceptionv3, EfficientNet B0, Xception and VGG16. We gained 79.34%, 91.32%, 28%, 87.94% and 94.01% accuracy respectively from them. Hence, we can see that our proposed CNN model outperformed them in these experimental results.

Keywords: Image Processing , Computer vision, CNN, Image Segmentation, CNV, DME, DRUSEN, Resnet50, Inceptionv3, EfficientNet B0, Xception, VGG16.

Dedication

This essay is written in honor of our families and coworkers. The team members' perseverance and the family's unwavering support were crucial in the achievement of this paper. Without the assistance of our outstanding supervisor who have been a constant source of guidance and counsel, we would not have been able to complete our thesis. This paper is also dedicated to him.

Acknowledgement

First and foremost, we want to thank Allah, the Almighty, for giving us the tools, chances, and direction we needed to finish this research on time. As a second tribute, we would like to express our gratitude to Mr.Dewan Ziaul Karim, our thesis supervisor. We shall always be grateful for that. The whole staff and student body deserves praise for creating a welcoming learning atmosphere that allowed us to advance professionally.

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Nomenclature:

This part describes the symbols and their abbreviation that we are going to use in our whole thesis paper over and over. This part will help to recognise them easily.

AI ————— Artificial Intelligence
CNN ————— Convolutional Neural Network
AMD ————— Age related macular degeneration
DR ————— Diabatic retinopathy
CNV ————— Choroidal neovascularization
DME ————— Diabetic macular edema
AUC ————— Area Under Curve
RGB ————— Red Green Blue

Chapter 1

Introduction

1.1 Background

In the sector of health, AI came out with a revolutionary change in terms of detecting diseases with high accuracy and made life easier. It's quite difficult for human beings to detect diseases so fast, of the huge population. AI is helping a lot to detect diseases perfectly and quickly. It has become easy to store data of all the diseases. But for human beings, it's quite difficult to analyze this huge amount of data with good accuracy and swiftly. Here, AI has played the trump card. Deep learning is a subsection of AI, which analyzes a big amount of data and gives the result faster with good accuracy. Which is quite impossible for human beings. Here, Deep learning can help us a lot. We are trying to implement the power of Deep Learning in the sector of health. We have noticed that, nowadays, eye problems among our population are gradually increasing. Most of the patients among them are suffering from retinal diseases. According to a research at General Hospital, Jamalpur, Bangladesh, out of 7164 patients 173 patients were suffering from retinal diseases. Which is 2.42 percent [1]. This statistics shows us the tremendous increase of retinal diseases among our population. Not only in Bangladesh, it's a matter of concern for the world. According to research by National Alliance for Eye and Vision Research (NAEVR), more than 1.8 million of American people were suffering from advanced AMD before 2020. And they were expecting this would have increased by the year 2020. They also mentioned that, above 3.3 million people will be affected by Glaucoma after the year 2020 [2]. It's a very alarming situation. Deep learning is helping mankind in all aspects. It's a revolution of modern technology. In health care it's demand is increasing for its accuracy and performance. Convolutional Neural Network (CNN) analyzes a huge amount of data sets and gives the result with high accuracy. Convolutional Neural Network uses Image processing algorithm to analyze the image pattern, RGB colors. The pre-trained model uses image as input and finds the similarity by cross matching and gives results with high accuracy and much quickly. The accuracy also can be improved by customizing the CNN models. Which we have tried to implement here to improve the quality of CNN model as well as to help in the medical sector.

1.2 Problem Statement

Retina is an essential part of our eyes. A large number of people every year suffer from blindness due to retinal tissue damage. In developing countries like Bangladesh, where people are not aware of retinal diseases that much, it's a very common scenario that people suffer from blindness due to retinal diseases. So if the diseases could be detected early with modern tools, this problem can be reduced. We need help from Machine learning algorithms to detect retinal diseases of this vast population. We can use algorithms like: SVM, CNN, RIICT etc. Algorithms must work accurately to detect the diseases. But in [3] only RIICT performed with 96.7% accuracy. But SVM and CNN gave accuracy 86.4% and 86.6% respectively. Which is not upto the mark.According to, [4] detecting images from OCT images using CNN algorithm the accuracy came 96%. They also faced challenges because the retinal size of different races are different. And the main problem was, the algorithm had to train differently to detect the fundus images. In this research we will attempt to apply the algorithm of deep learning which is Convolutional Neural Network (CNN) to detect three retinal diseases. Which are: CNV, DME and DRUSEN. We will detect these diseases compared with the normal retinal images.

1.3 Motivation

Modern age of the medical sector is highly dependent on computer based decision systems to detect diseases and proper treatment. Doctors collect the sample of the diseases and give the data as input. Then a computerized decision system analyzes the data and matches them with previous data-set to give the accurate result swiftly. Which we call AI. Our main motive through this research is to understand how Deep learning is helping us in the medical sector by using Convolution Neural Network models. We also tried to customize the CNN model to get better accuracy and high efficiency. Our motives through this research are:

- To know details about Deep learning and how this can be implemented in desired sectors
- To understand the process of implementing different CNN models.
- To learn how we can customize a CNN model to get better and efficient results from different data-sets.
- To develop a better CNN model which can analyze huge data-sets and give high accuracy in a shorter time.
- Helping mankind to reduce retinal diseases by addressing them swiftly and accurately

1.4 Thesis Orientation

This is the summary part that we have done in this thesis. This segment describes all the chapters of our thesis works. In this segment, our main intention of this thesis work and what we have done to complete our thesis is described. The chapters summary is given here sequentially:

- **Chapter 1:** This chapter is the introduction part of our thesis
- **Chapter 2:** This chapter includes the summary of other works of different authors which is related to our thesis.
- **Chapter 3:** This chapter describes about our thesis objective.
- **Chapter 4:** This chapter includes the methodology and our working plans
- **Chapter 5:** In this chapter we have described our proposed CNN models in detail.
- **Chapter 6:** In this chapter we have done performance evaluation of our all CNN models with different graphs, matrix and calculation.
- **Chapter 7:** In this part we have concluded our thesis paper and added our future working plan.
- **Bibliography:** This segment includes all the related work that we used as our references.

Chapter 2

Related Work

The most significant aspect of human beings is their vision. In terms of prevalence, glaucoma, diabetic retinopathy, and age-related macular degeneration are the three most important factors that contribute to bad eyesight. DR is such an eye disease that damages the retina. The disease has minimal symptoms in its early stages due to its slow progression, making disease detection difficult. As a result, to aid in the early detection and screening process, a fully automated system is required. The main symptoms of DR, which affects the retina, are blurred vision, floaters, and sudden visual loss. Hemorrhages, microaneurysms, and hard and soft exudates are all abnormal markers of DR. An eye disease that occurs in patients who already have DR and causes vision loss is known as DME . In those with DME, other medical problems caused by poor blood sugar control increase the chance of blindness. Blindness can occur at any stage of the disease, however it is more common as the condition progresses. DME causes fluid to accumulate in the macula, resulting in macula enlargement. Here[5] To heighten image brightness, noise reduction, and intensity spectrum normalization, Sian S. initially processed the grouped photographs using the refined contrast-limited adaptive histogram filter. A pre-trained, fine-tuned RESNET50 was used to generate the suggested model utilizing the transfer learning technique. The developed framework underwent performance assessment criteria, and the results showed that it had a classification precision of 100% sensitivity, 100% specificity, and 100% accurateness.. Here[6] The evaluation of the nerve fiber layer (NFL) is an important step in diagnosing and treating glaucoma. Due to the poor quality of fundus pictures, NFL identification is challenging since the reflectance background is mellow and the contrast is low. NFL can be detected in fundus pictures using optical coherence tomography (OCT). OCT is commonly used to judge the inner anatomy of retina, such as glaucoma and pathological diseases of the outer stratum. Clinicians usually assess NFL because its level is a good predictor of disease progression, and the forms of NFL are crucial for illness treatment and diagnosis.The streamlined The sequence of processing image data for glaucoma diagnosis is shown in this article's figure. Multimodalities such as The methods of elliptical fitting, convex hull, and In order to make these borders less abrupt, level set segmentation might be utilized. in the suggested method. The results are superior to the state-of-the-art ARGALI system. The proposed Random Implication Image Classifier Technique (RIICT) approach is created in paper[4] use this method to categorize the imagery in a wide range of color areas and obtain outstanding accuracy in various image analyses. The Discrete Image Clustering

