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``````Dissertation Submitted for the partial fulfillment of the **M.Sc. (Integrated) Five Years Program AIML/Data Science** degree to the Department of AIML & Data Science.

## M.Sc. Project Dissertation

# Retinal OCT Image Classification

**(Optical coherence Tomography)**

*submitted to*

*By*


**Zakariya Mansuri**
**Charchil Singh**


**Semester- VII**

**M.Sc. (Integrated) Five Years Program AIML/Data Science**


Department of AIML & Data Science
School of Emerging Science and Technology
Gujarat University

**December, 2022**

# DECLARATION

This is to certify that the research work reported in this dissertation entitled "**Retinal OCT Image Classification**" for the partial fulfilment of Master of Science in Artificial Intelligence and Machine Learning/Data Science degree is the result of investigation done by myself.

Place: Ahmedabad

Date: 19/12/2022

Name of Student

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## Index

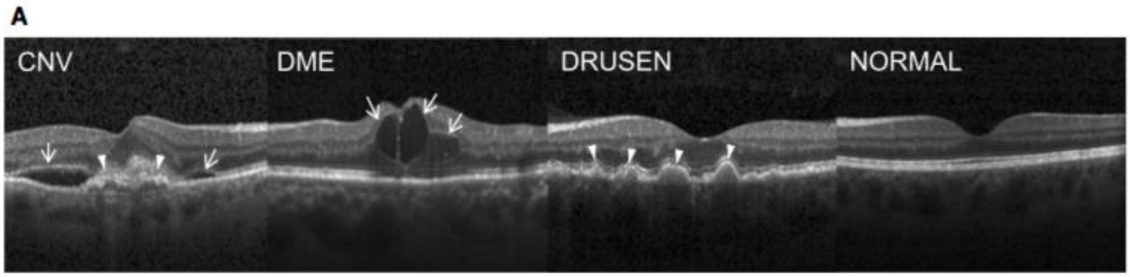
# Chapter 1
# Abstract & Key Words

# Abstract

The implementation of clinical decision supports algorithms for medical imaging faces challenges with reliability and interpretability. Here, we establish a diagnostic tool based on deep learning neural networks for the screening of patients with common treatable blinding retinal diseases. Our framework utilizes Convolution Network , which trains a neural network with a fraction of the data of conventional approaches. . Applying this approach to a dataset of optical coherence tomography images, we demonstrate performance comparable to that of human experts in classifying age related macular degeneration and diabetic macular edema. This tool may ultimately aid in expediting the diagnosis and referral of these treatable conditions, thereby facilitating earlier treatment, resulting in improved clinical outcomes

# Chapter 2

# Introduction




Artificial intelligence (AI) has the potential to revolutionize disease diagnosis and management by performing classification difficult for human experts and by rapidly reviewing immense amounts of images. Despite its potential, clinical interpretability and feasible preparation of AI remains challenging.

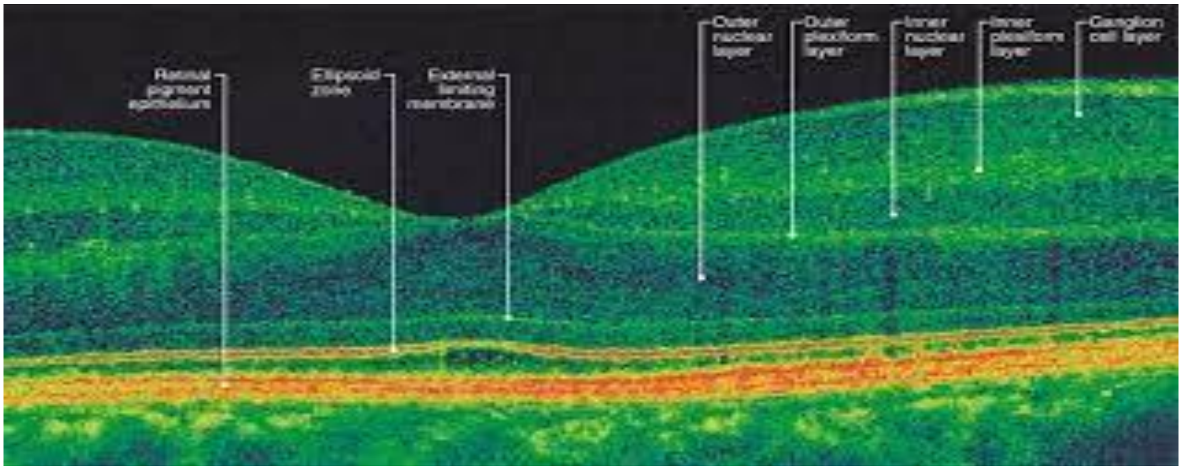
The traditional algorithmic approach to image analysis for classification previously relied on (1) handcrafted object segmentation, followed by (2) identification of each segmented object using statistical classifiers or shallow neural computational machine-learning classifiers designed specifically for each class of objects, and finally (3) classification of the image. Creating and refining multiple classifiers required many skilled people and much time and was computationally expensive

