AUTOMATIC RETINA DISORDER DETECTION USING OCT IMAGES

Enrol No(s)	16104013,16103243,16103193
Name of Student(s)	Ajay Kushwaha, Neelu Gupta, Somil Rastogi
Name of Supervisor	Pawan Kumar Upadhyay

Submitted in partial fulfilment of the Degree of

Bachelor of Technology

in

Computer Science Engineering

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING & INFORMATION TECHNOLOGY

JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY, NOIDA

(I)

TABLE OF CONTENT

(II)

DECLARATION

I/We hereby declare that this submission is my/our own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Place: Jaypee Institute of Information Technology, Noida

Date: 21st May 2020

Ajay Kushwaha , Neelu Gupta, Somil Rastogi

(16104013, 16103243,16103193)

(III)

CERTIFICATE

This is to certify that the work titled "**Automatic Retina Disorder Detection Using OCT Images**" submitted by "**Ajay Kushwaha, Neelu Gupta, Somil Rastogi**" in partial fulfillment for the award of degree of B.Tech of Jaypee Institute of Information Technology, Noida has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Name of Supervisor	Pawan Kumar Upadhyay
Date	21st May 2020

(IV)

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our evaluation committee for providing a just and fair evaluation to our efforts and understanding the core of our ideologies kept in mind while working for this project. We would especially like to thank our supervisor – Mr. Pawan Kumar Upadhyay for providing his invaluable guidance, comments and suggestions throughout the course of the project.

Date : 21st May 2020

Ajay NeelGupta. Somil

Ajay Kushwaha , Neelu Gupta, Somil Rastogi

(16104013, 16103243,16103193)

(V)

SUMMARY

This project makes use of the advancements done by OCT retinal scan to detect retinal disorders. We have proposed a multi classification model that discriminates the given input image into either DME, CNV, Drusen or Normal. We begin with processing the images using various image processing techniques followed by training the images on various CNN models like 3-layer, 5-layer and 7-layer custom models. Finally, the results are recorded and presented to give a comparative study of all the different models used.

Ajay NeelGupta Somil

Ajay Kushwaha , Neelu Gupta, Somil Rastogi

(16104013, 16103243,16103193)

Supervisor Name: Pawan Kumar Upadhyay

Date: 21st May 2020

(VI)

LIST OF FIGURES

(VII)

LIST OF SYMBOLS & ACRONYMS

1. **CNN -** Convolutional Neural Network
2. **CNV** - Choroidal neovascularization
3. **DME** - Diabetic Macular Edema
4. **AMD** - Age-related macular degeneration
5. **DL** - Deep Learning
6. **VGG** - Visual Geometry Group
7. **OCT** - Optical Coherence Tomography
8. **CAD** - Computer Aided Diagnosis

CHAPTER 1

INTRODUCTION

1.1 General Introduction

The retina is the light-sensing thin layer of tissue that is present in the back of your eye on the inside. The primary aim of the retina is to translate the light received into neural signals and send these to the brain for recognition of the visual. A healthy retina ensures that you can read, see and drive. A retinal disorder or disease damages this very important tissue, which, in turn, can affect vision to the point of blindness.

Optical coherence tomography (OCT) is a non-invasive imaging test that uses light waves to take cross-section pictures of the retina. The main difference between OCT and ultrasound imaging is that the former uses light while the latter uses sound. To obtain high-resolution images of the retina and anterior segment, OCT is used heavily by ophthalmologists. Many retina related eye diseases can be scanned using OCT images.

Currently, the main retinal disorder diagnosis technique is visual inspection of the optical coherence tomography (OCT) images by the experienced clinicians. We propose a computer-aided diagnosis (CAD) model to discriminate between Diabetic macular edema (DME), Choroidal neovascularization (CNV), , Drusen and normal macula using OCT images of patients.

1.2 Problem Statement

Any type of retinal disorder can lead to partial or complete blindness. With millions of people across India reporting CNV, DME and Drusen annually, it has become very crucial to detect these disorders on time to start their treatment as some of these can not be cured after a point of time. With the aging of the population, the number of people suffering from vision-threatening macular diseases continue to increase. “Treatment of anti-VEGF injection or vitrectomy surgery is generally most effective if carried out earlier. In the present, OCT is the best modality for the detection and treatment for decision-making of these four abnormalities in clinical practice.

Currently, trained ophthalmologists clinically examine the presence of any retinal disease like DME, CNV and Drusen. To enable remote identification of diseases and speed up the diagnostic process, automated analysis of OCT images has remained an active field of research since the early days of OCT imaging. The problem that our system is solving will be going to help a lot of clinicians to efficiently detect these damages and help the patients as it is very cost effective and reliable.

Visual checking of the OCT images by Ophthalmologists can lead to inconsistent and unreliable observations. We have developed a new intelligent system based on deep learning to automatically categorize OCT images to aid clinicians and make the process faster and more accurate. The framework has the capability to increment diagnostic efficiency, enable easier access to expert knowledge, facilitate remedial decision-making, and decrease overall healthcare costs.

1.3 Significance/Novelty of the problem

As an individual ages, the risk of suffering from vision threatening diseases increases. Treatment of these diseases is effective if carried out in the earlier phase. Hence, it is very crucial to detect these abnormalities for their timely treatment. Currently, the diagnosis of retinal diseases such as DME, CNV and Drusen respectively is based primarily on clinical examination and the subjective analysis of OCT images by trained ophthalmologists. To speed up the diagnostic process and enable remote identification of diseases, automated analysis of OCT images has remained an active field of research since the early days of OCT imaging. The problem that our automated system is solving will be going to help a lot of clinicians to efficiently detect these abnormalities and help the patients as it is very cost effective and reliable.

1.4 Brief Description of the Solution Approach

We planned to use Deep Learning algorithms to achieve our results as it outperforms other techniques when the data size is large. Convolutional Neural Networks (CNN) is a class of deep learning neural networks and has made a breakthrough in image recognition and classification. Compared to other image classification techniques, CNN uses very little pre-processing. A CNN model extracts features from images and eliminates the need for manual feature extraction. They learn feature detection through several hidden layers. Each layer increases the complexity of the learned features.

Our approach aims to compare various CNN models on the same dataset on the basis of their accuracy. Each image belongs to one of the categories from CNV, DME, Drusen and Normal. We have resized the images to 64x64. After processing the images to extract important features and testing them on various models, we have plot loss curve, accuracy curve and confusion matrix to compare the efficiency and reliability of each model.

1.5 Comparison of existing approaches to the problem framed

There has been done a lot of research in this domain, but there were certain shortcomings in each of them

- There are many studies that involved multiple classes, however, they mainly focused on the staging of diseases.
- Most AI studies based on OCT focused on the image segmentation, which involved complicated feature selection and extraction.
- Very limited dataset or dataset obtained from a single source.
- Not considered the diverse combination of abnormalities like we have.

CHAPTER 2

LITERATURE SURVEY

2.1 Summary of papers studied

Paper Title	Deep learning-based automated detection of retinal diseases using optical coherence tomography images
Dataset	They gathered an aggregate of 21,355 retinal OCT pictures from 2,796 grown-up patients from the Shanghai Zhongshan Hospital and the Shanghai First People's Hospital. Additionally, they likewise gathered a short clinical history of the patients like age, individual record of retinal ailment, and individual retinal issue related treatment.
Summary	This paper is centered around a 4-class grouping issue to consequently identify CNV, DME, DRUSEN, and NORMAL using OCT scans. The proposed method used an arrangement of four classification model occurrences to recognize retinal OCT pictures, every one of which depended on an improved ResNet50. The analysis followed a patient-level 10-fold cross-validation process. The used model was pre trained on ImageNet database. Also, to train the improved RestNet50 they inserted the raw data of medical history of patients into the last fully connected layer of the network. This had an improved effect on the specificity and sensitivity.
Conclusion	Accuracy achieved was 97.3% , sensitivity 0.963 and specificity 0.985. ROC curve was plotted to analyse the system performance, AUC was 0.995 They then also verified their approach on the DHU dataset and UCSD dataset.

Paper Title	Deep Learning-Based Automated Classification of Multi-Categorical Abnormalities From Optical Coherence Tomography Images
Dataset	Their dataset consisted of about 60,000 OCT scans from the Wuhan University Eye Center. After removing images with poor quality and images containing more than 2 or none of the required abnormalities were removed resulting into 25134 images. It contained images of adults, children, males and females. Infact, the dataset also included scans of people who underwent OCT in their follow ups over a range of time.
Summary	The author has implemented a deep learning-based system to classify images into one of the 4 categories- Serous macular detachment, cystoid macular edema, macular hole, and epiretinal membrane. They used the ResNet which is a 101 layer deep CNN which was pretrained on ImageNet. ResNet tackles the problem of accuracy getting saturated with increasing number of layers by shortcut connections among layers. Four Binary classifiers were trained to differentiate the abnormality from normal OCT images. In the testing phase, images go through 4 rounds of classifications and then the system selects the final categorization.
Conclusion	They achieved an accuracy of 95.9% , sensitivity of 94.2% and specificity of 96.4%. An ROC curve was plotted to evaluate the performance of the system, the AUC was 0.984. Limitations: The images were collected from only one source and small dataset used

Paper Title	Machine learning based detection of age-related macular degeneration (AMD) and diabetic macular edema (DME) from optical coherence tomography (OCT) images
Dataset	This study used the OCT images provided by Duke University, Harvard University and University of Michigan. It consists of about 3000 images from 45 patients. 15 each of AMD, DME and healthy. They used 2D horizontal cross-sectional retinal slices from the 3D macular imaging data.
Summary	The study focuses on classification of OCT images in one of the 3 categories- AMD, DME and normal macula. They used a 4 step process- image preprocessing, feature extraction, training of classification model and finally predicting the groups. They tested the data set using one representative from each classification algorithm group, i.e. the quadratic programming based algorithm sequential minimal optimization (SMO), the neural network algorithm multi-layer perceptron based on back propagation, the kernel based algorithm Support Vector Machine with polynomial kernel (SVM), the linear regression based classification algorithm Logistic Regression, the Bayesian algorithm Naïve Bayes, the tree based algorithm J48 decision tree and the ensemble forest algorithm Random Forest. They compared the performance of all the classification algorithms on the same dataset.
Conclusion	SMO- Ranked 1 on AMD (accuracy 97.8%), 2nd on DME(0.3% less than the classifier that was ranked 1) LR-Ranked 1 on DME(Accuracy 94.3%). However, since SMO performed best in Normal samples and on the overall dataset, it was proposed as the default classifier for the study.

Paper Title	Evaluation of age-related macular degeneration with optical coherence tomography
Summary	This study discusses the present comprehension of OCT scans in patients with AMD and depicts how OCT can best be applied in clinical practice. OCT images sets are commonly focused on the fovea.They precisely considered that in old patients griping of intense or subacute one-sided visual misfortune, the blend of biomicroscopic and tomographic (e.g., PED, subretinal liquid) discoveries regularly permits finding of neovascular AMD to be made with certainty. This is especially the situation with the approach of otherworldly space OCT, given that zones of central macular pathology are less inclined to be missed on raster checking of the macula.
Conclusion	They reasoned that OCT has evidently changed the evaluation of patients with AMD and other macular disorders; in any case, the maximum capacity of OCT for chorioretinal imaging stays to be figured out. Current business OCT frameworks, in view of phantom space innovation, permit thick checking of the macula with high pivotal resolution;112 similarly as with more established frameworks dependent on time area innovation, be that as it may, the transverse goals of ghostly space OCT is restricted by the optics of the eye. With the quick improvement of new advances, it shows up likely that OCT will give further bits of knowledge into the pathophysiology and treatment of AMD.