Technique (DICT) techniques are used to separate the image foreground and background of the input image, making it easier to discover the afflicted region based on similarities. This system's lesion outcomes are classified using the Random Implication Image Classifier Technique (RIICT) technique. That technique swiftly detects diseases such as cotton wool spots and lesions, and distinguishes between different iris pictures method of construction. The RIICT system has a higher accuracy score of 96.7%. Laser Coherence Tomography offers high-resolution measurements, as well as cross-sectional images of the retina and RNFL. Here [6], a series of 100 axial reflectance profiles are obtained for glaucoma applications by scanning a circular or linear operator-defined route around the optic disk. The OCT's current iteration, the Stratus OCT, has been enhanced.. With 128 to 768 measurements of nerve fiber layer height throughout the disk, there is a higher resolution and a less varied representation of nerve fiber layer thickness. The morphological, developmental, physiological, pathological (inflammation, oxidative stress, endothelial dysfunction, and microangiopathy) and biological similarities between the kidney and the eye include the renin-angiotensin-aldosterone hormone cascade. Patients who have clinically obvious retinal microvascular symptoms (such as retinopathy, arteriolar narrowing, or venular dilatation)have a higher likelihood of developing chronic renal disease, suggesting that the retina may offer new screening data to complement existing methods. Here[3], they used information from three cross-sectional studies that were population-based, multiethnic, and used data from three studies to design (5188 patients) and validate (1297 patients) the DLA (SEED, patients aged 40 years). For external testing, data from the Beijing Eye Study (BES, 1538 patients aged 40 years) and the Singapore Prospective Study Program (SP2, 3735 patients aged 25 years) were used. Chronic renal illness glomerular filtration rate of less than 60 mL/min per 173 m2 was deemed to meet this criteria. The guided glaucoma screening algorithms in retinal pictures are covered in this[7] study. Through the use of deep learning and non-deep learning techniques, the studies in this article were categorized. As a result, its main goals are to assess current algorithms provided by various groups and to outline the key processes in the development of an automated diagnosis system. Additionally, glaucoma and other abnormal eye disorders can be detected early and automatically with the use of machine learning algorithms. We talked about the benefits and drawbacks of using machine learning techniques in retinal image processing for glaucoma detection and diagnosis. In order to identify research convergences and divergences, an analysis was conducted. The first deep learning architecture implementation for OD segmentation was proposed by Lim et al.[8] in 2015. The suggested CNN is utilized to determine the cup-to-disc ratio as a sign of glaucoma using the MESSIDOR and SEED datasets. The Daubechies wavelet transform was used to choose the area closest to OD that was most likely to be localized. Due to the existence of noise, the probability of a pixel being inside or outside the OD zone was calculated. This strategy's AUC was 0.847. A convolution neural network is used in this paper's [7] method for automatically segmenting the retinal layers (CNN). The inner limiting membrane (ILM) and retinal pigmented epithelium (RPE) used while calculating the cup-to-disc ratio for the examine of glaucoma (CDR). The suggested approach first extracts structural tensors from candidate layer pixels, then extracts a patch over each candidate layer pixel, which is subsequently classified using CNN. The suggested system makes use of the VGG-16 architecture to extract features from and classify retinal layer pixels. With the help of the SoftMax layer, which creates a probability map for each patch's center pixel and detects whether it is an ILM, RPE, or background pixel, the resulting feature map is utilized to classify data. A technique for learning that is transferable that is dependent on the inception network and by using retinal OCT images was proposed by Karri et al. [9] for diagnosing retinal disorders. The collection also comprised OCT images of healthy persons, dry AMD patients, and DME patients. According to their research, the customized CNN was more successful at identifying diseases than conventional learning methods. The classifying OCT method can be improved even when trained on non-medical images with limited training data. Normal, AMD, and DME had average prediction accuracy's of 99 %, 89 , and 86 , respectively. A pre-trained CNN model was employed by Awais et al. [10] to specify diabetic macular edema (DME). First of all, they took a 16 volume OCT image of DME and 16 volume of Normal. All volume contains 128-B scans and resolution is 1024px $\times$ 512px. They gained an accuracy of 87.50%. Lee et al [11] classified AMD and the usual macular imagery they use. They have taken 52690 Normal macular and 48312 AMD macular OCT images as dataset. They have trained a deep neural network to detect Normal macular images and AMD macular images. They gained under the ROC curve of 97.45% with an accuracy of 93.45%. Perdomo et al [12] proposed a 12 layer CNN model to detect Diabetic Macular Edema. They took 16 DME and 16 Normal OCT volumes as a dataset. Each of their volumes contains 128-B scans of 1024px $\times$ 512px resolution. They analyzed their result using k-fold cross validation. They detected the images with 93.75% of accuracy, 87% of sensitivity and 100% of specificity. Rajagopalan et al [13] proposed a deep learning based diagnosis system to detect Drusen Macular Degeneration (DMD) and Diabetic Macular Edema (DME). They used their proposed Convolutional Neural Network (CNN) to classify DMD, DME and Normal images. They also used a K-fold validation system to complete usage of the dataset. Their model performed with 95.7% of accuracy.

Chapter 3

Research Objective

In developing countries like Bangladesh, life expectancy is growing. To maintain this life expectancy, we need good quality of treatment. To ensure the quality of treatment of eyesight, we can use modern technologies. If we can detect retinal diseases at an early stage, we might be able to protect the eyesight of a patient. Common eye diseases:

- **Age related macular degeneration (AMD):** AMD is basically damage to retinal tissues. Above 35% of people suffer from AMD after the age of 80. As the damaged tissues can not be recovered, but it is possible to prevent the damages if the disease can be detected at an early age
- **Diabetic retinopathy (DR):** Another big reason for retinal damage is diabatic. 80% of the diabatic patients who are suffering from diabetes more than 20 years are affected with this disease. So it's essential for them to check their eyesight every 6 months.
- **Glaucoma:** Glaucoma is another very common eye disease in our country. Around 9-12% of blindness happens because of it.
- **Choroidal neovascularization (CNV):** CNV can develop quickly in people who have a deficiency in Bruch's membrane, the choroid's innermost layer. It's a very common retinal disease. It can be identified using fundus images.
- **Diabetic macular edema (DME):** DME is a diabetic complication characterized by fluid buildup in the macula, which can obstruct vision in the fovea. In the back of the eye, the most central part of the retina is known as the macula where vision is clearest. DME can cause vision loss that worsens over time and makes it difficult to focus.
- **Drusen:** Drusen is a condition that can cause a rapid and severe loss of vision because defective blood vessels rupture, hemorrhage, or leak fluid into the macula. Blind areas in the patients' vision is possible.

After the retina gets damaged there are very few chances to bring eyesight back. Hence, early detection of disease can help to prevent the loss of eyesight.Although it is quite impossible to detect the retinal diseases of this huge population of Bangladesh by clinicians. We need automated tools for detection, progress observation and keeping documents of this huge population.

Chapter 4

Methodology

4.1 Working Plan

For our research purpose, we will be using the Retinal Diseases Classification images that we have collected from the source [43] .After collecting the data, we move to our next step which is pre-processing. In the pre-processing part we reduce the noise of our image and improve the quality of our input images. The first part of pre-processing is GRAYSCALING. It is used for measuring the intensity of light in an image. After this we proceed to scaling which is a process to reduce the pixel amount of the image that is used as input. The last part of pre-processing is CLAHE. Basically it raises the contrast in the image to make it more clear. Then we move to our next procedure which is segmentation. In this portion we use region based approach techniques. We use this method to detect similar pixels in the image according to a selected threshold. In threshold we convert an image color or grayscale into a binary image. Furthermore , in the algorithms part we are applying Convolutional Neural Network (CNN). We can classify our retinal disease image using convolution neural network algorithms.