The development of convolutional neural network layers has allowed for significant gains in the ability to classify images and detect objects in a picture . These are multiple processing layers to which image analysis filters, or convolutions, are applied. The abstracted representation of images within each layer is constructed by systematically convolving multiple filters across the image, producing a feature map that is used as input to the following layer. This architecture makes it possible to process images in the form of pixels as input and to give the desired tomography (OCT) images of the retina, but the algorithm was also tested in a cohort of pediatric chest radiographs to validate the generalizability of this technique across multiple imaging modalities.

# Chapter 3

# Basic Terminology

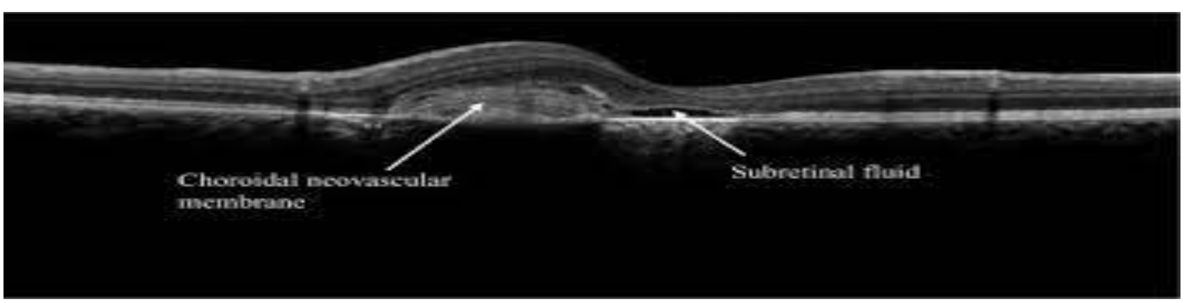
# Optimal Coherence Topography




Optical coherence tomography (OCT) is a non-invasive imaging test. OCT uses light waves to take cross-section pictures of your retina.

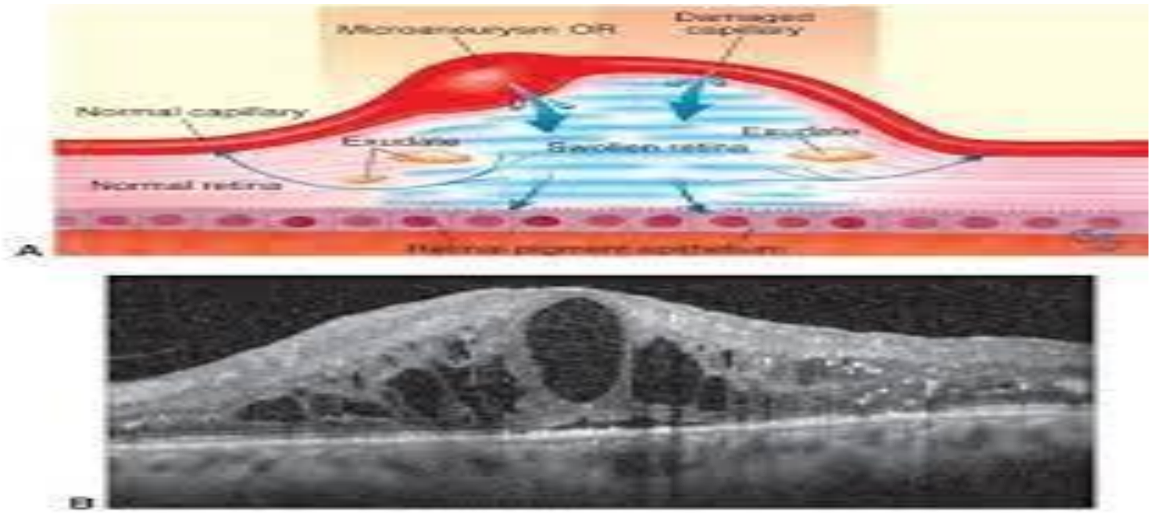
With OCT, your ophthalmologist can see each of the retina's distinctive layers. This allows your ophthalmologist to map and measure their thickness. These measurements help with diagnosis. They also provide treatment guidance for glaucoma and diseases of the retina. These retinal diseases include age-related macular degeneration (AMD) and diabetic eye disease.