Paper Title	Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs
Dataset	The EyePACS-1 informational index comprised of 9963 pictures from 4997 patients (mean age, 54.4 years; 62.2% ladies; commonness of RDR, 683/8878 completely gradable pictures); the Messidor-2 informational index had 1748 pictures from 874 patients (mean age, 57.6 years; 42.6% ladies; predominance of RDR, 254/1745 completely gradable pictures)
Summary	To apply profound figuring out how to make a calculation for mechanized location of diabetic retinopathy and diabetic macular edema in retinal fundus photos. A particular kind of neural system advanced for picture order called a profound convolutional neural system was prepared utilizing a review improvement informational collection of 128 175 retinal pictures, which were evaluated 3 to multiple times for diabetic retinopathy, diabetic macular edema, and picture gradability by a board of 54 US authorized ophthalmologists and ophthalmology senior inhabitants among May and December 2015. The affectability and explicitness of the calculation for distinguishing referable diabetic retinopathy (RDR), characterized as moderate and more regrettable diabetic retinopathy, referable diabetic macular edema, or both, were produced dependent on the reference standard of the greater part choice of the ophthalmologist board. The calculation was assessed at 2 working focuses chose from the advancement set, one chose for high particularity and another for high affectability.
Conclusion	For identifying RDR, the calculation had a zone under the recipient working bend of 0.991 (95% CI, 0.988-0.993) for EyePACS-1 and 0.990 (95% CI, 0.986-0.995) for Messidor-2. Utilizing the primary working cut point with high particularity, for EyePACS-1, the affectability was 90.3% (95% CI, 87.5%-92.7%) and the explicitness was 98.1% (95% CI,97.8%-98.5%). For Messidor-2, the affectability was 87.0% (95% CI, 81.1%-91.0%) and the explicitness was 98.5% (95% CI, 97.7%-99.1%). Utilizing a second working point with high affectability in the advancement set, for EyePACS-1 the affectability was 97.5% and explicitness was 93.4% and for Messidor-2 the affectability was 96.1% and particularity was 93.9%.

Paper Title	Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning
Dataset	Retinal fundus pictures from 48,101 patients from the UK Biobank and 236,234 patients from EyePACS and approved these models utilizing pictures from 12,026 patients from the UK Biobank and 999 patients from EyePACS The UK Biobank populace was transcendently Caucasian, while the EyePACS patients were dominatingly Hispanic. Hemoglobin A1c (HbA1c) estimations were accessible just in 60% of the EyePACS populace
Summary	To begin with, they tried the capacity of our models to foresee an assortment of cardiovascular hazard factors from retinal fundus pictures (Tables 2 and 3). Due to the absence of a set up standard for foreseeing these highlights from retinal pictures, we utilize the normal incentive as the gauge for nonstop expectations, (for example, age). The mean total mistake (MAE) for anticipating the patient's age was 3.26 years (95% certainty span (CI):3.22 to 3.31) versus pattern (7.06; 95% CI: 6.98 to 7.13) in the UK Biobank approval dataset.The calculations likewise anticipated systolic circulatory strain (SBP), BMI and HbA1c superior to standard. To additionally describe the exhibition of the calculations, we analyzed how as often as possible the calculations' forecasts fell inside a given mistake edge and contrasted this and the benchmark exactness. Analyzed the impact that retinal eye infection, for example, diabetic retinopathy may have on the presentation of the calculations utilizing the EyePACS-2K dataset, which has diabetic retinopathy reviews that have been arbitrated by retinal experts in a procedure recently depicted. They prepared a model to foresee the beginning of major unfavorable cardiovascular occasions (MACE) inside five years. They utilized delicate consideration (Methods) to recognize the anatomical locales that the calculation may have been utilizing to make its expectations
Conclusion	To survey the measurable importance of the outcomes, we used the non-parametric bootstrap method: from the approval dataset of n patients, we tested in patients with substitution and assessed the model on this example. By rehashing this testing and assessment multiple times, we acquired a dissemination of the presentation metric, (for example, AUC) and detailed the 2.5 and 97.5 percentiles

Paper Title	Retinal Vessel Segmentation via deep learning network and fully connected conditional random fields.
Dataset	Optical cognizance tomography (OCT) pictures (Spectralis OCT, Heidelberg Engineering, Germany) were chosen from review partners of grown-up patients from the Shiley Eye Institute of the University of California San Diego. The 207,130 pictures gathered were decreased to the 108,312 OCT pictures (from 4686 patients) and utilized for preparing the AI stage.
Summary	This paper acquaints the profound learning design with improve the presentation of retinal vessel division. Profound learning design has been shown having the ground-breaking capacity in naturally learning the rich various leveled portrayals. In this paper, we figure the vessel division to a limit recognition issue, and use the completely convolutional neural systems (CNNs) to create a vessel likelihood map. a completely associated Conditional Random Fields (CRFs) is likewise utilized to join the discriminative vessel likelihood map and long-extend connections between pixels. At long last, a double vessel division result is acquired by our strategy. The first HED has five phases. Each stage incorporates various convolutional and ReLU layers, and the side-yield layers are associated with the last convolutional layer in each phase to assume the profound layer management. In the engineering, they utilize four phases to create vessel likelihood map
Conclusion	This technique acquires the best Acc score than other methods,even including the other DL strategy. The second and third side yield the preferable exhibitions over the other two layers. It may very well be seen that in the optic plate limit and neurotic district (set apart by red square shape in the third segment), there are numerous bogus positive pixels delivered by the current technique. We have built up a retinal vessel division dependent on profound learning engineering and completely associated CRFs. The discriminative highlights learned by CNNs engineering completely manage the difficult neurotic areas in fundus pictures. A great vessel likelihood map is created to get a parallel division result by utilizing completely associated CRFs division.

Paper Title	An effective retinal blood vessel segmentation method using multi-scale line detection
Dataset	Among the three eyewitnesses, the main onlooker (Obs. 1) is an ophthalmic pro, the second (Obs. 2) is a pro optometrist and the third (Obs. 3) is a prepared grader.6 Hence, we utilize the mean estimations of the estimations gave by the two authorities (Obs. 1 and Obs. 2) as the ground truth estimations while the estimations of the prepared grader (Obs. 3) are assessed for examination reason.
Summary	They proposed a compelling strategy for naturally extricating veins from shading retinal pictures. The proposed strategy depends on the way that by changing the length of an essential line locator, line finders at different scales are accomplished. To keep up the quality and wipe out the downsides of every individual line locator, the line reactions at different scales are straightly joined to deliver the last division for every retinal picture. The exhibition of the proposed strategy was assessed both quantitatively and subjectively on three freely accessible DRIVE, STARE, and REVIEW datasets. On DRIVE and STARE datasets, the proposed strategy accomplishes high neighborhood exactness (a measure to survey the precision at locales around the vessels) while holding practically identical exactness contrasted with other existing strategies. Visual investigation on the division results shows that the proposed technique produces precise division on focal reflex vessels while keeping close vessels all around isolated.
Conclusion	Estimations delivered by the proposed technique are more precise than the Ricci-line strategy. Furthermore, it ought to be noticed that the mistake of the proposed technique is even lower than the blunder of the prepared grader (Obs. 3). This has exhibited the way that the proposed strategy delivers exceptionally exact division which can be utilized for programmed vessel width estimation process. Proposed a novel retinal vein division strategy which depends on the direct blend of line finders at different scales. Trial results have demonstrated that the proposed strategy produces practically identical exactness while giving high nearby precision (78.33% for DRIVE and 76.30% for STARE, which is higher than some other techniques) on DRIVE and STARE datasets.

Paper Title	Fusing Results of Several Deep Learning Architectures for Automatic Classification of Normal and Diabetic Macular Edema in Optical Coherence Tomography
Dataset	The dataset utilized in the referenced investigation was acquired from Singapore Eye Research Institute(SERI) and Chinese University of Hong Kong(CUHK). These pictures were caught utilizing a Carl Zeiss Meditec, OCT Device. The first dataset contains 16 volumes of DME cases and 16 volumes of ordinary cases, though the second dataset contains 4 volumes of DME cases and 79 volumes of typical cases. Every volume has outputs of size 128 B and measurements of 1024 x 512 px
Summary	This paper proposes 2 methods The first method is a simple framework that uses feature extraction from different CNN models and combines them. The CNN models from which the features are extracted are VGGNet, AlexNet and GoogleNet. The features are then shortlisted using Principal Component Analysis which reduces the dimensions and then the features are used to classify the data as DME or Normal A Decision Model was structured and the consequences of different CNN models were utilized to get a solitary outcome with the assistance of the dominant party casting a ballot dependent on the majority rule. In the first proposed technique, AlexNet and VggNet have 3 Fully associated layers , and the resultant removed highlights bring about 4096 highlights for every cut from the initial 2 completely associated layers and 1000 highlights for every cut from the last completely associated layer, where as the GoogleNet has just 1 Fully Connected layer and thus it brings about 1000 highlights for every cut class and afterward the framework yields a final order
Result	After feature extraction the data was fed to different classifiers and then majority voting was performed and the accuracy of the entire model came out to be 90.63%

Paper Title	Diabetic Macular Edema Grading Based on Deep Neural Networks
Dataset	The study by these authors used a dataset known as MESSIDOR in this research for training and evaluation. It consists of 1200 images classified as either normal or DME.
Summary	In the proposed technique there are 3 obstructs, the main square comprises of 2 (5x5) convolution layers with 32 channels, 1 (5x5) with 64 channels and 2 (3x3) convolution layers with 64 channels and 3 (3x3) convolution layers with 128 channels. The subsequent square comprised 3 (3x3) convolution layers with 256 channels, while the third square comprised 2 (3x3) convolution layers with 512 channels.
Result	The model was evaluated on 357 images where the model was able to achieve an accuracy of 88.8%, 74.7% sensitivity and 96.5% specificity.

Paper Title	CNN-Based Algorithm for Drusen Identification
Dataset	The images were obtained from a local ophthalmic center and the images were completely raw and had a lot of noises. Drusen can be easily detected with monochromatic red free images, so the data was altered, firstly the red channel from all the RGB images were deleted and then it was converted into a black and white image.
Summary	The proposed method consisted of 4 steps which were - Selection, Noise Removal, Histogram Normalization and Segmentation. It makes use of a threshold map which is made using 2 maps - mean and variance of the local neighbourhood. After that a binary image is generated using the threshold map
Result	The results of this study prove that the proposed algorithm is able to provide accurate identification of the drusen

Paper Title	Automatic macular edema identification and characterization using OCT images
Dataset	The dataset was firstly processed to find the points of interest in the images. Macular Edemas are detected using specific retinal layers. Firstly the four retinal layers are identified and then they are divided into 2 sub-regions - inner and outer retina
Summary	In the first proposed method, AlexNet and VggNet have 3 Fully connected layers , and the resultant extracted features result in 4096 features per slice from the first 2 fully connected layers and 1000 features per slice from the last fully connected layer, where as the GoogleNet has only 1 Fully Connected layer and hence it results in 1000 features per slice.
Result	The proposed method had a precision of 90.13%. The system was able to achieve a global measure of 91.99%. The model was finally able to get a recall of 93.93%

Paper Title	Automated Drusen Segmentation and Quantification in SD-OCT Images
Dataset	The dataset consisted of images of 6x6 mm macular area (512x128px) along with a 2 mm axial depth which were captured using Carl Zeiss Meditec's CirrusHD-OCT 4000. The images were processed for removal of noise and RNFL, RPE retinal layers were removed.
Summary	The proposed method consisted of 4 steps which were - Selection, Noise Removal, Histogram Normalization and Segmentation. In segmentation an output image is generated which has relevant information. It makes use of a threshold map which is made using 2 maps - mean and variance of the local neighbourhood. After that a binary image is generated using the threshold map
Result	Aut. Seg. - Error - 10.29 ± 8.9

Paper Title	Deep-learning based, automated segmentation of macular edema in optical coherence tomography
Dataset	The dataset consisted of 1289 OCT images. The images were resized to 432 x 432 px size. Probability distribution map was created for each pixel to classify intraretinal fluid which is indistinguishable even by medical professionals. First the threshold was taken to be 0.5 and each pixel with a probability of greater than it was considered
Summary	The CNN model utilized was a changed adaptation of the U-net engineering which comprises of 18 convolution layers. For the enactment work sigmoid was the undeniable decision because of the equivalent dissemination of information in both the classes. The model was prepared with 200,000 cycles and occasionally evaluated against the approval set (cross-approval). Preparing time was 7.25 days utilizing parallelized preparing across 8 x NVIDIA P100 GPUs
Result	To evaluate the dataset results were compared to the segmentation performed by clinical professionals. First of all the dice correlation coefficients were calculated among the 4 clinicians and then it was calculated with the model included. The average correlation among the clinicians was about 0.715 whereas with the model it was about 0.750.