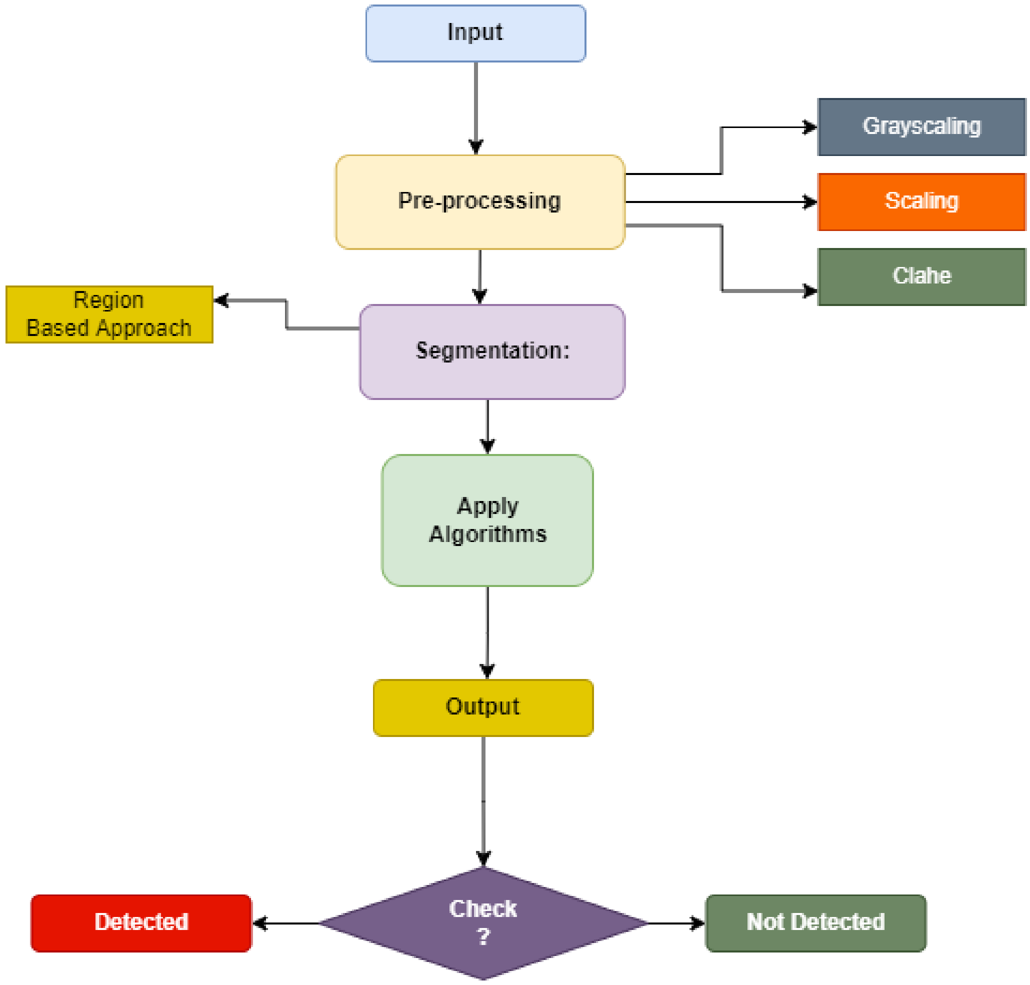

Figure 4.1: Data Flow Diagram

4.2 Data Analysis

Any research project must begin with data analysis. We structured our data analysis into two sections for our suggested system: input data and data pre-processing.

4.3 Input Data

In the procedure of segmenting the retinal region and detecting retinal illness automatically takes place.Deep learning algorithms have the capability to provide highly accuracy in retinal disease detection. In automated tasks, convolutional neural networks (CNN) have outperformed all other deep neural networks in detecting multiple image detection and segmentation. The CNN takes raw picture pixel data as input, extracts features, and successfully infers about the object. In the detection of retinal disease we gathered 28,972 images of retina's from kaggle. Moreover,we gradually divided the images into three parts in three particular folders named Train,Test and Validation to differentiate CNV, DME, DRUSEN, and Normal with another four folders into those.

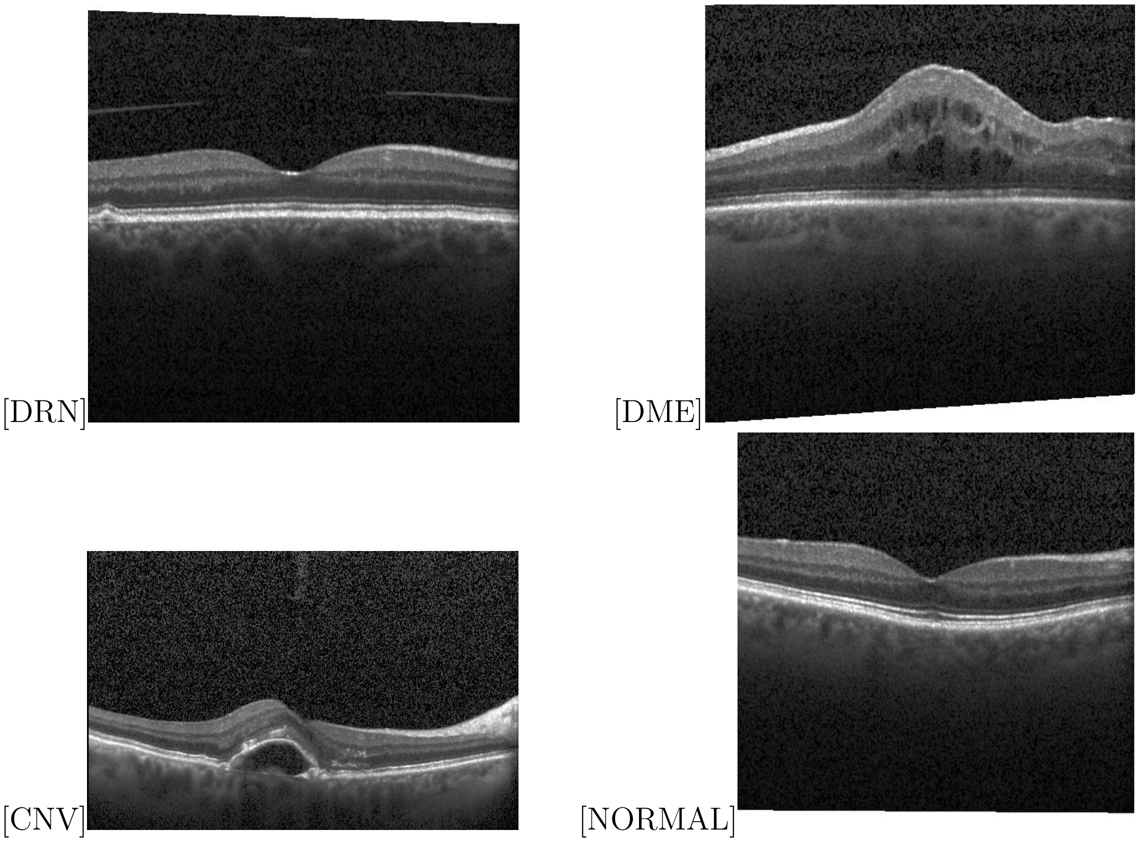

Figure 4.2: Sample Data

4.4 Data Preprocessing

Preprocessing data is a vital step in preparing material for use in the Convolutional Neural Network (CNN) method. This procedure is used to eliminate variables that do not contribute to increasing the CNN model's accuracy or outcomes[19]. However, this stage lets us apply all necessary transformations on the raw data, which can aid in boosting the CNN model's performance and accuracy. To develop our suggested system for detecting retinal diseases, we first divided our image dataset of retinal disease into four portions, which included CNV, DME, DRUSEN and NORMAL images in different folders. There are three types of datasets: training, test and validation. We included 72% of the photographs in the train folder which is identically 28972 images.Additionally, 3% of the images stored in the test folder also for validation folder 25% images are stored.
In addition, we have modified our training dataset. Setting the image sizes, batch size, rescaling, rotation, zooming, and horizontal flipping are all part of this procedure. All of these have the following values:
Convolutional Neural Network(CNN):- Proposed Model

- Image size : 244x244
- Batch size : 32
- Rescalling size : 1/255.0
- Zoom range : 0.2

- Horizontal Flip : True

Convolutional Neural Network(CNN):- Vgg16, Inceptionv3, Resnet50,Xception, EfficientNetB0

- Image size : 224x224
- Batch size : 32
- Rescalling size : 1/255.0
- Zoom range : 0.2
- Horizontal Flip : True

We have used 'categorical' class mode as here our classification result fall in one of the four classes i.e. CNV, DME, DRUSEN AND NORMAL.We applied the same image and batch size to our test dataset as well. We've also preserved the categorical class mode.We went on to the next phase, which is constructing the Convolutional Neural Network model, where we can run the dataset for machine learning, after carefully applying these modifications to our raw dataset in order to enhance the performance of the CNN model.

Chapter 5

CNN Model Implementation

5.1 Introduction to CNN

A specific kind of neural network called a convolutional neural network, or CNN for short, is created to analyze data having a grid-like layout, such as an image. One of the numerous components that make up neural networks is the convolutional neural network (CNN). CNNs detect people, identify objects, and recognize other things using visual recognition and classification. They are made up of neurons, and training can change the weights and biases of those neurons. Most typically, CNNs are used to categorize photos, group them based on similarities, and then identify particular items. CNN-based algorithms can identify people, animals, street signs, and other distinguishable objects[16]. The human brain starts processing a huge quantity of data as soon as we perceive a picture. The visual field is represented by a network of neurons, each of which has its own receptive field but which together covers the entire visual field.Similar to how each neuron in the biological vision system only responds to stimuli in its own restricted region of the visual field, each neuron in a convolutional neural network (CNN) performs analysis only in its receptive field. Layer one is tasked with recognizing basic forms like lines and curves; layer two moves on to more complex stuff like human faces and other things. A convolutional neural network (CNN) might be used to give computers eyes. It is usual practice to employ a CNN with one or more convolutional layers, a pooling layer, and a fully-connected layer. Pictorial Representation No. 3 The Methodology Behind CNN

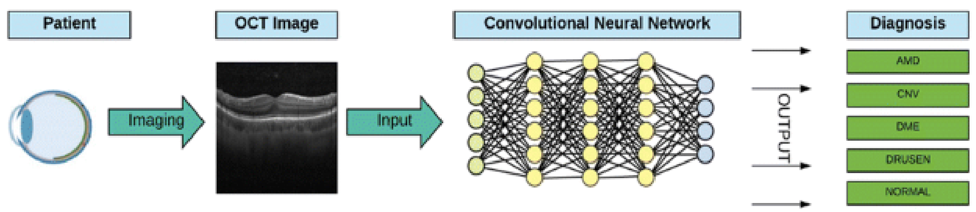

Figure 5.1: Working Process of CNN

5.1.1 Optimizer Adam

An optimizer is a process or technique that improves the parameters and learning rate of a CNN architecture. As a result, it helps to reduce damage overall and actually improves efficiency. Adam is a development of stochastic gradient descent, a computational intelligence technique that has been prominent in computer vision and natural language processing. These include methods for voice recognition and image processing. A deep-learning technique is to repeat the optimizer. The "Adam" optimizer function is described by equation (1). wt + 1 = wtamt (1) mt = aggregate of gradients at time t, a = learning rate at time t, wt = weights at time t, wt+1 = weights at time t + 1.