# Choroidal Neovascularization



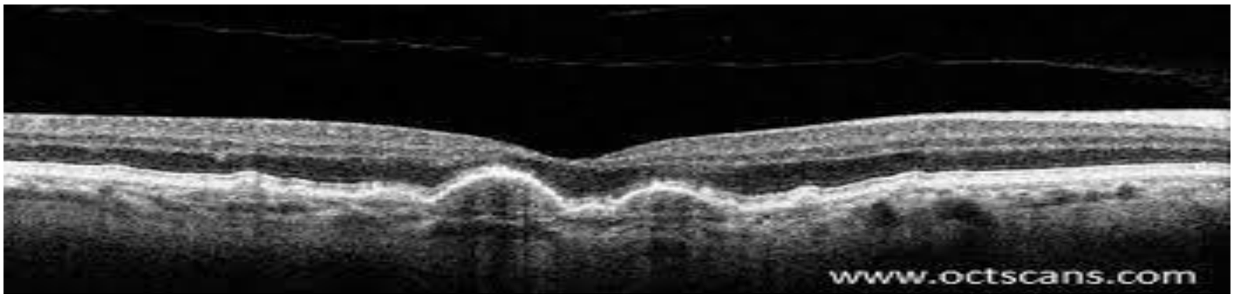

Choroidal neovascularization (CNV) is the growth of new blood vessels in the choroid, a layer of blood vessels located between the retina and the sclera (white part of the eye) in the back of the eye. These new blood vessels are abnormal and can cause vision problems because they can leak fluid and blood, leading to swelling and scarring of the retina.

# Diabetic Macular Edema




Diabetic macular edema (DME) is a complication of diabetes that affects the retina, the light-sensitive layer at the back of the eye. It occurs when excess fluid builds up in the macula, the part of the retina responsible for central vision. This can cause the macula to swell, leading to vision loss.
DME is a common cause of vision loss in people with diabetes, especially those who have had diabetes for a long time or who have poorly controlled blood sugar levels

# DRUSEN




Drusen are small, yellowish or white deposits that can form under the retina of the eye. They are composed of various substances, including fats and proteins, and are a common finding in the eyes of older individuals. In most cases, drusen do not cause any symptoms and do not affect vision.

However, in some cases, drusen can be a sign of age-related macular degeneration (AMD), a condition that can lead to vision loss. If you have drusen and are experiencing vision loss or other eye symptoms, it is important to speak with an eye care professional for proper evaluation and treatment.

# Deep Learning

The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones. If we draw a graph showing how these  concepts are built on top of each other, the graph is deep, with many layers. For this reason, we call this approach to AI deep learning

# Categorical Crossentrophy :

Categorical crossentropy is a loss function used in classification tasks where the output is a probability distribution over multiple classes. It is a measure of the difference between the predicted distribution and the true distribution.