Paper Title	Macular OCT Classification using a Multi-Scale Convolutional Neural Network Ensemble
Dataset	The images in this dataset were acquired using Heidelberg SD-OCT imaging systems. They were taken from Noor Eye Hospital in Tehran consisting of 50 normal, 48 Dry AMD’s and 50 DME OCT images. Images from some other sources were also included. To preprocess the data, firstly it was normalized which was followed by retinal flattening. The region of interest were identified from the flattened data
Summary	This study proposes a total of 4 CNN models having 19,16,13 and 10 layers respectively. MaxPooling layer of size 2 x 2 was common in all the models. The no. of parameters of the models were 2993, 1901, 1381 and 997 respectively. A dropout factor of 70% was considered across all first fully connected layer. The results were combined using Ave ensemble learning technique. In Ave Ensemble Learning all the models were given equal weightage.
Result	The model average about an AUC of 0.994 by utilizing the ensembled yield of all the CNN Models - CNN1, CNN2, CNN3, CNN4. The model utilizing a similar yield of the ensembled model gave a general accuracy of about 96.45%. Information driven highlights and the agent capacity of the proposed model advantage to decrease the multi-faceted nature and analyse the mistakes to get a general normal accuracy pace of 98.86% on two datasets of 148 and 45 retinal OCT volumes including dry AMD, DME, and ordinary subjects.

2.2 Integration Summary of Literature Studied

Paper	Algorithm
1	In this study, a deep learning-based system was designed to automatically identify four-category OCT images-Serous macular detachment, cystoid macular edema, macular void, and epiretinal membrane. Perhaps the most prominent benefit of this research is the attempt to tackle the multi-class OCT image classification. The ResNet was pre-trained on ImageNet. When testing the system, each OCT image passes through four-category rounds and then a final categorization is generated by the system.
2	This work researched the grouping issue of three retinal OCT pictures, for example, age-related macular degeneration (AMD), diabetic macular edema (DME), and the typical macula. The trial method has four stages, for example, OCT picture preprocessing, includes extraction and determination, fabricating the order model, and foreseeing every pathology gathering. They tried the informational index utilizing one agent from every characterization calculation gathering, for example, the quadratic programming based calculation successive insignificant advancement (SMO), the neural system calculation multi-layer perceptron dependent on the back spread, the piece based calculation Support Vector Machine with the polynomial bit (SVM), the direct relapse based arrangement calculation Logistic Regression, the Bayesian calculation Naïve Bayes, the tree-based calculation J48 choice tree and the outfit backwoods calculation Random Forest. A far-reaching relative examination was directed to assess how unique grouping calculations perform on this informational collection.
5	This investigation talked about how Image-based profound learning groups macular degeneration and diabetic retinopathy utilizing retinal optical cognizance tomography pictures and has potential for summed up applications in biomedical picture translation and clinical choice making.s. The system uses Transfer learning, which prepares a neural system with a small amount of information on traditional methodologies. Applying this way to deal with a dataset of optical soundness tomography pictures, they showed execution similar to that of human specialists in ordering age-related macular degeneration and diabetic macular edema. Utilizing the Tensorflow they adjusted an Inception V3 design pre-trained on the ImageNet dataset. In this examination, the convolutional layers were solidified and utilized as fixed component extractors. Endeavors at "calibrating" the convolutional layers by unfreezing and refreshing the pre-trained weights on the clinical pictures utilizing backpropagation would in general decline model

	execution due to overfitting. Training of layers was performed by Stochastic Gradient Descent in groups of 1,000 pictures for each progression utilizing an Adam Optimizer with a learning pace of 0.001.
9	The CNN model utilized was a changed adaptation of the U-net engineering which comprises of 18 convolution layers. For the enactment work sigmoid was the undeniable decision because of the equivalent dissemination of information in both the classes. The model was prepared with 200,000 cycles and occasionally evaluated against the approval set (cross-approval). Preparing time was 7.25 days utilizing parallelized preparing across 8 x NVIDIA P100 GPUs
15	This examination proposes a sum of 4 CNN models having 19,16,13 and 10 layers separately. Max-Pooling layer of size 2 x 2 was regular in all the models. The no. of parameters of the models was 2993, 1901, 1381, and 997 individually. A dropout factor of 70% was considered the overall first completely associated layer. The outcomes were joined utilizing ave ensemble learning method. In Ave Ensemble Learning all the models were given equivalent weightage.

CHAPTER 3

Requirement Analysis and Solution Approach

3.1 Overall Description of Project

3.1.1 Product Perspective

This product is a sub product of a larger system which can be used to classify the retinal OCT images. It can be integrated with a User Interface which can input an OCT image of a patient and can provide on the spot results without the intervention of an opthamologist.

It is a self learning system. With time, it can incorporate more images thereby increasing the accuracy.

3.1.2 Product Functions

The product is a categorical classification model that is, it classifies an image into any of the 4 categories- DME, CNV, Drusen and Normal macula. It also differentiates between various CNN models that are custom made and compares the accuracy and loss of each model. An efficient combination of various parameters and deep learning techniques are used to provide an efficient and reliable result.

3.1.3 User Characteristics

The product can either be used to aid opthamologists by providing them faster results and a reliable source of second judgement or by patients at remote locations who cannot afford the consultation fee or require a second judgement can upload the OCT image of their retina and acquire the result.

3.1.4 Constraints

- The model needs to run several epochs on a large unbiased dataset to achieve best results.
- However, as the size of the dataset increases it takes more and more time to train and test the dataset.

3.1.5 Dependencies

- Python version 3.0 or more
- Keras API
- Tensorflow as backend
- scikit learn
- matplotlib

3.2 Requirement Analysis

3.2.1 Functional Requirements

- The system takes OCT images as input.
- The system is capable of classifying that input image as either CNV, DME, Drusen or Normal.
- The system after iterating over the training and testing dataset outputs the accuracy, confusion matrix, loss and accuracy curves of various CNN models.
- To avoid the risk of overfitting, hyperparameters were chosen carefully.

3.2.2 Non Functional Requirements

- The system must be reliable, that is, it shall not fail or crash while running.
- The system shall predict the accuracy of the used models on any dataset, provided that the dataset is not biased.

- The system shall be customizable to suit the user's system's computational power."

3.2.3 Logical Database Requirements

- Dataset should be chosen from a medicinal source.
- Dataset shall not be biased i.e. it should contain enough number of images for every class.
- The number of epochs should be based on the system's computation power. It should neither be too low nor too high.

3.2.4 Dataset

The data was collected from Kaggle.com which was uploaded by Paul Mooney and is licensed by NonCommerical-ShareLike 4.0 which gives the permission to Share and Adapt. We have used this particular data set in our project, whose summary is as follows:

Total Images: 84495

Final Evaluation: 968 Images

242 Images per category

There are 84,495 OCT images (JPEG) and 4 categories (NORMAL,CNV,DME,DRUSEN).

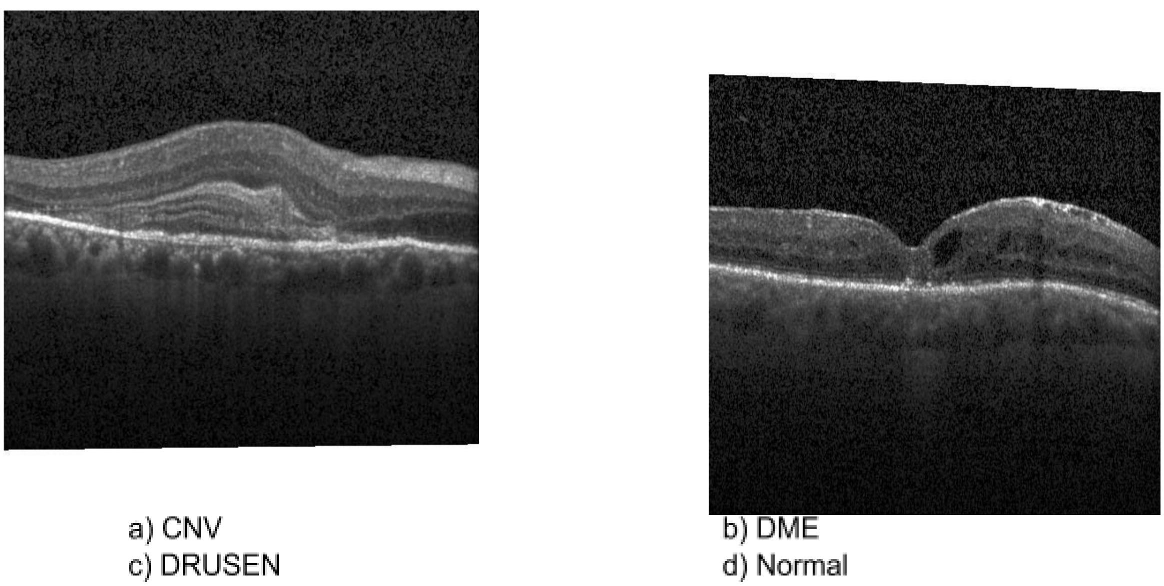
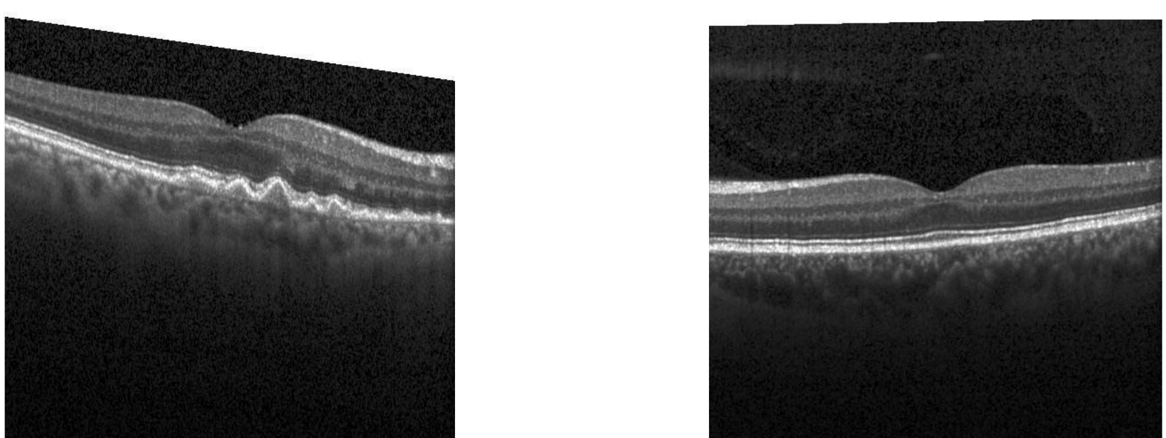


Figure 1(OCT-Images of each class of the dataset)



3.2 Infrastructure Requirements

Hardware:

- CPU: 500MHz processor
- Computer processor: Intel i5 or higher
- Ram: 8GB

Software:

- OS used: MacOS, Windows
- Language: Python
- Tool:Kaggle Kernels
- Python Libraries: numpy, matplotlib, keras, tensorflow

3.3 Solution Approach

CNN is the backbone of our project. A CNN is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms.

We have leveraged CNN models with the help of Keras API to process images to be classified into the 4 classes- DME, CNV, Drusen and normal.

We have tested our dataset in basic baseline models with 3 Layer, 5 Layer and & 7 Layer Convolutional Neural Networks. Image Rescaling has been done to reduce the size from 256X256 to 64X64 in order to ease the process and feed the images to our neural networks.

In order to make our models more robust and avoid overfitting, we have used dropout 50% in the dense layers. Dropout is a technique used to tackle overfitting. The dropout method in keras.layers module takes in a float between 0 and1, which is the fraction of the neurons to drop in that particular layer.

We have constructed a confusion matrix, plotted loss and accuracy curve for each model to analyse their outputs.