5.1.2 Softmax

Softmax when neural networks are employed for pattern classification tasks, a non-linear softmax output layer is frequently used. We are all aware that this is usual practice.The soft-max output layer of a neural network has the capacity to significantly alter the frequency at which the network generates outputs because of its non-linearity.

5.2 Model Architecture Using CNN

Deep learning is a type of machine learning that teaches computers to emulate human behavior. It's a three-layer neural network that's also a subset of machine learning. From photos, text, or voice, a computer model learns to categorize. To train models, multi-layer neural network typology's and a large amount of labeled data are used. Each algorithm in the hierarchy performs a nonlinear modification on its input before creating a statistical model as an output. Convolutional neural networks are one of the most often used deep learning techniques for analyzing visual input. It serves as the centerpiece of a CNN and is where the majority of computation takes place. The CNN recognizes bigger components or forms of the item as the visual input moves through its levels, finally recognizing the desired object.

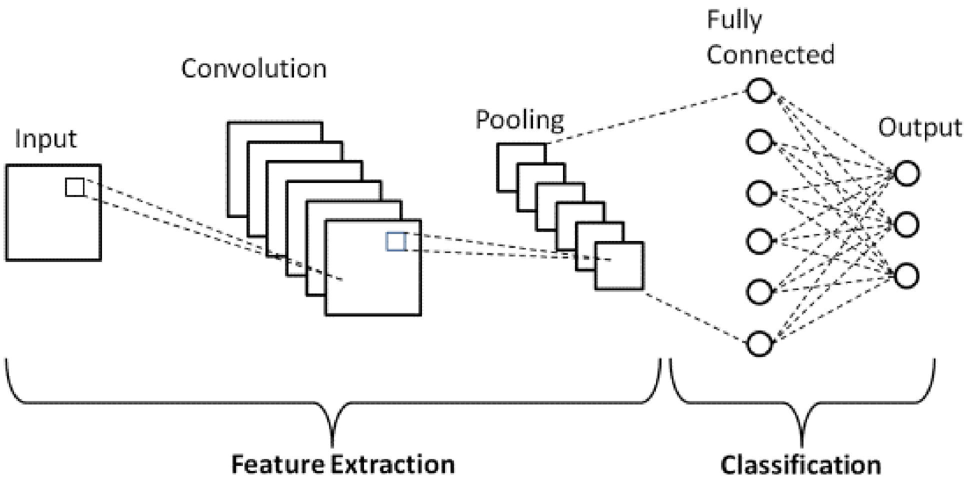

Figure 5.2: Architecture of CNN model

Convolutional neural networks perform more efficiently than conventional neural networks when inputs include images, voice, or audio signals. Convolutional, Pooling, and Fully Connected (FC) layers are their three unique layers. A CNN architecture is produced when all of these layers are combined. In addition to these three layers, there are two other important parameters: the dropout layer and the activation function.

5.3 Convolutional Layer

The CONVOLUTIONAL LAYER, the top layer of a CNN network, is the central component and main performer of computational activity. Convolution is the process of combining data with kernels or filters. In this process, the discernible values for each sliding motion are combined together after the component product of the image's filters is calculated. Convolution with a 3D color filter would provide a 2d matrix. The CNN's convolution layer acts as its structural base. It is the primary source of the network's computational load.There were three 2D convolutional layers used.However, to match the size of our input images, we set the first layer's input size to 244x244. For this layer, we used 'relu' activation and set our kernel to 32.
Wout = (W-F+2P)/S+1
Here, W =the spatial size of the output volume
F=field size of the Conv Layer neurons
P=the amount of zero padding used on the border.
S=the stride

5.4 Pooling Layer

After the convolutional layer, a new layer called a pooling layer is added. Specifically, following the implementation of a nonlinearity to the feature maps produced by a convolutional layer. The pooling layer minimizes the image size between convolution layers, allowing the total parameters in succeeding layers to be minimized. Several pooling algorithms are available, including the L2 norm of the rectangle

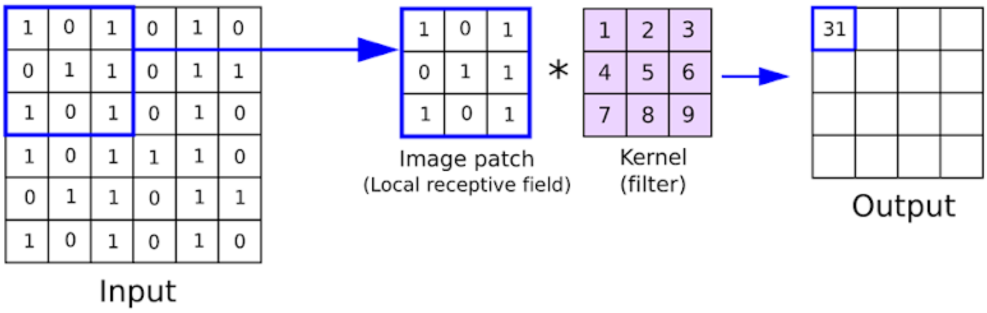

Figure 5.3: Convolution Operation[14]

neighborhood, the average of the rectangular neighborhood, and a weighted average based on the distance from the central pixel. However, max pooling, which reflects the highest output from the neighborhood, is the most well-liked method.

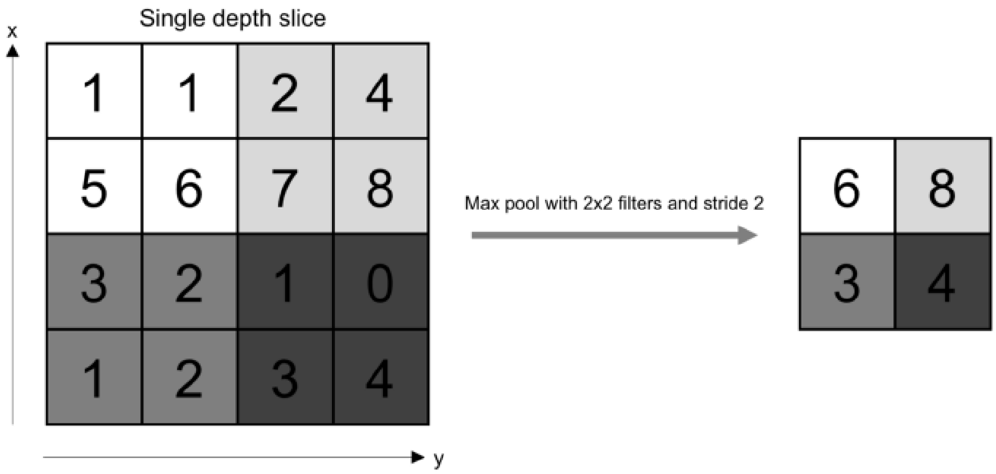

Figure 5.4: Pooling Layer

5.5 Fully Connected Layer

The flattened layer, which involves connectivity, In order to process the neural network, this entails converting the entire convolutional feature map sequence into a single column. We assembled these features into a model using the fully connected layers. In order to categorize the output, we have an activation function like softmax (or matrix multiplication).Every neuron in one layer is linked to neurons in other layers in the Fully Connected layer. All of the neurons' connections operate as feature classifiers, which are sent to the final output layer.

- **Flatten Layer :** A single flatten layer will be used after the fourth MaxPooling layer has been implemented. In the long term, this is favorable for the network as a whole.
- **Dense Layer :** This model has two dense layers in addition to the flattening layer.All of the neurons in this layer receive the outputs from the aforementioned levels.
- **Dropout Layer :** In order to prevent the model from becoming excessively precise during training, this layer will periodically reset all of the inputs to zero.

5.6 Proposed CNN Model

5.6.1 Implement to Proposed Model

We have developed a Convolutional Neural Network (CNN) model that, using picture data, can recognize various retinal disorders. This classification issue will take features from a given image to find distinct patterns and be able to distinguish between different photos based on those features, recognizing which retinal images are damaged and which are not. In order to process the input data for this task of classification using images, graphic processing capacity is needed. Therefore, a dedicated GPU is necessary (Graphics Processing Unit). We needed a dedicated GPU because the GPU can undertake substantial graphic processing operations. As Python is the most popular programming language for this assignment, we are also using Python as the basis programming language.

5.6.2 Proposed model Summary

The total amount of "learnable" (if such a concept exists) components for a filter, sometimes referred to as the filter's parameters in a specific layer, is the number of parameters in that layer. After dividing the dataset into train, test, and validation data, we created a sequential CNN model for the suggested system using the keras neural network toolbox. This was done to evaluate the model's accuracy. We used a total of 17 layers in our model. We added six max pooling layers in addition to a total of seven 2d convolutional layers. Then we put two layers of dense paint, then one layer of flatten. Ultimately, we were able to accurately collect 532,484 trainable parameters for the model to use while training the photos.