# Chapter 4

# Literature review

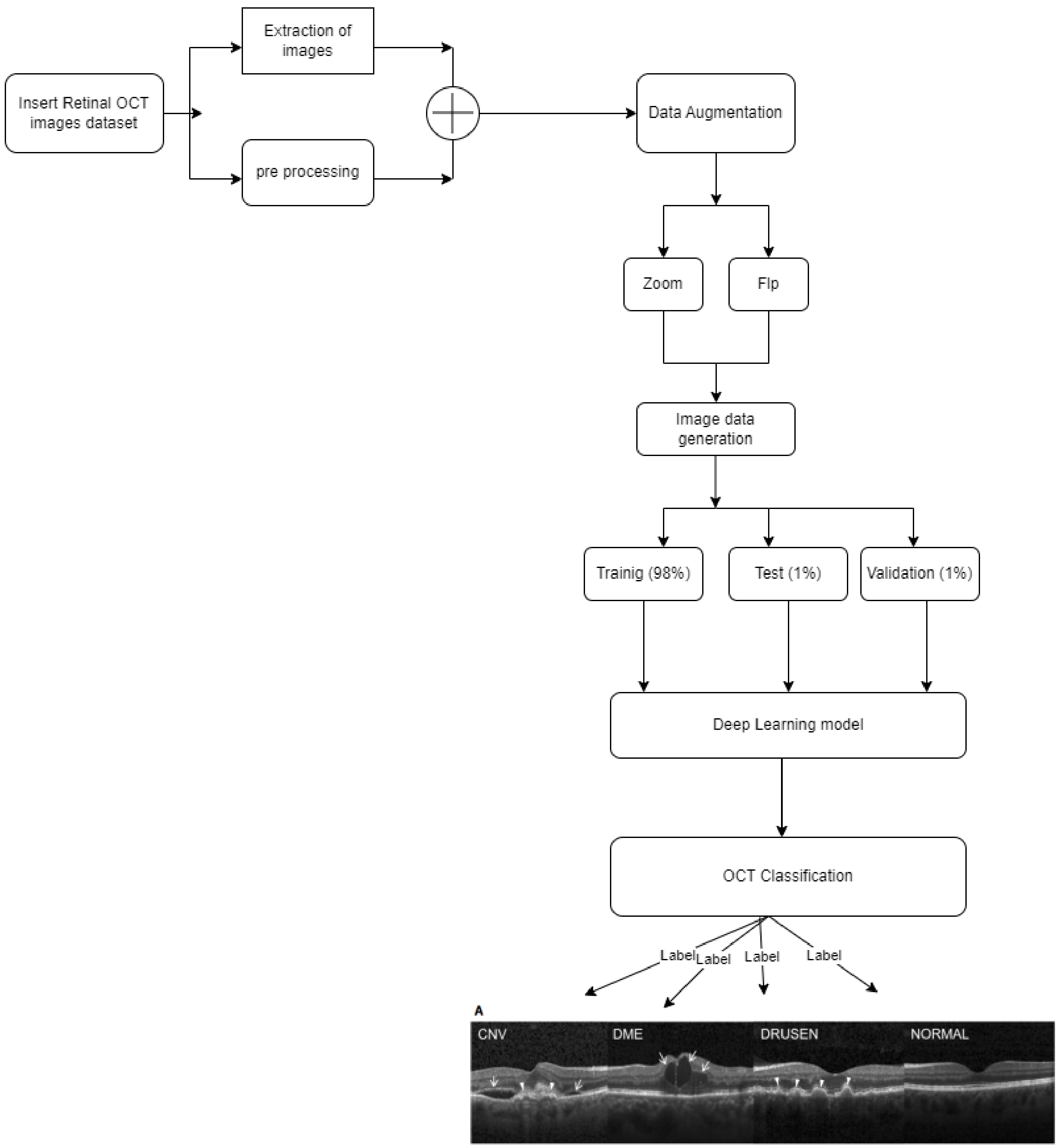
OCT images have made it more easy to identify the structure of normal and diseased retina, which can be used for early diagnosis of several diseases and monitor the effect of the treatment. OCT is one of the fast developing medical image modality in the last decade. It uses low coherence interferometry to map out back-scattering properties from different depths of samples. Varies retinal diseases can be detected efficiently by analyzing the OCT retinal images. Each retinal disease has some specific features, which can be effectively detected in OCT images. In this paper, we reviewed how OCT is capable of defining the structure of normal eye retinal layers as well as the structure of the diseased ones. We presented an overview of the current processing techniques as well as how can they applied to help in the diagnosis and treatment of the diseased eyes. In addition, we defined some of the challenges that face scientists in analyzing and extracting the necessary information from OCT retinal images. The promising experimental results for the reviewed techniques in a variety of clinical applications suggest that OCT is a clinically relevant imaging modality. Promising findings and experimental results for the reviewed techniques suggest that OCT is an effective imaging modality for retina and retinal diseases, which can be used for early diagnosis of different diseases. (Classification of optical coherence tomography images using a capsule network n.d.)