CHAPTER 4

Modelling and Implementation Details

4.1 Design Diagrams

4.1.1 Use Case Diagram

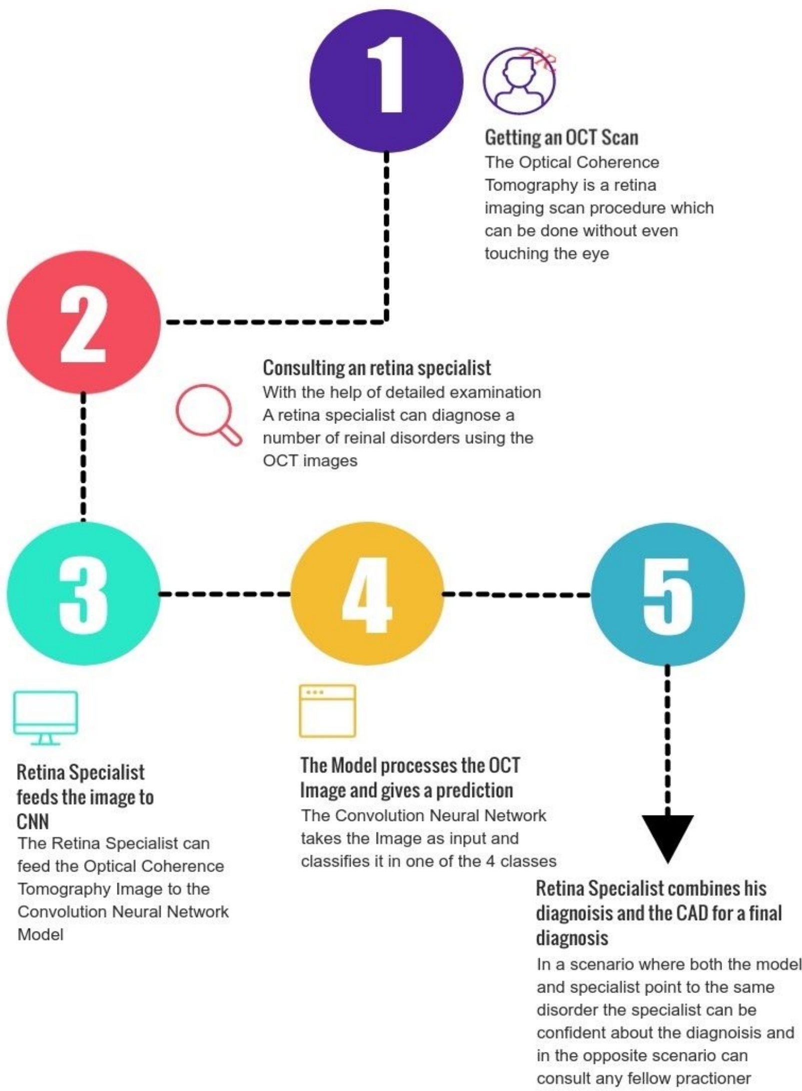


Figure 2 (Use Case Diagram)

4.1.2 Control Flow Diagrams

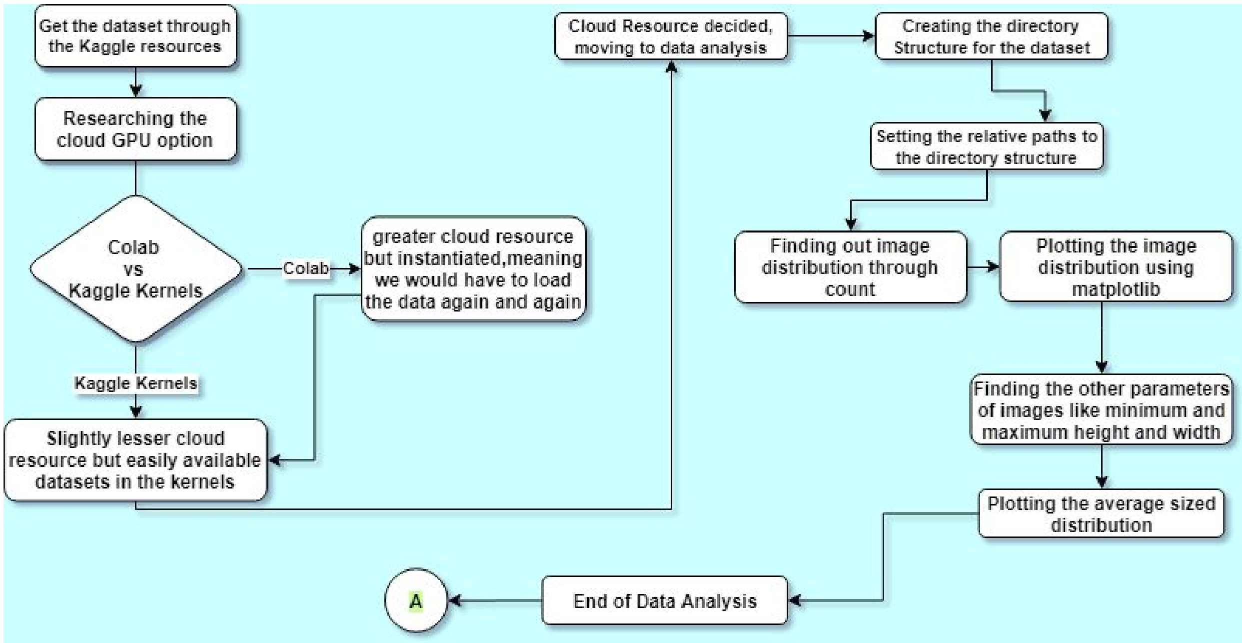


Figure 3(Data analysis)

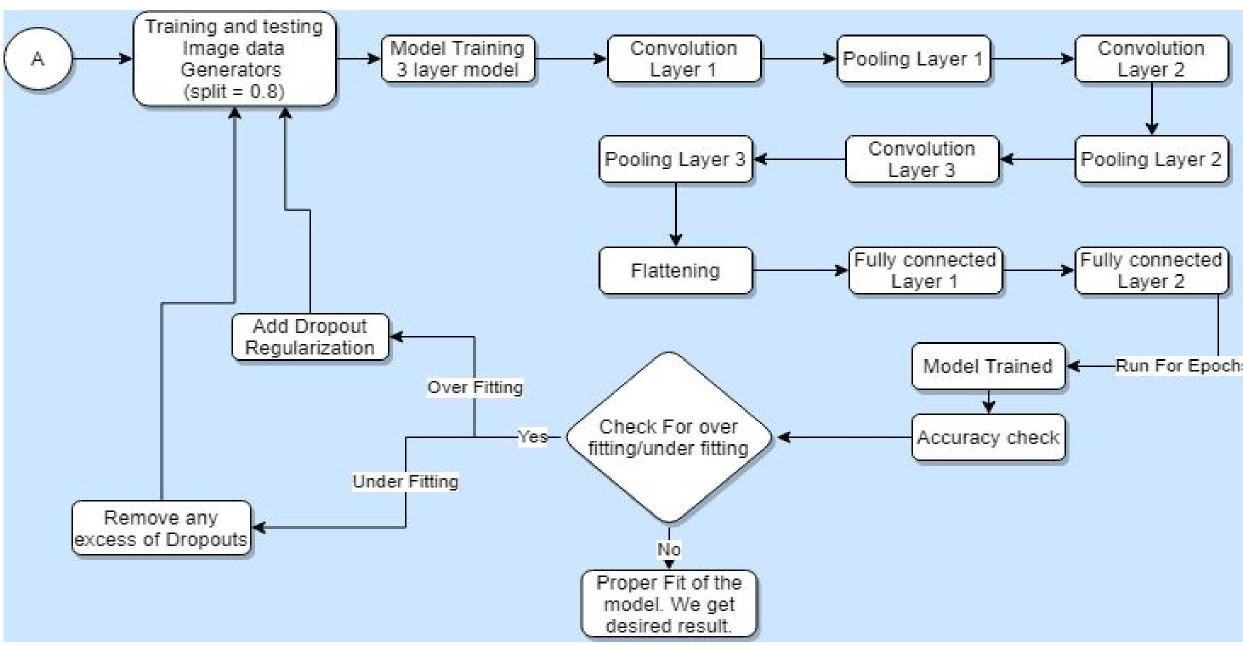


Figure 4 (3 Layer CNN)

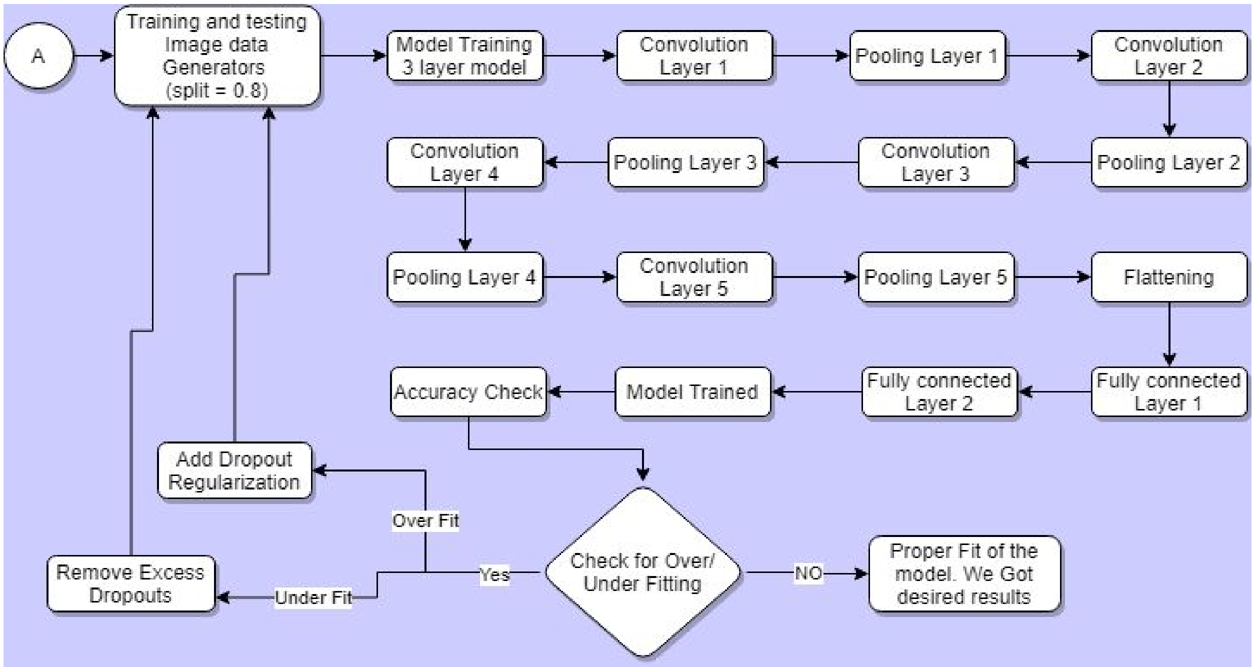


Figure 5 (5 Layer CNN)

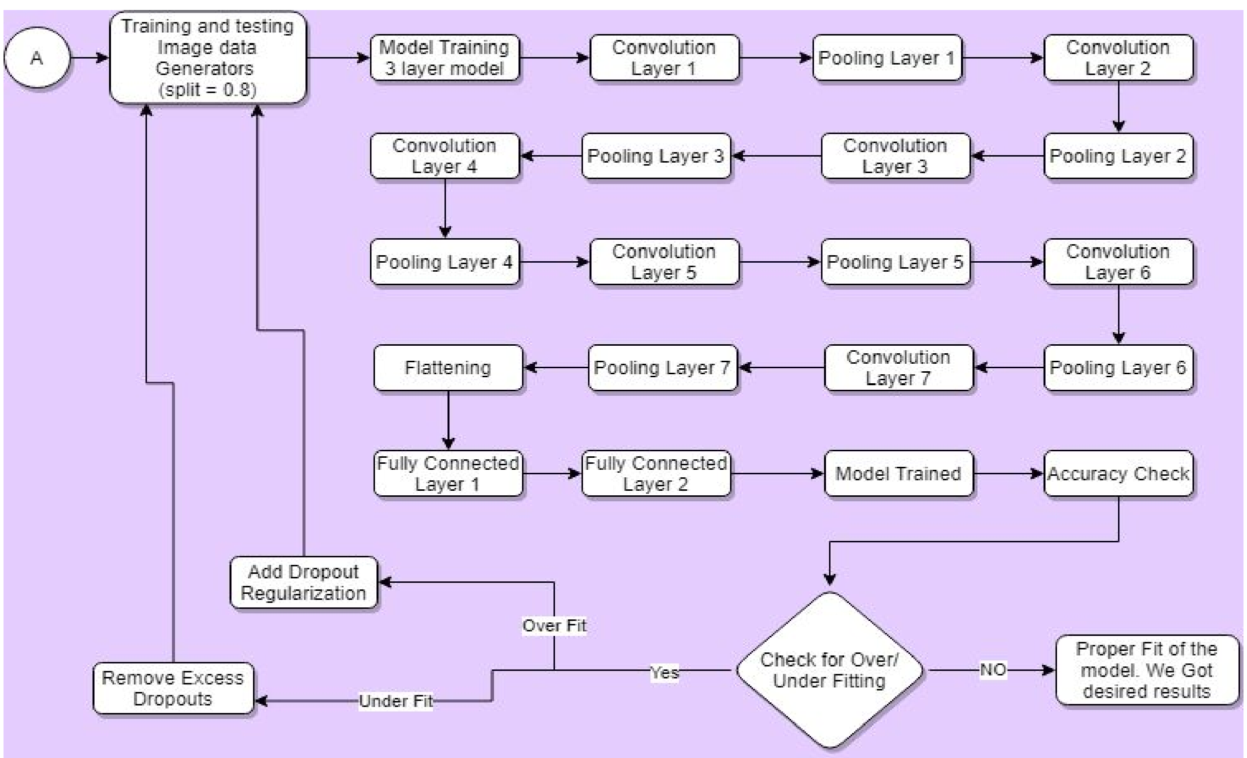


Figure 6 (7 Layer CNN)

4.2 Implementation Details

4.2.1 Data Collection

The data was collected from Kaggle.com which was uploaded by Paul Mooney and is licensed by Non Commerical-ShareLike 4.0 which gives the permission to Share and Adapt . The original dataset had 84,495 images in total belonging to 4 different classes.