Table 5.1: Table of proposed CNN model

Layer	Output Shape	Param#
conv2d_7(Conv2D)	None,242,242,32	896
conv2d_8(Conv2D)	None,240,240,64	18496
max_pooling2d_6(MaxPooling2D)	None,120,120,64)	0
conv2d_9(Conv2D)	None,118,118,64	36928
max_pooling2d_7(MaxPooling2D)	None,59,59,64	0
conv2d_10(Conv2D)	None,57,57,128	73856
max_pooling2d_8(MaxPooling2D)	None,28,28,128	0
conv2d_11(Conv2D)	None,26,26,128	147584
max_pooling2d_9(MaxPooling2D)	None,13,13,128	0
conv2d_12(Conv2D)	None,11,11,128	147584
max_pooling2d_10(MaxPooling2D)	None,5,5,128	0
conv2d_13(Conv2D)	None,3,3,64	73792
max_pooling2d_11(MaxPooling2D)	None,1,1,64	0
flatten_1(Flatten)	None,64	0
dense_5(Dense)	None,256	16640
dense_6(Dense)	None,64	16648
dense_7(Dense)	None,4	260
Total params:		532,484
Trainable params:		532,484
Non-trainable params:		0

5.6.3 Plotting the Covolutional Layer

To demonstrate the first 2D convolutional layer, we use an image from the CNV, DME, and DRUSEN classes from our dataset [43]. We can see that our model is actively looking for picture features in its first convolutional layer. As can be seen, there are certain filters that focus on the edges. Even edge detections are visible, as seen in the subplot. The model is analyzing the image's attributes and attempting to detect it. We can actually see that in some regions it is looking at roundedness and all if we go further into the convolutional layers.

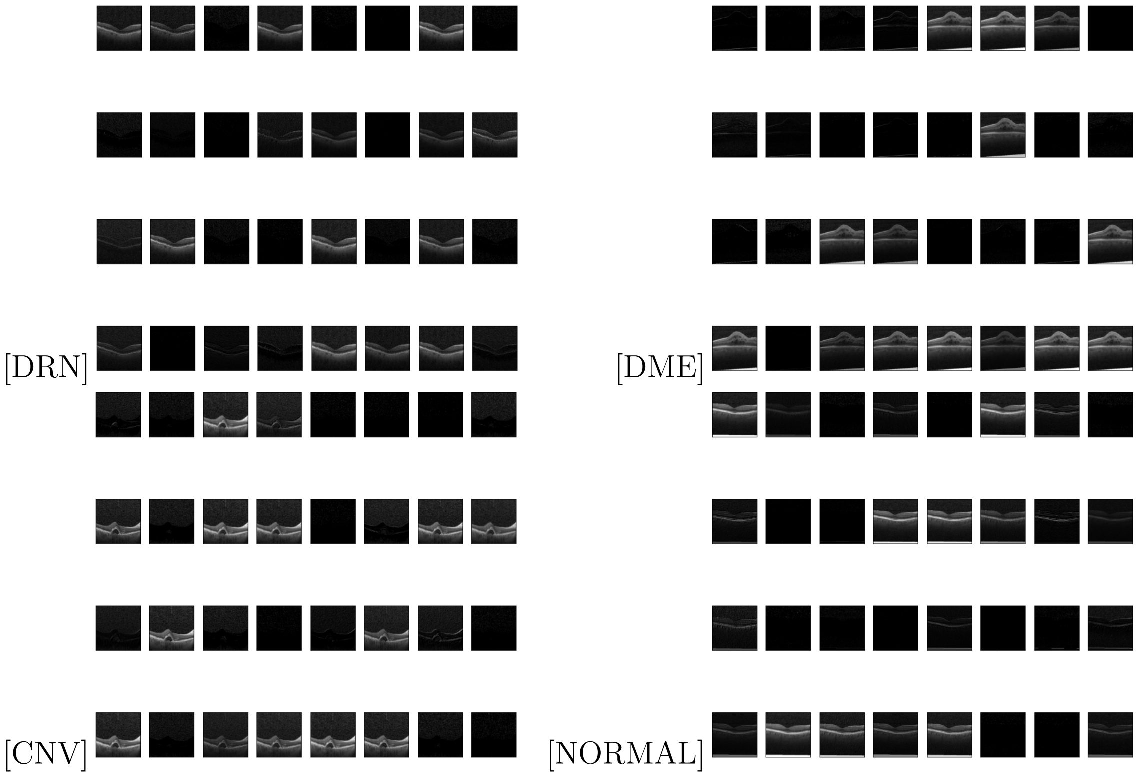

Figure 5.5: Plotting the first layer of proposed model

5.7 Pre-Trained Model of CNN

5.7.1 VGG16

It is universally acknowledged that VGG16 is one of the best vision model architectures ever created. This CNN architecture was first presented by Andrew Zisserman and Karen Simonyan at Oxford. The strategy was proposed in 2013, however it was first revealed during the 2014 ILSVRC Imagenet Large scale visual recognition. After the Oxford Visual Geometry Group, where they worked, they gave it the term VGG. Depending on depth, authors offered different network configurations. Every ImageNet Challenge configuration employs a stack of several convolutional layers (3 x 3, stride 1, padding 1), followed by a 2 x 2 maxpooling layer.To accomplish various depths, several stack combinations were cycled. The number for each configuration denotes the quantity of weight-parameter layers. Max pool layers and convolution are used consistently. concluding with a SoftMax and 2 FC. Using VGG16 16 has weighted layers. This network contains 138 million parameters.

Figure 5.6: VGG16 Architecture

5.7.2 ResNet50

ResNet50 is the name of a convolutional neural network with 50 layers. ResNet, an acronym forRemnant Networks, sometimes known as RNs, are a popular type of neural network that provides the foundation for several computer vision applications. ResNet's main idea was that it made it possible for us to train very complex neural networks with more than 150 layers. In their 2015 paper "Deep Residual Learning for Image Recognition," Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun introduced the world to this novel neural network. The "Vanishing Gradient Problem" is one of convolutional neural networks' major flaws. Backpropagation drastically lowers gradient value, thus weights hardly change at all. ResNet is employed to circumvent this limitation. It employs "SKIP CONNECTION."

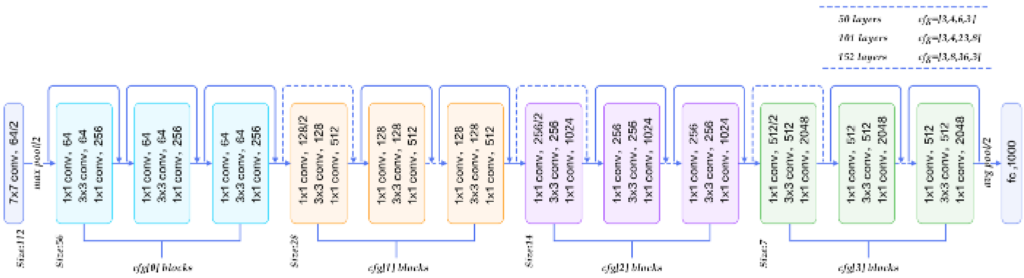

Figure 5.7: ResNet50 Architecture

5.7.3 InceptionV3

The publication of The Revised Inception for Computer Vision was held in 2015. Inception Networks (GoogLeNet/InceptionV1) surpass VGGNets (memory and other resources) in terms of both the overall number of parameters provided by the system and the associated financial cost. Photos may be organized with this program into more than a thousand distinct object groupings. The Inception-v3 model is one of the most popular choices for transfer learning. This allows us to go back and train the last layers of the current products more quickly. The ImageNet database's Inception-v3 model was trained on more than a million images, showing that it can be applied to a smaller dataset with great accuracy.Without retraining, the model may be used to a smaller dataset with good classification accuracy.5 million (V1) and 23 million (V2) are the parameter sets (V3).classifications lacking retraining. A group of layers known as the Inception Layers (11 convolutional layers,33 and 55 convolutional layers, respectively), which merge the output filters into a single output vector that generates the stage's next set of parameters.Changes to a Creation Care must be used when handling the network to prevent any operational advantages.Since the performance of the new network is so hazy, updating an Inception network for different use scenarios becomes difficult. As of now, Inception v3 presented a number of approaches to enhance the network to remove constraints and hasten model acceptance. downsampling, batch normalization, and parallel Calculation is merely one of the methods used in parametric modeling.