For the classification of four classes of OCT images, the proposed method achieved high accuracy of 99.6% using the network model based on a capsule network. By contrast, the best accuracy obtained in earlier studies was 96.1%, obtained when using Inception-v3. This model has a pooling layer, which is a primary feature of CNN. In addition, the accuracy of Inception-V3 in the same condition was 99.8%. Therefore, the proposed model, which is much shallower than Inception-V3, compares favorably with it in terms of classification accuracy

# Chapter 5

# Methodology

# Project Workflow



# Dataset

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (NORMAL,CNV,DME,DRUSEN). There are 84,495 X-Ray images (JPEG) and 4 categories (NORMAL,CNV,DME,DRUSEN).

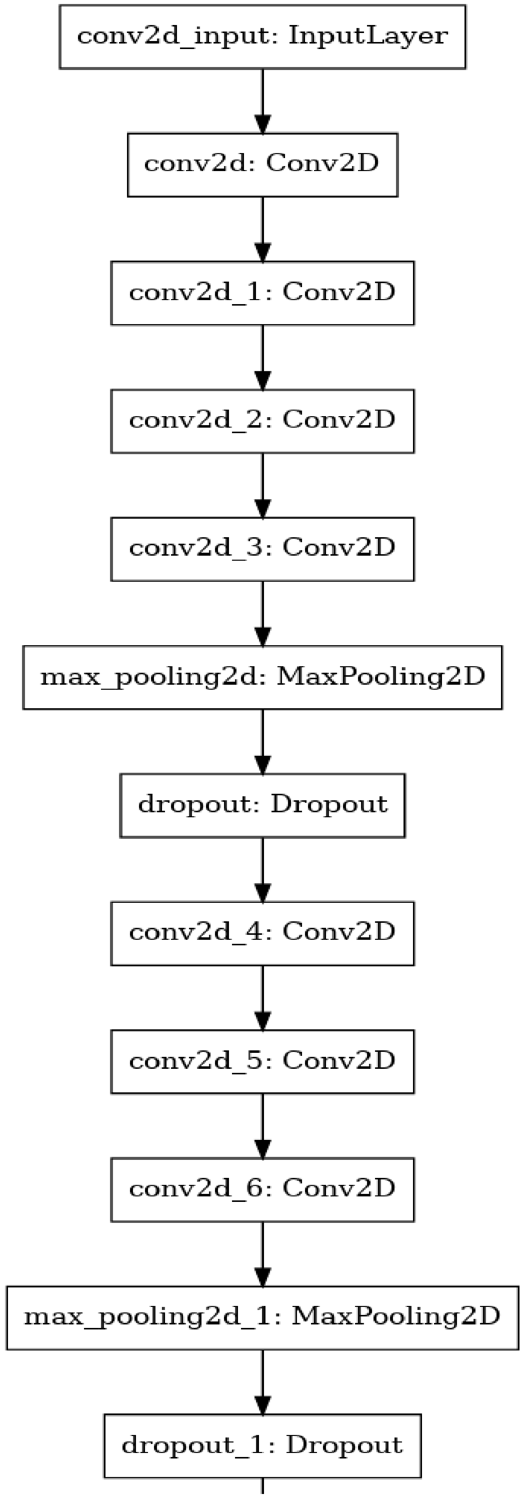
Images are labeled as (disease)-(randomized patient ID)-(image number by this patient) and split into 4 directories: CNV, DME, DRUSEN, and NORMAL.