The dataset used can be found on -Retinal OCT Images (Optical Coherence Tomography) hosted on Kaggle.We have used this particular data set in our project, whose summary is as follows:

Total Images: 84495

Final Evaluation: 968 Images

242 Images per category

There are 84,495 OCT images (JPEG) and 4 categories (NORMAL,CNV,DME,DRUSEN).

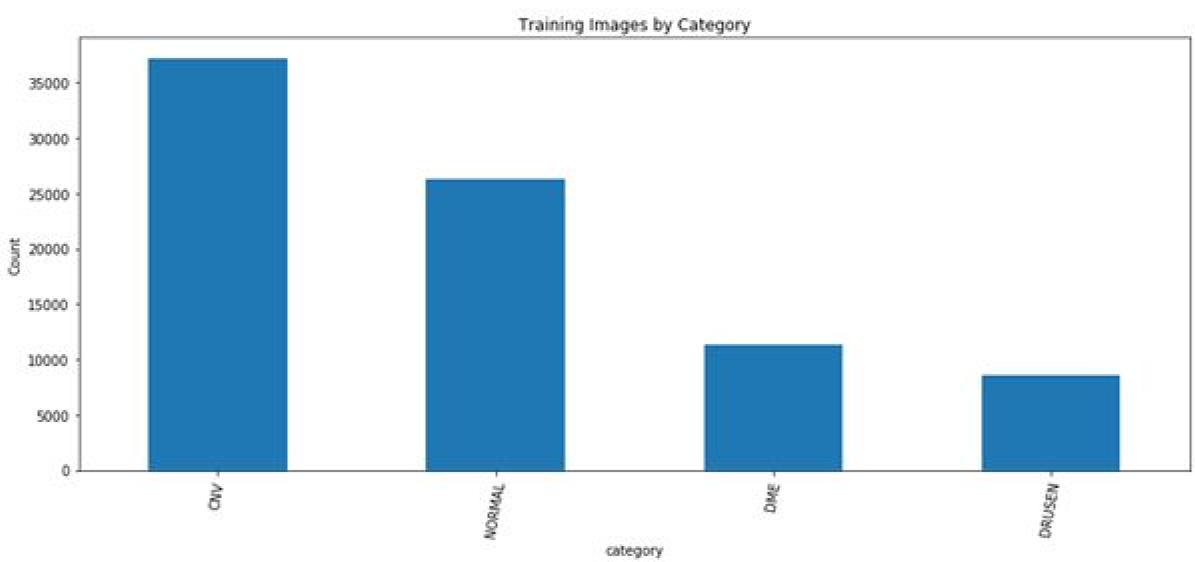


Figure 7(Training Images by Category)

4.2.2 Data Analysis

In order to draw insights and understand the dataset in better form, data visualization has been done. We have taken a few samples from each category and made their respective path directories to carry out the further process. The dataset has been divided into Training, Testing, Validation set whose distribution is as follows:

	NORMAL	DME	DRUSEN	CNV
TRAIN DATASET	26315	11348	8616	37205
TESTING DATASET	242	242	242	242
VALIDATION DATASET	8	8	8	8

A plot between Density and Pixels has been drawn to demonstrate the average height and width of images.

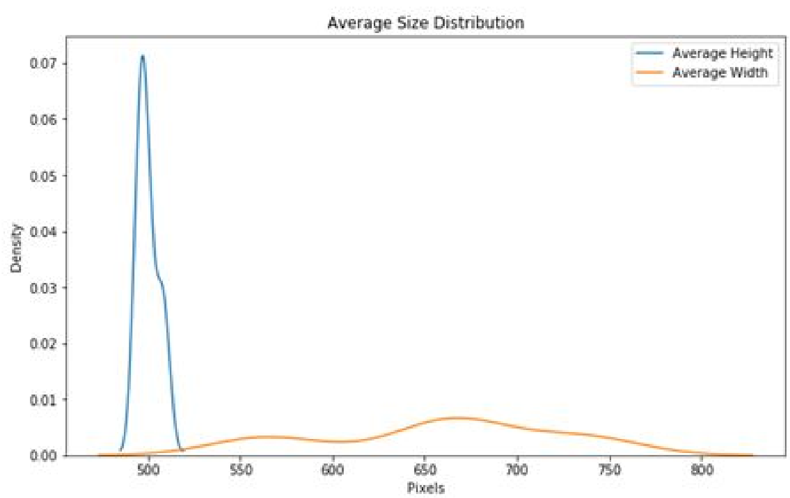


Figure 8(Density vs Pixels)

In addition to this, the variation in height and width in the form of mean, standard deviation, box plot features(Quartile) have been presented in the table below.

Out[17]:

	category	n_train	n_valid	n_test
3	CNV	37205	8	242
0	NORMAL	26315	8	242
2	DME	11348	8	242
1	DRUSEN	8616	8	242

Image Rescaling has been done to reduce the size from 256X256 to 64X64 in order to ease the process and feed the images to our neural networks.

4.2.3 Feeding the training dataset to the neural network

We trained the top layers of the Model using categorical_crossentropy as the loss function and with a learning rate of 0.001. A snapshot of a few epochs for the 5 and 7 layered model :

```
Epoch 1/30
2087/2087 [==============================] - 322s 154ms/step - loss: 0.8250 - accuracy: 0.7026 - val_loss: 0.8348 - val_accurac
y: 0.7925
Epoch 2/30
2087/2087 [==============================] - 317s 152ms/step - loss: 0.5302 - accuracy: 0.8191 - val_loss: 0.3568 - val_accurac
y: 0.8595
Epoch 3/30
2087/2087 [==============================] - 317s 152ms/step - loss: 0.4503 - accuracy: 0.8520 - val_loss: 0.9118 - val_accurac
y: 0.7190
Epoch 4/30
2087/2087 [==============================] - 317s 152ms/step - loss: 0.3939 - accuracy: 0.8736 - val_loss: 0.2688 - val_accurac
y: 0.8583
Epoch 5/30
2087/2087 [==============================] - 317s 152ms/step - loss: 0.3510 - accuracy: 0.8892 - val_loss: 0.1349 - val_accurac
y: 0.8818
Epoch 6/30
2087/2087 [==============================] - 319s 153ms/step - loss: 0.3113 - accuracy: 0.9029 - val_loss: 0.4642 - val_accurac
y: 0.8930
Epoch 7/30
2087/2087 [==============================] - 317s 152ms/step - loss: 0.1878 - accuracy: 0.9435 - val_loss: 0.1083 - val_accurac
y: 0.9060
Epoch 12/30
2087/2087 [==============================] - 314s 151ms/step - loss: 0.0957 - accuracy: 0.9707 - val_loss: 0.2588 - val_accurac
y: 0.8923
Epoch 20/30
2087/2087 [==============================] - 314s 150ms/step - loss: 0.0768 - accuracy: 0.9764 - val_loss: 0.6832 - val_accurac
y: 0.8991
Epoch 23/30
2087/2087 [==============================] - 316s 151ms/step - loss: 0.0551 - accuracy: 0.9830 - val_loss: 0.6023 - val_accurac
y: 0.9017
```

Figure 9(5 layer)

```
Epoch 1/30
2087/2087 [==============================] - 344s 165ms/step - loss: 0.6794 - accuracy: 0.7530 - val_loss: 0.2898 - val_accurac
y: 0.8129
Epoch 2/30
2087/2087 [==============================] - 343s 164ms/step - loss: 0.4342 - accuracy: 0.8520 - val_loss: 0.5908 - val_accurac
y: 0.8202
Epoch 3/30
2087/2087 [==============================] - 337s 161ms/step - loss: 0.3598 - accuracy: 0.8792 - val_loss: 0.7256 - val_accurac
y: 0.8422
Epoch 4/30
2087/2087 [==============================] - 335s 161ms/step - loss: 0.3108 - accuracy: 0.8967 - val_loss: 0.2645 - val_accurac
y: 0.8972
Epoch 5/30
2087/2087 [==============================] - 333s 159ms/step - loss: 0.2749 - accuracy: 0.9085 - val_loss: 0.5769 - val_accurac
y: 0.8822
Epoch 6/30
2087/2087 [==============================] - 336s 161ms/step - loss: 0.2386 - accuracy: 0.9214 - val_loss: 0.3961 - val_accurac
y: 0.8919
Epoch 7/30
2087/2087 [==============================] - 340s 163ms/step - loss: 0.1100 - accuracy: 0.9637 - val_loss: 0.6170 - val_accurac
y: 0.8765
Epoch 13/30
2087/2087 [==============================] - 337s 162ms/step - loss: 0.0758 - accuracy: 0.9751 - val_loss: 1.0280 - val_accurac
y: 0.8962
Epoch 17/30
2087/2087 [==============================] - 336s 161ms/step - loss: 0.0607 - accuracy: 0.9793 - val_loss: 0.6549 - val_accurac
y: 0.8946
Epoch 20/30
2087/2087 [==============================] - 337s 161ms/step - loss: 0.0599 - accuracy: 0.9804 - val_loss: 0.7440 - val_accurac
y: 0.9018
Epoch 22/30
2087/2087 [==============================] - 339s 162ms/step - loss: 0.0417 - accuracy: 0.9866 - val_loss: 1.0994 - val_accurac
y: 0.9037
Epoch 28/30
 899/2087 [===========>..................] - ETA: 2:38 - loss: 0.0400 - accuracy: 0.9862
```

Figure 10(7 layer)

4.3 Deep Learning Algorithms Used

4.3.1 Convolution Neural Networks :

Convolution Neural Networks are Artificial Neural Networks which take Images as input and process them for different applications such as Classification, Segmentation, Style Transfer etc. Convolution Neural Networks have several different types of layers such as -

Convolution Layer - The input to a CNN is a tensor which has a shape - (No. of Images) * (Image Width) * (Image Height) * (Image Depth). Each convolution layer abstracts the image to a feature map with a shape of (No. of Images) * (Feature Map Width) * (Feature Map Height) * (Feature Map Depth).

Pooling Layers - are used to streamline the computation. Pooling Layers reduce the dimensions of the image data by merging outputs of different neurons at a layer into a single output for the next layer. Max Pooling replaces the cluster of output with maximum of all the output values.

Fully Connected Layer - A fully connected layer connects every neuron from one layer to every other neuron in another layer. This layer is usually used for classifying the images, to do so The Feature Map is flattened and passed on to the fully connected layer for classification.