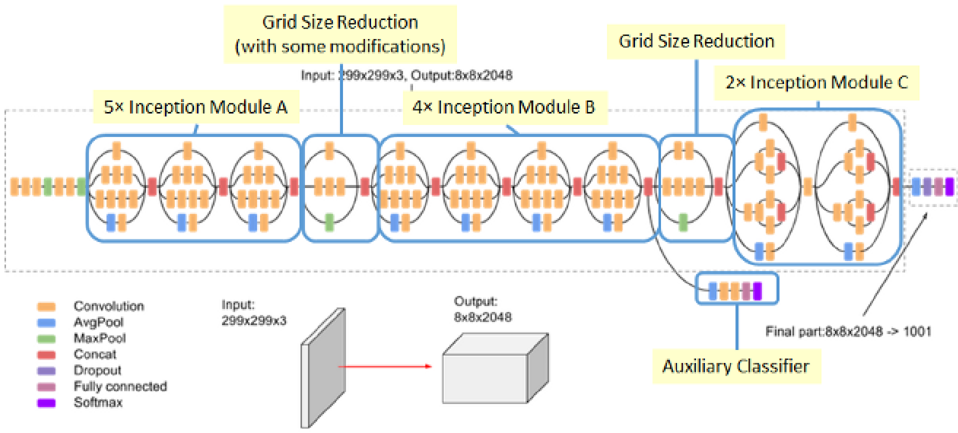

Figure 5.8: InceptionV3 Architecture

5.7.4 EfficientNetB0

EfficientNet is a convolutional neural network architecture and scaling technique It use a composite coefficient in order to scale all depth, breadth, and resolution in a consistent manner parameters.The EfficientNet model was constructed with the concept that comparable architectures may tackle both of these concerns, despite their being several distinct models that are either focused on performance or computational efficiency. They offered three parameters—the breadth, depth, and resolution—along with a common CNN skeleton design. The depth of the model is the number of layers, the resolution is the size of the input picture for the model, and the breadth of the model is the number of channels present in different layers. They asserted that one might build a competitive yet computationally effective CNN model by keeping all these parameters modest. On the other hand, one may build a heavier model that is more accuracy-focused simply by raising the value of these parameters.Squeeze and Excitation Layers were the first to include this concept into conventional CNNs, despite the fact that it had previously been suggested. SE layers provide cross-channel interactions that are independent of spatial information. By doing this, the influence of less significant channels can be lessened. In addition, they substituted Swish activation for ReLU, which had a significant role in performance improvement. In terms of a variety of compute resource availability categories, EfficientNets now perform the best.

5.7.5 Xception

The 71-layer convolutional neural network known as Xception. Included in the ImageNet database is a version of the network that has already been pretrained on a large number of photos. The pretrained network can divide a picture into one of a thousand different categories, including various animals, a keyboard,

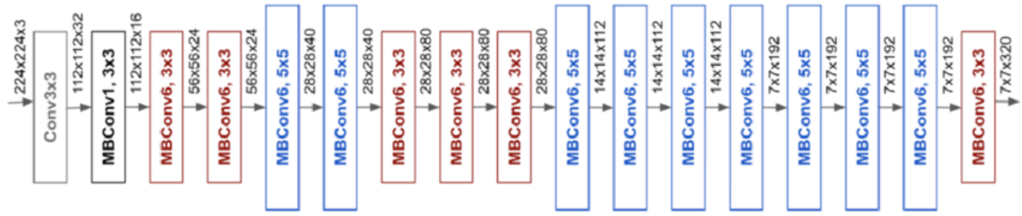

Figure 5.9: EfficientNetB0 Architecture

a mouse, and a pencil. The maximum input size for images into the network is 244x244. As an acronym for "Architecture Xception," "Extreme Inception" makes perfect sense. In Xception, a total of 36 convolutional layers provide the network's feature extraction foundation. The first progression of the data includes the entry flow, the middle flow (which is repeated eight times), and the exit flow. Batch normalization occurs after each Convolution and Separable Convolution layer, so keep that in mind (not included in the diagram). Each layer of Separable Convolution has its depth multiplier set to 1. (no depth expansion).

model = xception('Weights','imagenet') returns an Xception network trained on the ImageNet data set.

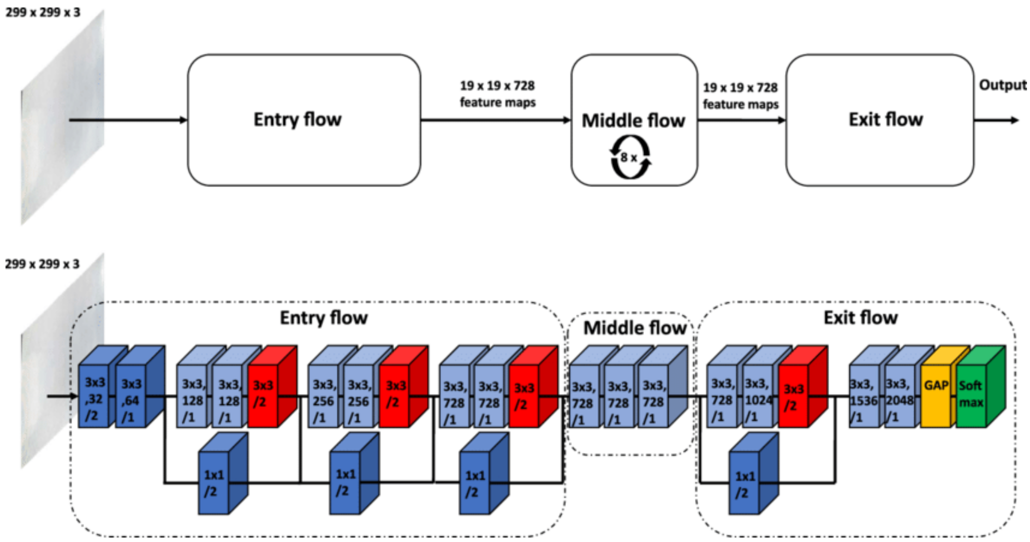

Figure 5.10: Xception CNN Architecture

Chapter 6

Performance Analysis

6.1 Performance of Proposed model

A total of 28972 images were used for our custom model . Images were divided among four categories:'CNV' 'DME', 'DRUSEN': , 'NORMAL': . The model we proposed achieved 98.97% accuracy. The table below shows the training accuracy , validation accuracy, precision, recall of our proposed model.

Training accuracy	Validation accuracy	Precision	Recall
96.85%	98.97%	98.97%	98.97%

Table 6.1: Accuracy of proposed model

The below graph shows the training accuracy and validation accuracy of our proposed model.

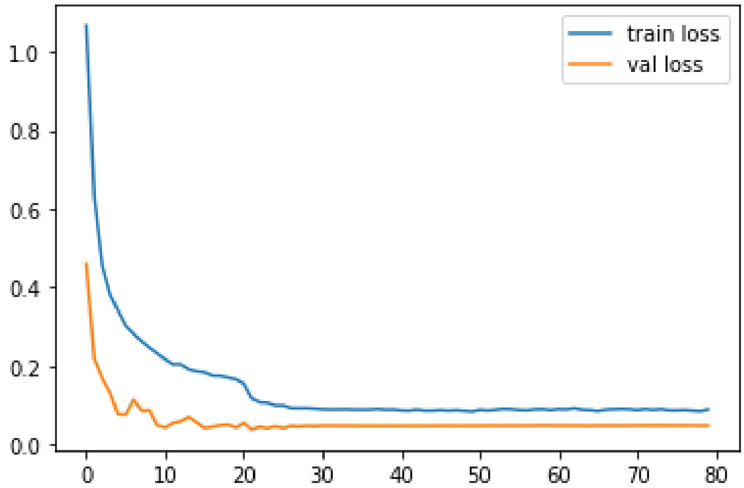

Figure 6.1: Training and Validation loss graph of proposed model

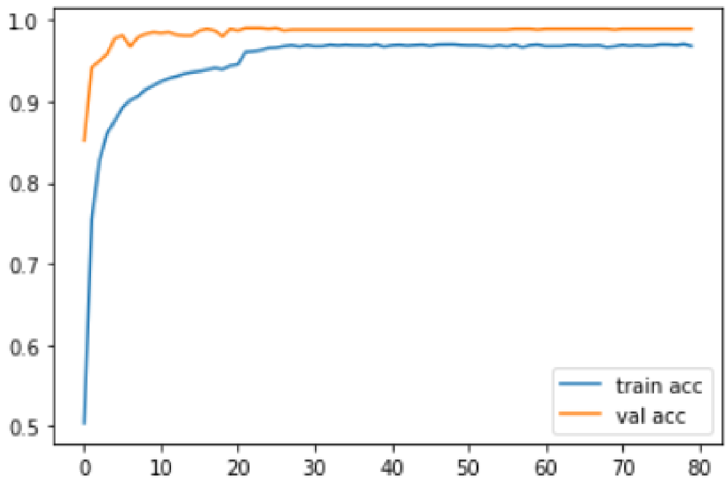

Figure 6.2: Training and Validation accuracy graph of proposed model

As mentioned earlier, our training accuracy was 96.85% and our testing accuracy was 98.97%. From the above figures we can see how fast training loss decreased with time and how fast training accuracy increased with time . For this reason our validation accuracy increases with the time .

6.2 Performance of pre -trained models

6.2.1 VGG16

94.01% accuracy were achieved by using VGG16 model . Figure 16 and 17 shows the training and validation graph of VGG16. From the graph, we can see that training loss has been decreased with the time. By that we can say regression is not occurring. By looking at figure 8.4 we can also say that training accuracy increased with the time .