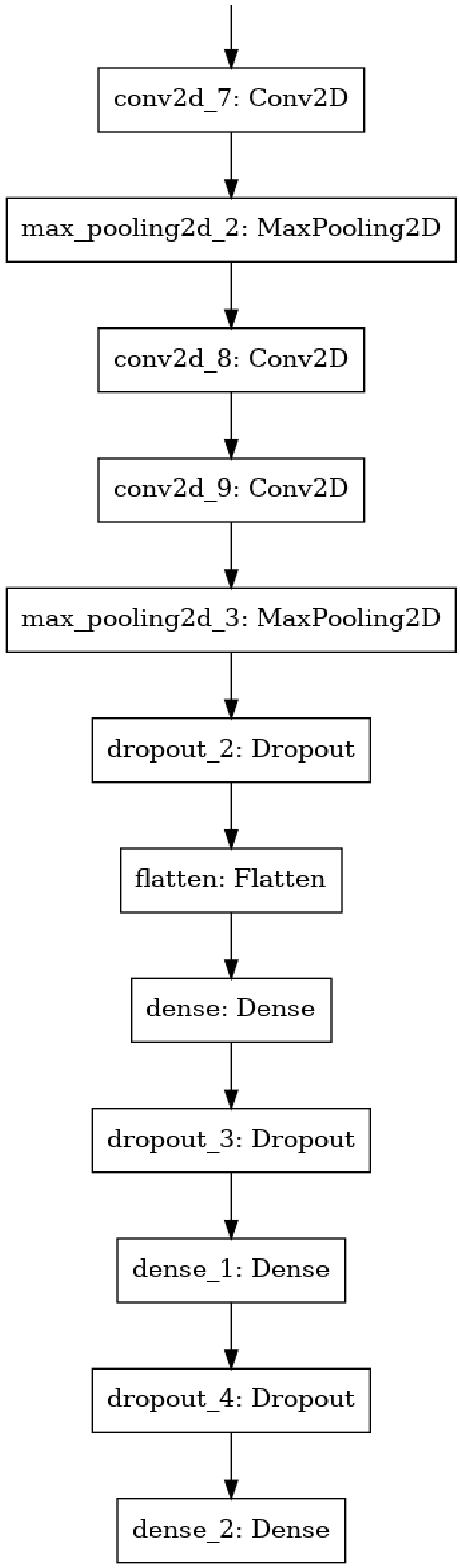
Optical coherence tomography (OCT) images (Spectralis OCT, Heidelberg Engineering, Germany) were selected from retrospective cohorts of adult patients from the Shiley Eye Institute of the University of California San Diego, the California Retinal Research Foundation, Medical Center Ophthalmology Associates, the Shanghai First People's Hospital, and Beijing Tongren Eye Center between July 1, 2013 and March 1, 2017.

Before training, each image went through a tiered grading system consisting of multiple layers of trained graders of increasing exper- tise for verification and correction of image labels. Each image imported into the database started with a label matching the most recent diagnosis of the patient. The first tier of graders consisted of undergraduate and medical students who had taken and passed an OCT interpretation course review. This first tier of graders conducted initial quality control and excluded OCT images containing severe artifacts or significant image resolution reductions. The second tier of graders consisted of four ophthalmologists who independently graded each image that had passed the first tier. The presence or absence of choroidal neovascularization (active or in the form of subretinal fibrosis), macular edema, drusen, and other pathologies visible on the OCT scan were recorded. Finally, a third tier of two senior independent retinal specialists, each with over 20 years of clinical retina experience, verified the true labels for each image. The dataset selection and stratification process is displayed in a CONSORT-style. To account for human error in grading, a validation subset of 993 scans was graded separately by two ophthalmologist graders, with disagreement in clinical labels arbitrated by a senior retinal specialist.

(Dataset n.d.)

# Model

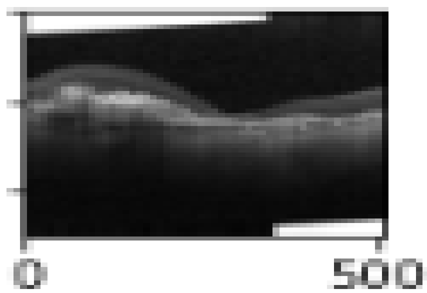

conv2d_input: InputLayer
conv2d: Conv2D
conv2d_1: Conv2D
conv2d_2: Conv2D
conv2d_3: Conv2D
max_pooling2d: MaxPooling2D
dropout: Dropout
conv2d_4: Conv2D
conv2d_5: Conv2D
conv2d_6: Conv2D
max_pooling2d_1: MaxPooling2D
dropout_1: Dropout


conv2d_7: Conv2D
max_pooling2d_2: MaxPooling2D
conv2d_8: Conv2D
conv2d_9: Conv2D
max_pooling2d_3: MaxPooling2D
dropout_2: Dropout
flatten: Flatten
dense: Dense
dropout_3: Dropout
dense_1: Dense
dropout_4: Dropout
dense_2: Dense