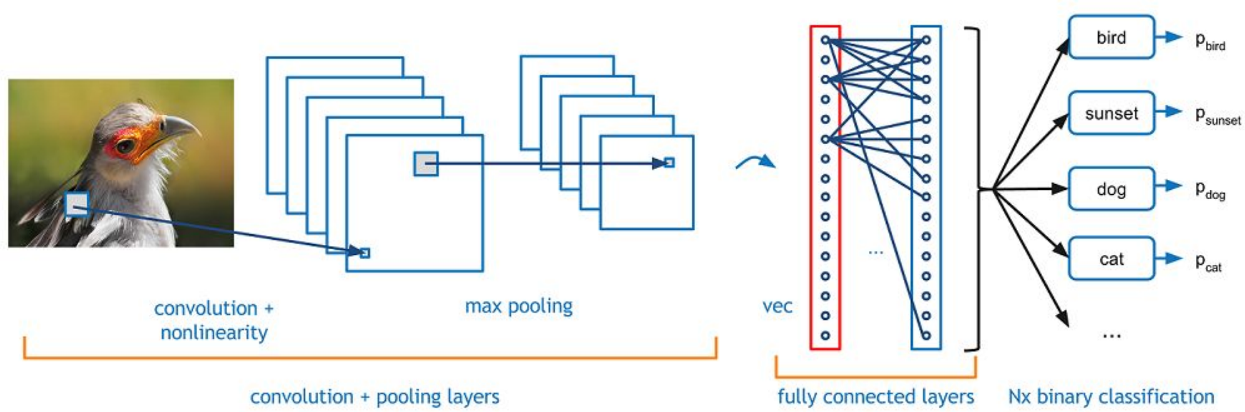


Figure 11 (CNN)

4.3.2 Models of CNN used

3 Layer Model-

This is the baseline model for our implementation. Since we are working with Deep Neural Networks and a network is called deep only if it has a number of hidden layers >= 3, we decided to work on this model as the baseline model. The model is supposed to have 3 convolutional layers, followed by max pooling after every convolutional layer, followed by flattening and dense layers. Dense layers are in itself just a simple artificial neural network to which we feed data so as to obtain our results.

After importing all the necessary libraries we define the model to be of sequential nature so that we can stack layers. Three convolutional layers with the number of filters at each layer being 256, 128 and 64, with each filter of size 3X3 and moving at a stride of 1. We also define the activation function in the convolution layer as Relu (Rectified linear unit). Then we add the pooling layers with the pooling filter size as 2X2, moving at the stride of 2, performing its core task of reducing the size of the image, before sending it to the next layer.

After the image has passed through all the pooling and convolutional layers, it goes to the flattening layer, where the image, which is essentially a two dimensional matrix gets converted to a singular one dimensional array which can be fed to the dense layers to perform our task.

With the convolutional neural network created we can start training it by giving it the basic hyper-parameters as

Image size = 256X256

Batch size = 16

Epochs = 10(starting initially)

To avoid overfitting, we added a dropout of 0.25 after every layer in the convolutional layers and a dropout of 0.5 in the final fully connected layer.

We assigned the train and test generator by assigning a train test split of 0.8, i.e out of the total dataset of 84495 images, 67596 images are kept for training purpose while 16899 images are kept for validation purpose. We then trained our model according to the specifications mentioned.

5 Layer Model-

Now since we have worked out our baseline model, we can now start to increase our Convolution layers. We increased our convolutional layers to 5 each followed by a pooling layer with the same specifications as done in the case of 3 layer model.

In this model to deal with overfitting we have also used the concept of BatchNormalization. A batch normalization has been added after every convolutional layer. The filter size is 3X3 with the number of filters in the consecutive layers being 256,256,128,64,32. After that the pooling filters with size 2X2 and a stride a 2 are kept so as to reduce our images and maintain the necessary features. Since the model can over fit we are already adding a dropout of 0.4 after every layer in the convolution layers and adding a dropout of 0.5 in the fully connected region.

After creating the network to train it we would do the same train test split of 0.8 as done previously but in this case we are also considering the factor of balancing the unbalanced data.
Image size = 256X256

Batch size = 16

Epochs = 10

After complete training of the model when applied upon the test dataset the model gave a very good accuracy but we sensed that the model is underfit.

We optimized a hyper parameter, which is image size from 256x256 to 64x64.

We removed the dropouts after every convolution layer and added it only after the fully connected layer with the dropout rate as 0.5. Then we trained the model with the following new parameters :

Image size = 64X64

Batch size = 32

Epochs = 30

Final accuracy of our 5 layered model was better than the 3 layered model.

Moreover, it seems that model accuracy seems to be rising with increasing depth of the neural network. So we should really increase our model layers to seven to ascertain this assumption of ours.

7 Layer Model-

We created our network as sequential and added the 7 convolutional layers with the filter size of 3X3 with the stride of 1 and the number of filters as 256,256,128,64,64,32,32. This is followed by maxpooling layers of pooling filters of size 2X2 and stride of 2 so as to reduce our image dimensions.

The parameters used in the training process were-

Image size = 256X256

Batch size = 16

Epochs = 10

We analysed that this model was also underfitted, so we removed the excess of dropouts added after every convolutional layer and let the dropout active on the fully connected layer.

So the new parameters are:

Image size = 64X64

Batch size = 32

Epochs = 30

Upon successful completion of training and testing we do find out that the model performance has increased from 94.79% to 96.45%, indicating that previously the model was indeed not properly fit.

Upon comparison with the 5 layer model we see that the accuracy in 7 layer model is actually lesser than the 5 layer model, so our assumption that the model accuracy increases with increase in depth proved to be at fault.

CHAPTER 5

Testing

5.1 Testing Plan

Type of Test	Will Test be Performed?	Comments/Explanation	Software Component
Requirement	Yes	We have covered all the stages such as defining test completion criteria, design and execute test cases, and verifying test results	Kaggle Kernel
Unit	Yes	We have made different modules for different tasks therefore it is easy for one to review and make required changes in the modules.	Operating Procedures
Integration	Yes	We have verified the functional and performance and reliability between the modules that are integrated.	Individual Software modules
Performance	Yes	We tested all the classifiers on the test data.	Confusion Matrix, Accuracy curve and Loss Curve
Volume	Yes	Amount of data to be handled and processed.	Dataset, divided into training and testing
Security	Yes	We need to train the model with updated data with time and make sure integrity of data is not lost.	

5.2 Component Decomposition and type of testing required

TestID	List of various Components	Type of Testing	Technique
1	Dataset Integrity	System Testing	Black Box – Only the developer updates and trains the model with new dataset.
2	Layer parameters	Unit Testing	White Box – User lands in different stages of machine learning.
3	Testing on unseen data	Performance Testing	Black Box – As the data is new to the model, therefore we use various evaluation matrices to check the performance of it

5.3 Limitations of Solution

The major limitation of the project is the efficient use of resources. As we were limited in GPU resources and Convolutional Deep Neural Networks require extensive training, taking up a good chunk of GPU resource. As we know that deep learning models tend to perform better with extensive training the major limitation of our project is to increase the number of epochs on our original image size of 256×256 we had to resize our image to 64×64. The effect of resizing images is handled well by CNN but there is no denying the fact that when we resize the image, some amount of image features are lost. Had we had better resources we would have trained our model with our original image size of 256×256 retaining our original features and maybe achieving a better accuracy.

CHAPTER 6

Findings, Conclusion, and Future Work

6.1 Finding

On training 3 different models on the same dataset we find that the 5 layered model is very powerful for classifying GrayScale OCT Images.

A very significant finding was that increasing the number of layers in the model does not necessarily improve the accuracy. Upon comparison with the 5 layer model we see that the accuracy in the 7 layer model is actually lesser than the 5 layer model, so our assumption that the model accuracy increases with increase in depth proved to be at fault. A possible logical explanation to this can be that we might not have selected the right set of parameters for the 7 layer model, in contrast, we might have stuck on the jackpot in the case with the 5 layered model. As evident, data science and specially deep learning is all about finding the right amount of parameters so as to maximize the performance of our model, and that actually comes from repeated hit and trial and data analysis through experience.

6.1.2 Confusion Matrix, Accuracy and Loss Curves

3 Layer Model

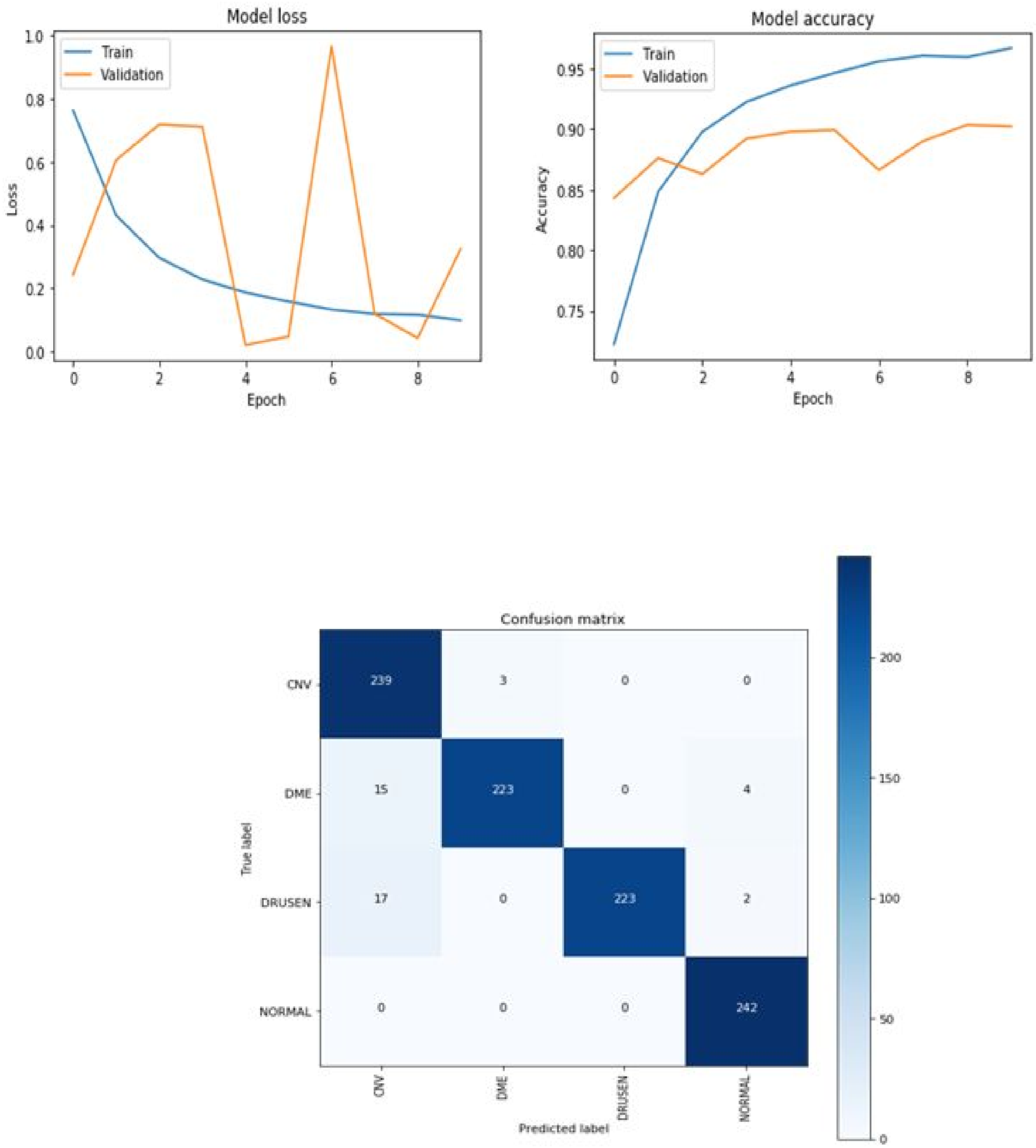


Figure 12(3-Layer Model: Loss Curve, Accuracy Curve and Confusion Matrix)