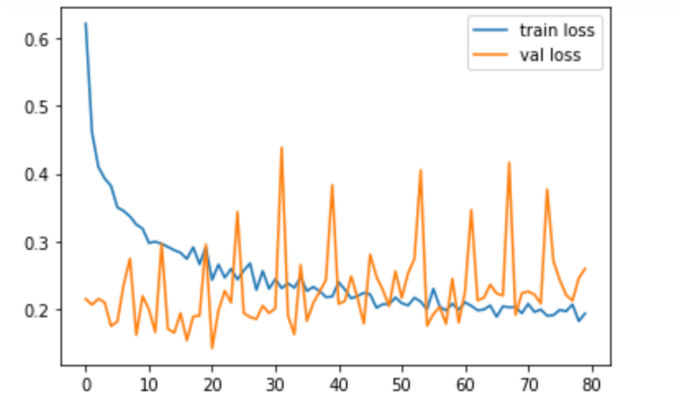

Figure 6.3: Training and Validation loss graph of VGG16 model

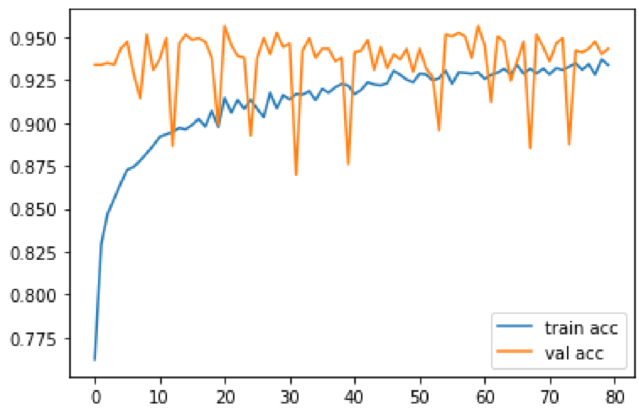

Figure 6.4: Training and Validation accuracy graph of VGG16 model

6.2.2 Resnet50

79.34% accuracy was obtained by the Resnet50 model. Figures 18 and 19 display a training graph and a validation graph, respectively..By looking at the graph we can say that training accuracy and validation accuracy increases with time .

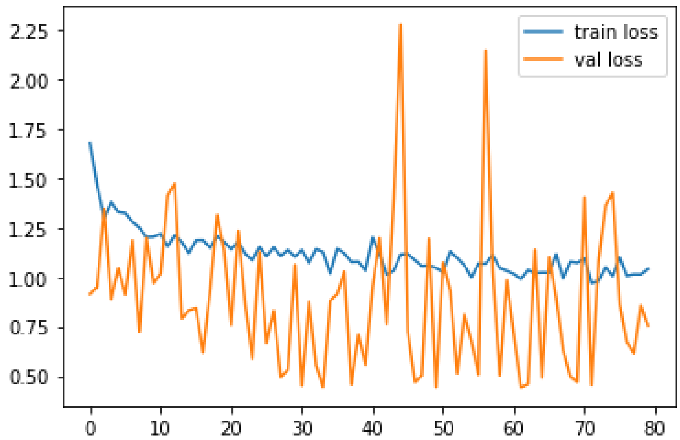

Figure 6.5: Training and Validation loss graph of Resnet50 model

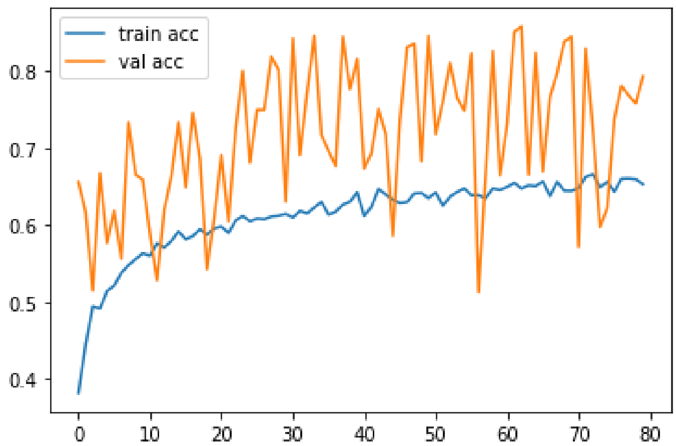

Figure 6.6: Training and Validation accuracy graph of Resnet50 model

6.2.3 Inceptionv3

91.32% accuracy was obtained by inceptionv3 . Figure 20 shows the training graph of inceptionv3 and figure 21 shows the validation graph of inceptionv3.By looking at figure 21 we can say that training accuracy increases with the time.

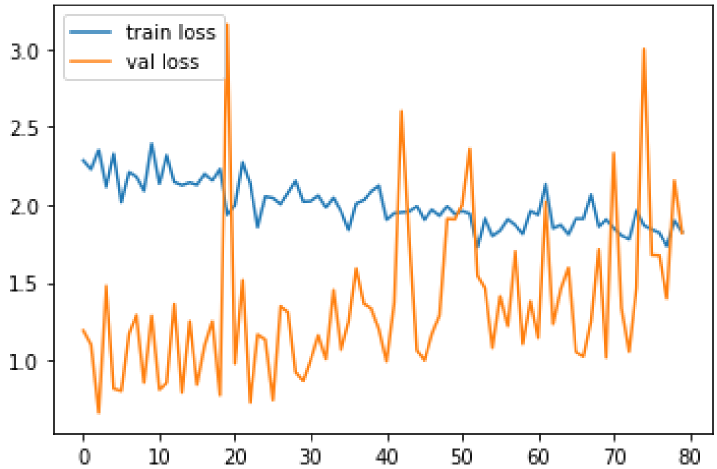

Figure 6.7: Training and Validation loss graph of inceptionv3 model

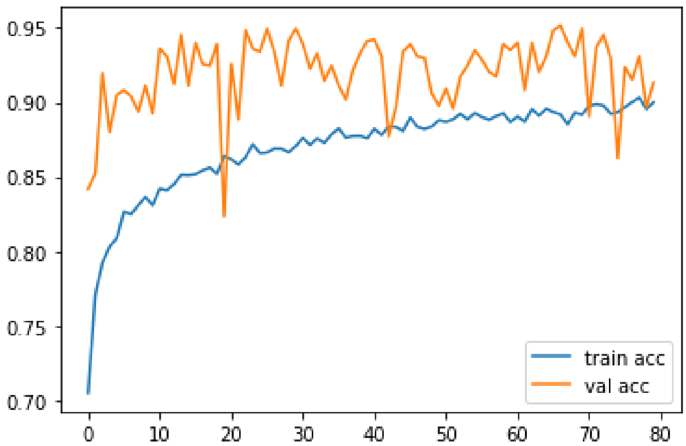

Figure 6.8: Training and Validation accuracy graph of inceptionv3 model

6.2.4 EfficientNet B0

28% accuracy was obtained by EfficientNet B0 . Which is lowest aming all pre-trained model . Figure 22 shows the training graph of EfficientNet B0 and figure 23 shows the validation graph of EfficientNet B0. From the figure 23 we can see that training accuracy slightly increases with time . Training accuracy is the lowest among all other pre- trained model.

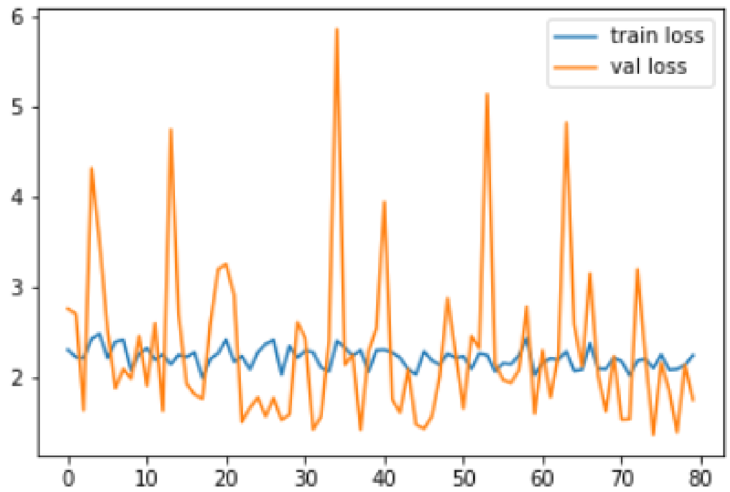

Figure 6.9: Training and Validation loss graph of EfficientNet B0 model

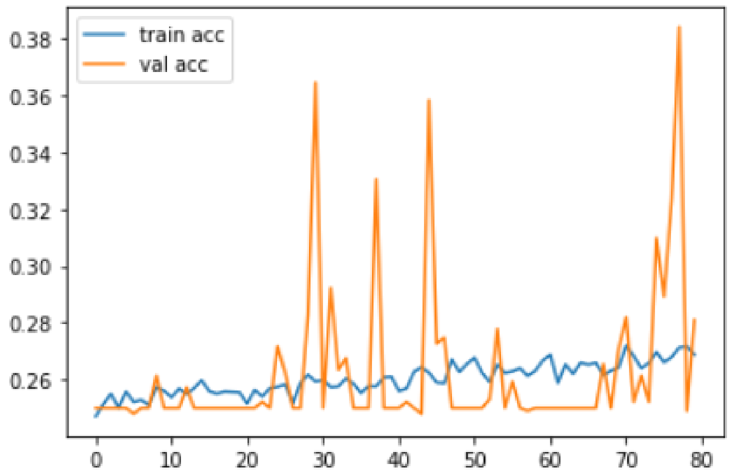

Figure 6.10: Training and Validation accuracy graph of EfficientNet B0 model

6.2.5 Xception

87.94% accuracy was obtained by Xception model. Figure 24 shows the training graph of Xception model and figure 25 shows the validation graph of Xception model. From the validation graph we can see that validation accuracy increases with the time and it almost get the same accuracy as training accuracy.