5 Layer Model

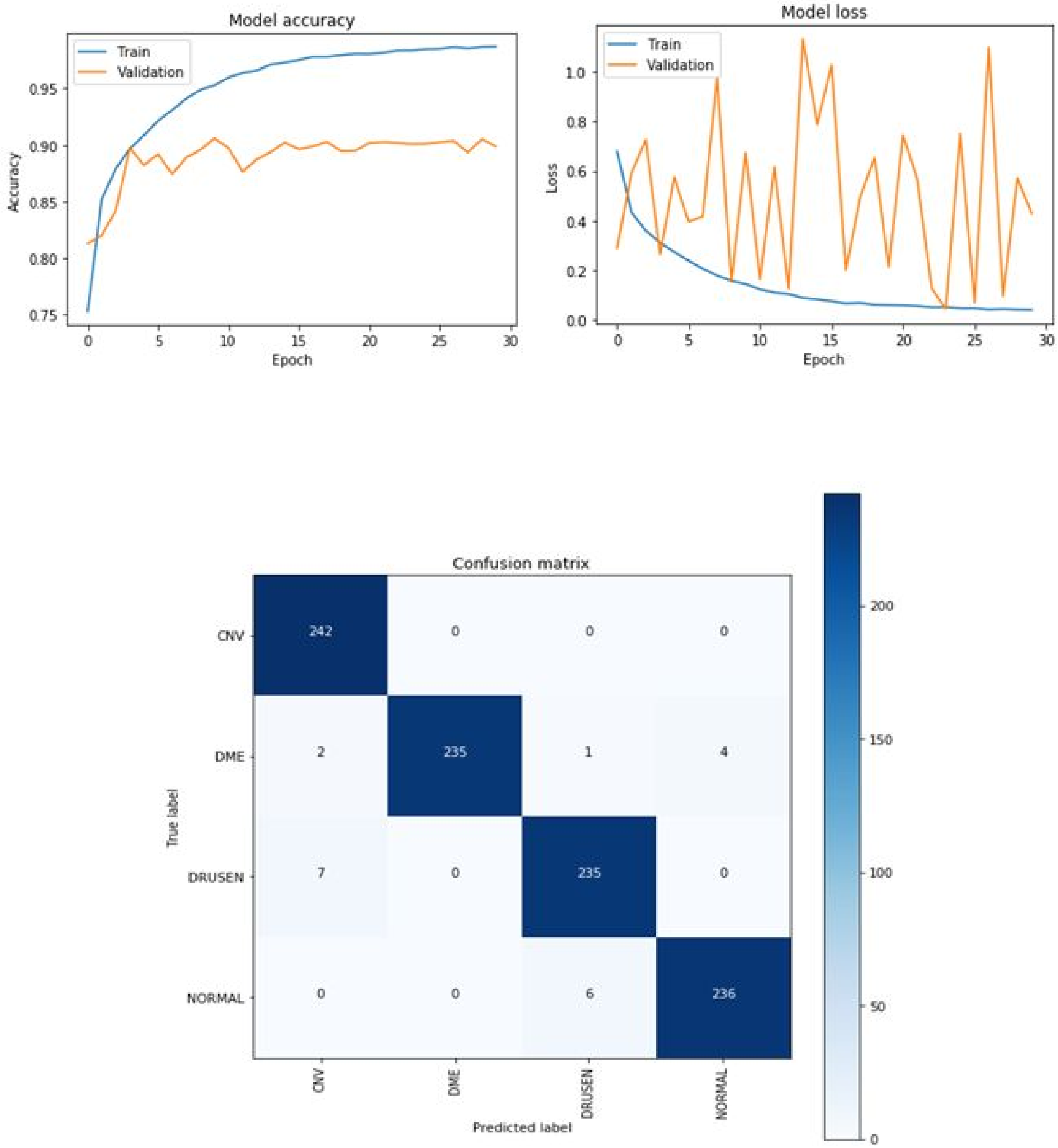
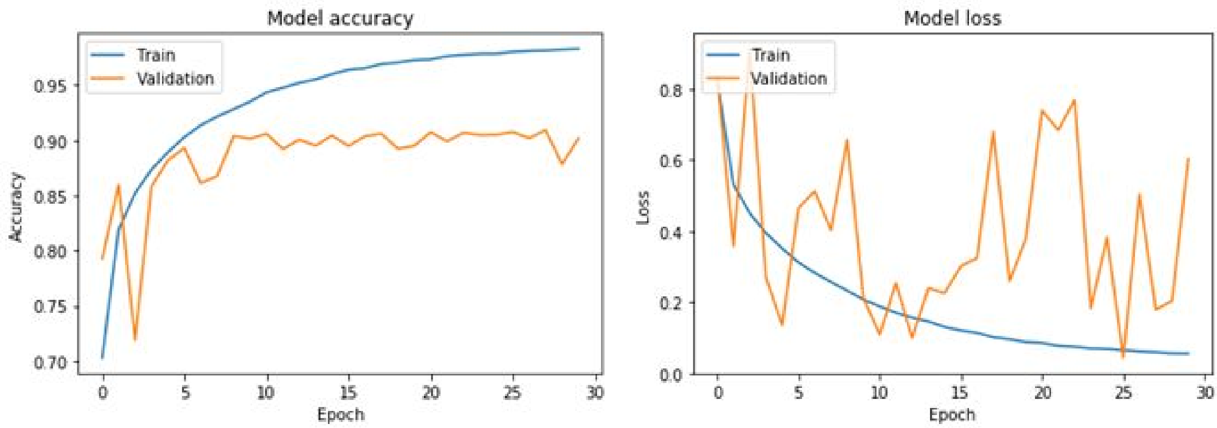


Figure 13(5-Layer Model: Loss Curve, Accuracy Curve and Confusion Matrix)

7 Layer Model



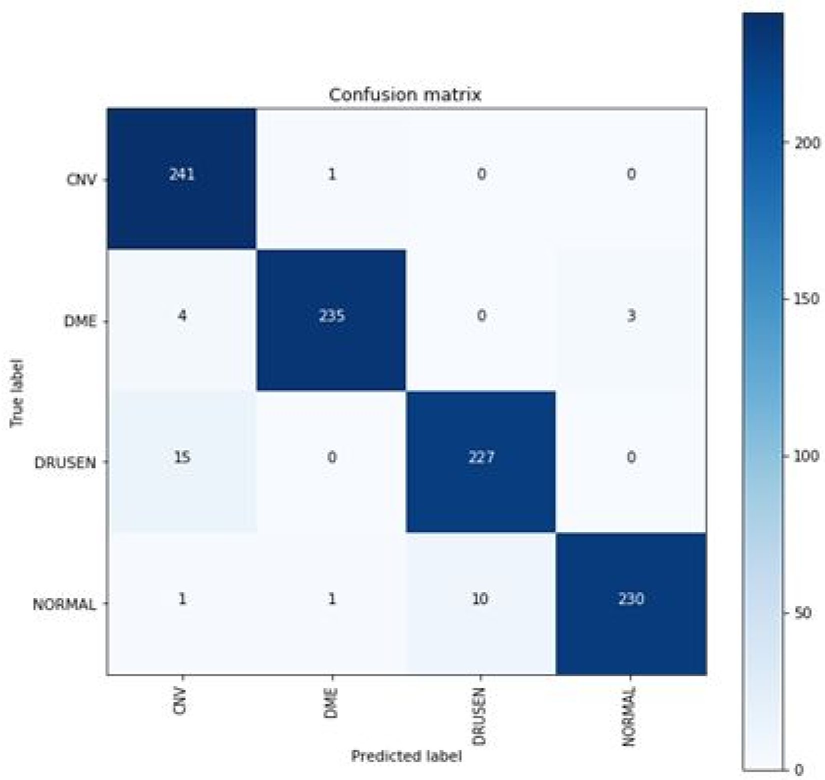


Figure 14(7-Layer Model: Loss Curve, Accuracy Curve and Confusion Matrix)

6.2 Conclusion

A table depicting the comparative performance of all the models .

Model Specification	Image Size	Epochs	Model Loss(Testing)	Model Accuracy(Testing)
Baseline model(3 layers)	256X256	10	0.03542	0.95833
5 layer model	256X256	10	0.03535	0.97500
5 layer model	64X64	30	0.00173	0.97916
7 layer model	256X256	10	0.02414	0.94791
7 layer model	64X64	30	0.12601	0.96458

6.3 Future Work

We have only used the manually constructed models of 3, 5 and 7 layers and not increased the layers. For the future we can use the technique of transfer learning, which is the idea of overcoming the isolated learning paradigm and utilizing knowledge acquired for one task to solve related ones.

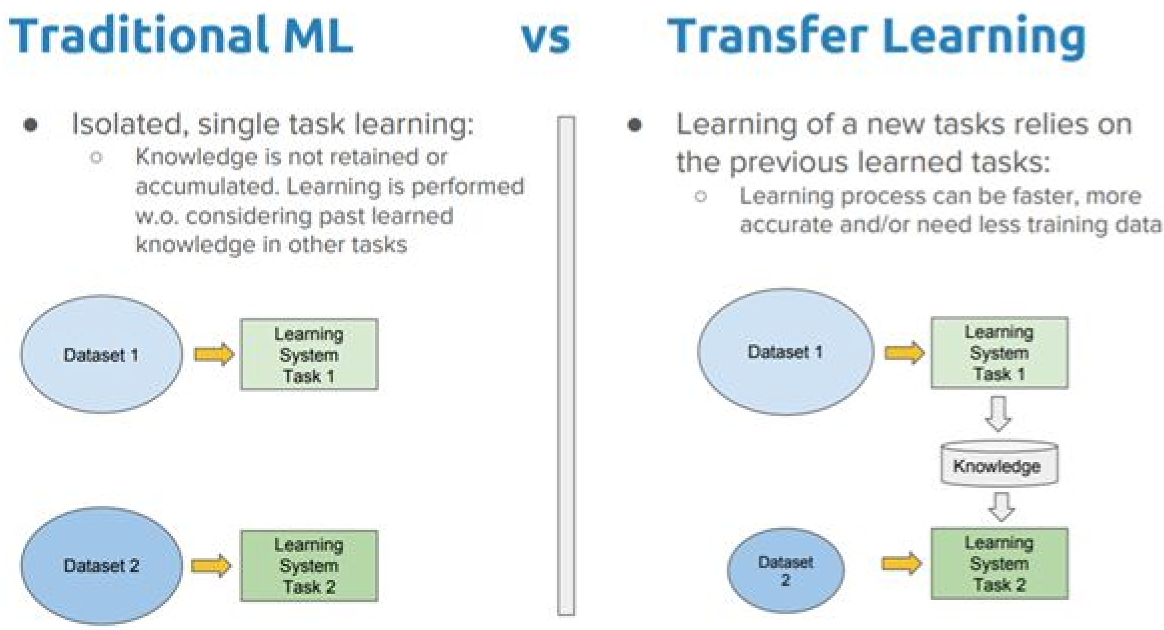


Figure 15(Traditional ML vs Transfer Learning)

There are various models which are pretrained on large datasets such as the Imagenet, the pretrained models include VGG16, Resnet, MobileNet, Inception v3, etc. These models are actually very deep models with number of hidden layers ranging between 16 to even greater than 100. These models are actually very compute intensive and require sufficiently larger datasets and a long amount of time to train from scratch. Transfer learning makes the job easier by utilising the pre-trained weights generated during the model learning, and only allowing us to train the lower layers of our neural network, thus reducing time, and also utilising the well optimised weights of the complete network.

REFERENCES

1. Al-Bander, Baidaa, et al. "Diabetic Macular Edema Grading Based on Deep Neural Networks." *Proceedings of the Ophthalmic Medical Image Analysis Third International Workshop*, Nov. 2016, doi:10.17077/omia.1055.
2. Awais, Muhammad, et al. "Classification of SD-OCT Images Using a Deep Learning Approach." *2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, 2017, doi:10.1109/icsipa.2017.8120661.
3. Chan, Genevieve C. Y., et al. "Transfer Learning for Diabetic Macular Edema (DME) Detection on Optical Coherence Tomography (OCT) Images." *2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, 2017, doi:10.1109/icsipa.2017.8120662.
4. Chan, Genevieve C. Y., et al. "Fusing Results of Several Deep Learning Architectures for Automatic Classification of Normal and Diabetic Macular Edema in Optical Coherence Tomography." *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, doi:10.1109/embc.2018.8512371.
5. Checco, P., and F. Corinto. "CNN-Based Algorithm for Drusen Identification." *2006 IEEE International Symposium on Circuits and Systems*, doi:10.1109/iscas.2006.1693051.
6. Chen, Qiang, et al. "Automated Drusen Segmentation and Quantification in SD-OCT Images." *Medical Image Analysis*, vol. 17, no. 8, 2013, pp. 1058–1072., doi:10.1016/j.media.2013.06.003.
7. Fang, Leyuan, et al. "Automatic Segmentation of Nine Retinal Layer Boundaries in OCT Images of Non-Exudative AMD Patients Using Deep Learning and Graph Search." *Biomedical Optics Express*, vol. 8, no. 5, 2017, p. 2732., doi:10.1364/boe.8.002732.
8. Fu, Huazhu, et al. "Retinal Vessel Segmentation via Deep Learning Network and Fully-Connected Conditional Random Fields." *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, 2016, doi:10.1109/isbi.2016.7493362.

9. Gargeya, Rishab, and Theodore Leng. “Automated Identification of Diabetic Retinopathy Using Deep Learning.” *Ophthalmology*, vol. 124, no. 7, 2017, pp. 962–969., doi:10.1016/j.ophtha.2017.02.008.
10. Gulshan, Varun, et al. “Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs.” *Jama*, vol. 316, no. 22, 2016, p. 2402., doi:10.1001/jama.2016.17216.
11. Jaffe, Glenn J., and Joseph Caprioli. “Optical Coherence Tomography to Detect and Manage Retinal Disease and Glaucoma.” *American Journal of Ophthalmology*, vol. 137, no. 1, 2004, pp. 156–169., doi:10.1016/s0002-9394(03)00792-x.
12. Kermany, D., Goldbaum, M., Cai, W., Valentim, C., Liang, H., Baxter, S., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M., Pei, J., Ting, M., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., Shi, A., Zhang, R., Zheng, L., Hou, R., Shi, W., Fu, X., Duan, Y., Huu, V., Wen, C., Zhang, E., Zhang, C., Li, O., Wang, X., Singer, M., Sun, X., Xu, J., Tafreshi, A., Lewis, M., Xia, H. and Zhang, K. (2018). “*Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning”*. Cell, 172(5), pp.1122-1131.e9.
13. Lang, Andrew, et al. “Retinal Layer Segmentation of Macular OCT Images Using Boundary Classification.” *Biomedical Optics Express*, vol. 4, no. 7, 2013, p. 1133., doi:10.1364/boe.4.001133.
14. Lang, Andrew, et al. “Retinal Layer Segmentation of Macular OCT Images Using Boundary Classification.” *Biomedical Optics Express*, vol. 4, no. 7, 2013, p. 1133., doi:10.1364/boe.4.001133.
15. Lee, Cecilia S, et al. “Deep Learning Is Effective for the Classification of OCT Images of Normal versus Age-Related Macular Degeneration.” 2016, doi:10.1101/094276.
16. Lee, Cecilia S., et al. “Deep-Learning Based, Automated Segmentation of Macular Edema in Optical Coherence Tomography.” Sept. 2017, doi:10.1101/135640.
17. Liu, Yu-Ying, et al. “Automated Macular Pathology Diagnosis in Retinal OCT Images Using Multi-Scale Spatial Pyramid and Local Binary Patterns in Texture and Shape Encoding.” *Medical Image Analysis*, vol. 15, no. 5, 2011, pp. 748–759., doi:10.1016/j.media.2011.06.005.

18. Lu, Wei, et al. “Deep Learning-Based Automated Classification of Multi-Categorical Abnormalities From Optical Coherence Tomography Images.” *Translational Vision Science & Technology*, vol. 7, no. 6, 2018, p. 41., doi:10.1167/tvst.7.6.41.
19. Neri, P. “Advances in Optical Coherence Tomography for Age-Related Macular Degeneration.” *Acta Ophthalmologica*, vol. 86, Apr. 2008, pp. 0–0., doi:10.1111/j.1755-3768.2008.3217.x.
20. Nguyen, Uyen T.v., et al. “An Effective Retinal Blood Vessel Segmentation Method Using Multi-Scale Line Detection.” *Pattern Recognition*, vol. 46, no. 3, 2013, pp. 703–715., doi:10.1016/j.patcog.2012.08.009.
21. Perdomo, Oscar, et al. “OCT-NET: A Convolutional Network for Automatic Classification of Normal and Diabetic Macular Edema Using Sd-Oct Volumes.” *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, 2018, doi:10.1109/isbi.2018.8363839.
22. Poplin, Ryan, et al. “Prediction of Cardiovascular Risk Factors from Retinal Fundus Photographs via Deep Learning.” *Nature Biomedical Engineering*, vol. 2, no. 3, 2018, pp. 158–164., doi:10.1038/s41551-018-0195-0.
23. Prasad, Deepthi K., et al. “Early Detection of Diabetic Retinopathy from Digital Retinal Fundus Images.” *2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 2015, doi:10.1109/raics.2015.7488421.
24. Rasti, Reza, et al. “Macular OCT Classification Using a Multi-Scale Convolutional Neural Network Ensemble.” *IEEE Transactions on Medical Imaging*, vol. 37, no. 4, 2018, pp. 1024–1034., doi:10.1109/tmi.2017.2780115.
25. Samagaio, Gabriela, et al. “Automatic Identification of Macular Edema in Optical Coherence Tomography Images.” *Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, 2018, doi:10.5220/0006544105330540.
26. Schlegl, Thomas, et al. “Fully Automated Detection and Quantification of Macular Fluid in OCT Using Deep Learning.” *Ophthalmology*, vol. 125, no. 4, 2018, pp. 549–558., doi:10.1016/j.ophtha.2017.10.031.

27. Srinivasan, Pratul P., et al. “Fully Automated Detection of Diabetic Macular Edema and Dry Age-Related Macular Degeneration from Optical Coherence Tomography Images.” *Biomedical Optics Express*, vol. 5, no. 10, Dec. 2014, p. 3568., doi:10.1364/boe.5.003568.
28. Srinivasan, Pratul P., et al. “Automatic Segmentation of up to Ten Layer Boundaries in SD-OCT Images of the Mouse Retina with and without Missing Layers Due to Pathology.” *Biomedical Optics Express*, vol. 5, no. 2, July 2014, p. 348., doi:10.1364/boe.5.000348.
29. Sugmk, Jathurong, et al. “Automated Classification between Age-Related Macular Degeneration and Diabetic Macular Edema in OCT Image Using Image Segmentation.” *The 7th 2014 Biomedical Engineering International Conference*, 2014, doi:10.1109/bmeicon.2014.7017441.
30. Suzuki, Kenji. “Overview of Deep Learning in Medical Imaging.” *Radiological Physics and Technology*, vol. 10, no. 3, Aug. 2017, pp. 257–273., doi:10.1007/s12194-017-0406-5.
31. Ting, Daniel Shu Wei, et al. “Development and Validation of a Deep Learning System for Diabetic Retinopathy and Related Eye Diseases Using Retinal Images From Multiethnic Populations With Diabetes.” *Jama*, vol. 318, no. 22, Dec. 2017, p. 2211., doi:10.1001/jama.2017.18152.
32. Wang, Yu, et al. “Machine Learning Based Detection of Age-Related Macular Degeneration (AMD) and Diabetic Macular Edema (DME) from Optical Coherence Tomography (OCT) Images.” *Biomedical Optics Express*, vol. 7, no. 12, Mar. 2016, p. 4928., doi:10.1364/boe.7.004928.
33. Xiang, Dehui, et al. “Automatic Segmentation of Retinal Layer in OCT Images With Choroidal Neovascularization.” *IEEE Transactions on Image Processing*, vol. 27, no. 12, 2018, pp. 5880–5891., doi:10.1109/tip.2018.2860255.
34. Yang, Qi, et al. “Automated Layer Segmentation of Macular OCT Images Using Dual-Scale Gradient Information.” *Optics Express*, vol. 18, no. 20, 2010, p. 21293., doi:10.1364/oe.18.021293.

16104013_2_AUTOMATIC RETINA DISORDER DETECTION USING OCT IMAGES

ORIGINALITY REPORT

26%	17%	19%	15%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.ncbi.nlm.nih.gov Internet Source	2%
2	tvst.arvojournals.org Internet Source	2%
3	www.osapublishing.org Internet Source	2%
4	Submitted to Indian Institute of Technology Guwahati Student Paper	1%
5	Yu Wang, Yaonan Zhang, Zhaomin Yao, Ruixue Zhao, Fengfeng Zhou. "Machine learning based detection of age-related macular degeneration (AMD) and diabetic macular edema (DME) from optical coherence tomography (OCT) images", Biomedical Optics Express, 2016 Publication	1%
6	www.nature.com Internet Source	1%

7	researchdirect.westernsydney.edu.au Internet Source	1%
8	Huazhu Fu, Yanwu Xu, Damon Wing Kee Wong, Jiang Liu. "Retinal vessel segmentation via deep learning network and fully-connected conditional random fields", 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI), 2016 Publication	1%
9	de.slideshare.net Internet Source	1%
10	www.coursehero.com Internet Source	1%
11	Daniel S. Kermany, Michael Goldbaum, Wenjia Cai, Carolina C.S. Valentim et al. "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning", Cell, 2018 Publication	1%
12	K. Ramamohanarao, U. T. V. Nguyen, A. Bhuiyan. "Retinal vascular feature analysis using color fundus imaging", 2013 ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living (BRC), 2013 Publication	1%
13	Uyen T.V. Nguyen, Alauddin Bhuiyan, Laurence	

A.F. Park, Kotagiri Ramamohanarao. "An effective retinal blood vessel segmentation method using multi-scale line detection", Pattern Recognition, 2013
Publication | 1%

---

14 www.slideshare.net
Internet Source | 1%

---

15 Feng Li, Hua Chen, Zheng Liu, Xue-dian Zhang, Min-shan Jiang, Zhi-zheng Wu, Kai-qian Zhou. "Deep learning-based automated detection of retinal diseases using optical coherence tomography images", Biomedical Optics Express, 2019
Publication | 1%

---

16 www.thelearningmachine.ai
Internet Source | 1%

---

17 Cecilia S. Lee, Ariel J. Tyring, Nicolaas P. Deruyter, Yue Wu, Ariel Rokem, Aaron Y. Lee. "Deep-learning based, automated segmentation of macular edema in optical coherence tomography", Biomedical Optics Express, 2017
Publication | 1%

---

18 Genevieve C. Y. Chan, Ravi Kamble, Henning Muller, Syed A. A. Shah, T. B. Tang, Fabrice Meriaudeau. "Fusing Results of Several Deep Learning Architectures for Automatic Classification of Normal and Diabetic Macular | <1%

Edema in Optical Coherence Tomography",
2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2018
Publication

19 Submitted to Texas A&M University - Commerce <1%
Student Paper

20 dl.kums.ac.ir <1%
Internet Source

21 Ryan Poplin, Avinash V. Varadarajan, Katy Blumer, Yun Liu, Michael V. McConnell, Greg S. Corrado, Lily Peng, Dale R. Webster. "Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning", Nature Biomedical Engineering, 2018 <1%
Publication

22 Submitted to National Institute of Technology, Silchar <1%
Student Paper

23 Submitted to Cardiff University <1%
Student Paper

24 www.ijert.org <1%
Internet Source

25 Reza Rasti, Hossein Rabbani, Alireza Mehridehnavi, Fedra Hajizadeh. "Macular OCT Classification using a Multi-Scale Convolutional <1%

Neural Network Ensemble", IEEE Transactions on Medical Imaging, 2017
Publication

26	eyedoctorcostablanca.com Internet Source	<1%
27	towardsdatascience.com Internet Source	<1%
28	Submitted to Taylor's Education Group Student Paper	<1%
29	Submitted to October University for Modern Sciences and Arts (MSA) Student Paper	<1%
30	patents.google.com Internet Source	<1%
31	Submitted to Sri Lanka Institute of Information Technology Student Paper	<1%
32	Submitted to University of Florida Student Paper	<1%
33	eandv.biomedcentral.com Internet Source	<1%
34	scholarworks.iupui.edu Internet Source	<1%
35	Submitted to National College of Ireland Student Paper	<1%

36	Submitted to Associatie K.U.Leuven Student Paper	<1%
37	Submitted to University of Southern California Student Paper	<1%
38	link.springer.com Internet Source	<1%
39	Ali Mohammad Alqudah. "AOCT-NET: a convolutional network automated classification of multiclass retinal diseases using spectral-domain optical coherence tomography images", Medical & Biological Engineering & Computing, 2019 Publication	<1%
40	Hyunjin Kim, Sang Hong, Jinsul Kim, Jaecheol Ryou. "Intelligent Application Protection Mechanism for Transportation in V2C Environment", IEEE Access, 2020 Publication	<1%
41	Joseph D. Prusa, Taghi M. Khoshgoftaar. "Improving deep neural network design with new text data representations", Journal of Big Data, 2017 Publication	<1%
42	Wei Lu, Yan Tong, Yue Yu, Yiqiao Xing, Changzheng Chen, Yin Shen. "Deep Learning-Based Automated Classification of Multi-	<1%

Categorical Abnormalities From Optical Coherence Tomography Images", Translational Vision Science & Technology, 2018
Publication

43 Muhammad Mateen, Junhao Wen, Mehdi Hassan, Nasrullah Nasrullah, Song Sun, Shaukat Hayat. "Automatic Detection of Diabetic Retinopathy: A Review on Datasets, Methods and Evaluation Metrics", IEEE Access, 2020 <1%
Publication

Exclude quotes	On	Exclude matches	< 14 words
Exclude bibliography	On		