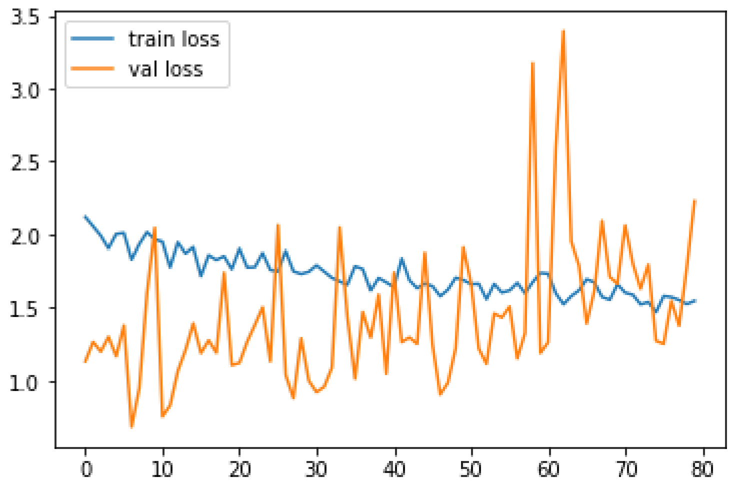

Figure 6.11: Training and Validation loss graph of Xception model

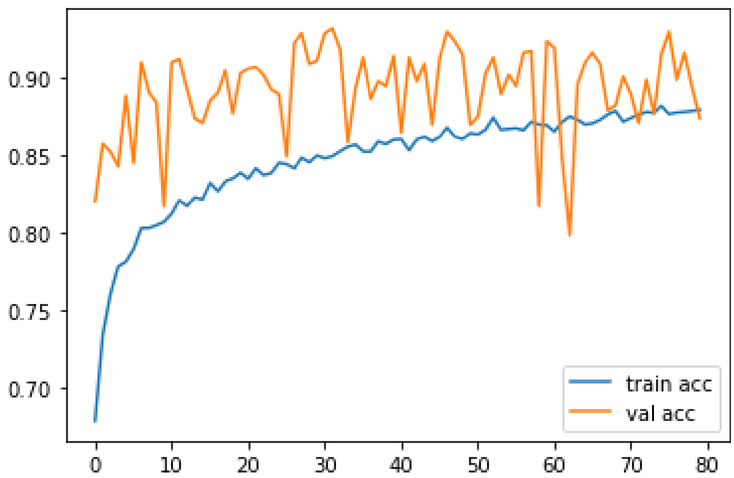

Figure 6.12: Training and Validation accuracy graph of Xception model

6.3 Compare and Analysis

In this section, we compared the performance of the proposed CNN model and five pre-trained models which are VGG16,Resnet50,Inceptionv3,EfficientNet B0, Xception .From the experimental results shown in Table 1 we can say that the performance of proposed model is greater than all the pre-trained models .Accuracy of pre-trained model and proposed model are represented by Table 8.1 .From the table we can say that propose model has the highest accuracy , Proposed model has the 98.97% accuracy.The second highest accuracy among all model and highest accuracy of pre-trained model is VGG16 which is 94.01%. Inceptionv3 has 91.32% accuracy which is third highest among all models and second highest among pre-trained models.Xception has the accuracy of 87.94% which is fourth highest among all models.Then,Resnet50 has the accuracy of 79.34% which is second lowest accuracy among all the models.And the lowest accuracy among all model is EfficientNet50. Which is only 28%.

Table 6.2: Comparison between all models

Model name	Training Accuracy	Validation Accuracy
Proposed Model	96.87%	98.97%
Resnet50	65.30%	79.34%
Inceptionv3	90%	91.32%
EfficientNet B0	26.88%	28%
Xception	87.94%	87.94%
VGG16	93.88%	94.01%

As the training accuracy of EfficientNet50 is very low comparative to all the other models. That's why it has the low accuracy.We can say that proposed model achieved better performance than all other models.Same number of dataset were used to find accuracy of the models.Proposed model obtained 98.97% accuracy where the pre-trained models which are VGG16, Resnet50, Inception v3, EfficientNet B0, Xception obtained 94.01%, 79.34%, 91.32%, 28%, 87.94% respectively.Which is lower than proposed model.The bar chart given below shows the accuracy of the models.

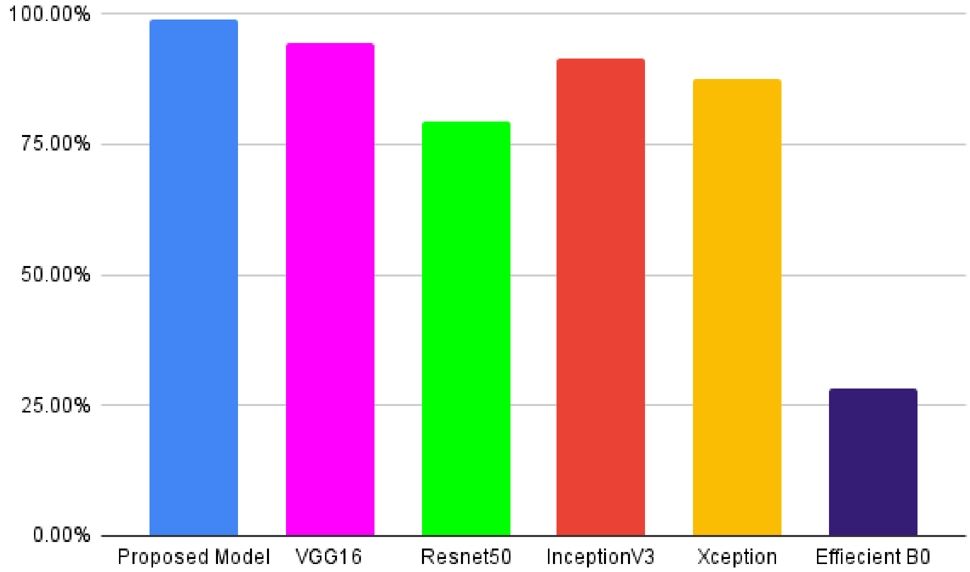

Figure 6.13: Accuracy comparison of all models

6.4 Accuracy Comparison on Related Work

We have observed some articles which are related to our work .The dataset are different but all used OCT images as dataset in the articles where We made a comparison between our proposed model and their methods .Perdomo et al. used OCT-NET method .It has been used for diagnose retinal diseases which is similar to our work . OCT-NET method achieved accuracy of 93.75%. Lee et al and Rajagopalan et al. both used CNN model for retinal disease detection .They achieved 93.45% and 95.70% respectively. On the other hand , Awais et al used ConvNet which is also know as feedforward neural network method . And that method achieved accuracy of 87.50%.Our proposed model achieved accuracy of 98.97%. By comparing to all other models we can say that our proposed model has achieved the maximum level of accuracy than all the other models. A comparison table between all the method used to related work is given below.

Table 6.3: Accuracy Comparison

Approaches	Methods	Accuracy
This Paper	CNN	98.97%
Awais et al.[10]	ConvNet	87.50%
Lee et al.[11]	CNN	93.45%
Perdomo et al.[12]	OCT-NET	93.75%
Rajagopalan et al.[13]	CNN	95.70%

Chapter 7

Conclusion

Eyes are an important part of our body . Retina is the most important part of our eyes .But retinal diseases are increasing day by day due to various diseases like Age related macular degeneration (AMD), diabetes, cataract and glaucoma: . Our goal is to develop retinal diseases detection using image processing with the help of machine learning algorithms like CNN .Many techniques called RESNET50, NFL, RIICT, DICT, OCT have been used to detect retinal diseases. We have also trained a CNN model. Which performed with 98.97% accuracy to detect the retinal diseases. With our model we hope we will be able to provide a better solution to detect retinal diseases. We are looking forward to working with our model. So that it can perform with more accuracy. We will train our model with various kinds of dataset to increase the accuracy of our model. It is going to be a challenge but we hope to have a solution to it . By making this model our goal is to reduce the number of retinal disease's patient.

7.1 Future Work

Our main motive is to increase the quality of technology in the sector of health worldwide.Moreover, we structured a custom model which shows sufficient rate of accuracy in detecting retinal diseases.Also, in this modern world with developed technology database are upgrading with a lot of data worldwide. Which will be increasing day by day and the accuracy will keep increasing.However, with our model we can detect faster with high accuracy which will save time and also bring an revolutionary change in the medical sectors.

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