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 220, 220, 32)      2432      
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 216, 216, 32)      25632     
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 213, 213, 64)      32832     
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 210, 210, 64)      65600     
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 105, 105, 64)      0         
_________________________________________________________________
dropout (Dropout)            (None, 105, 105, 64)      0         
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 101, 101, 32)      51232     
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 98, 98, 64)        32832     
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 95, 95, 64)        65600     
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 47, 47, 64)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 47, 47, 64)        0         
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 44, 44, 32)        32800     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 32)        0         
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 20, 20, 64)        18496     
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 18, 18, 64)        36928     
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 9, 9, 64)          0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 9, 9, 64)          0         
_________________________________________________________________
flatten (Flatten)            (None, 5184)              0         
_________________________________________________________________
dense (Dense)                (None, 1024)              5309440   
_________________________________________________________________
dropout_3 (Dropout)          (None, 1024)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800    
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 4)                 2052      
=================================================================
Total params: 6,200,676
Trainable params: 6,200,676
Non-trainable params: 0
```

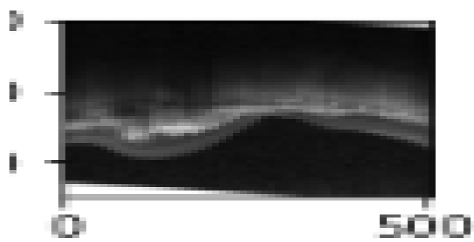
# Data Augumentation

## Zoom :



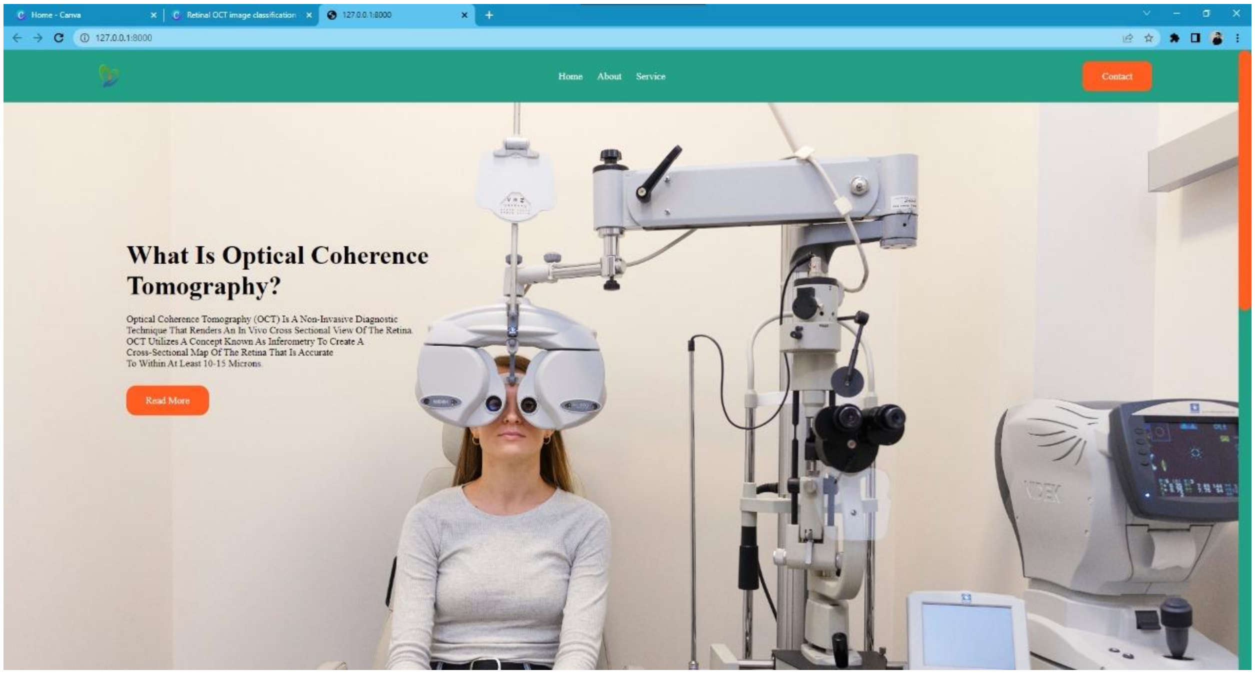

Zooming the image by 50% to get a new image

## Flip :



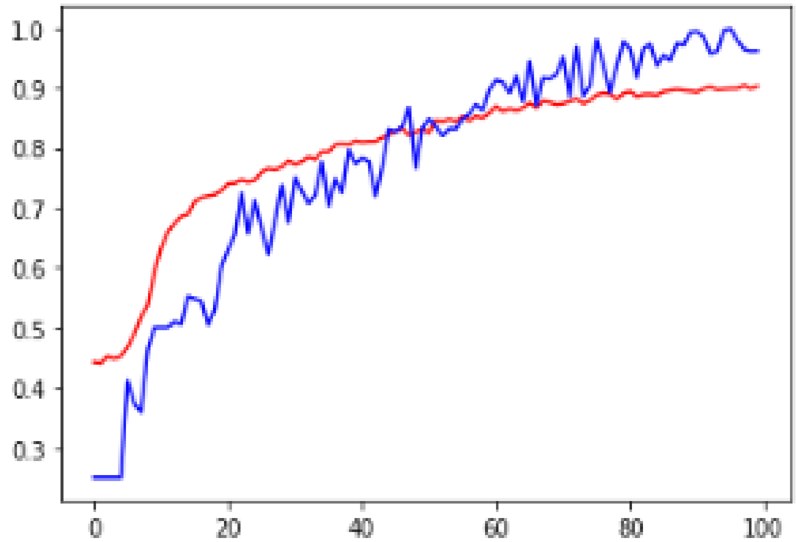

Flipping the image upside down

# Building API with Flask and website with HTML and CSS



# Chapter 6
# Results & Prediction

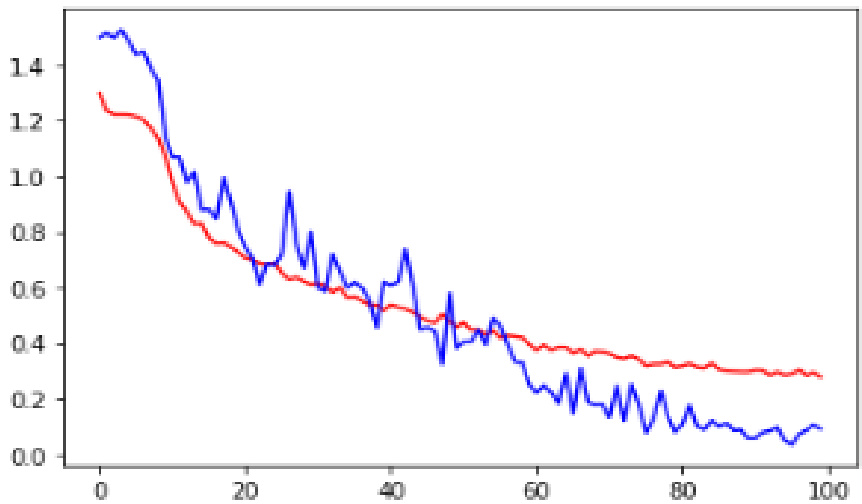
# Train Accuracy Vs Validation Accuracy




Validation Accuracy: 96%

Train Accuracy :90 %

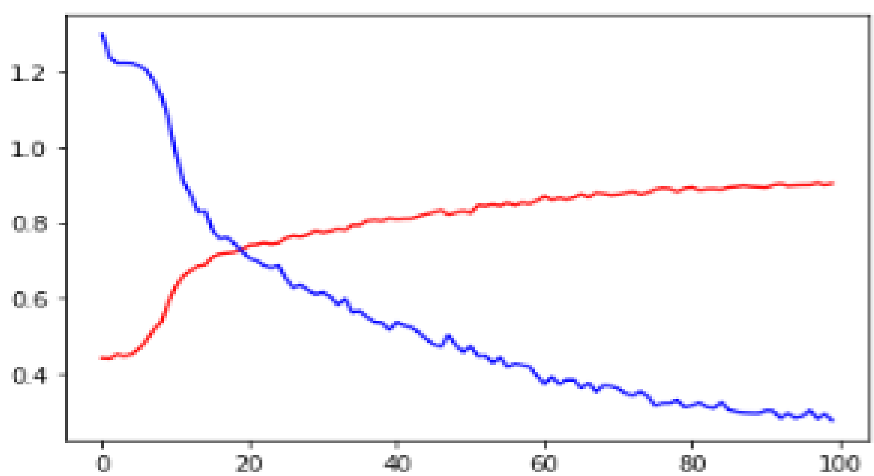
## Loss Vs Validation Loss




Validation Loss

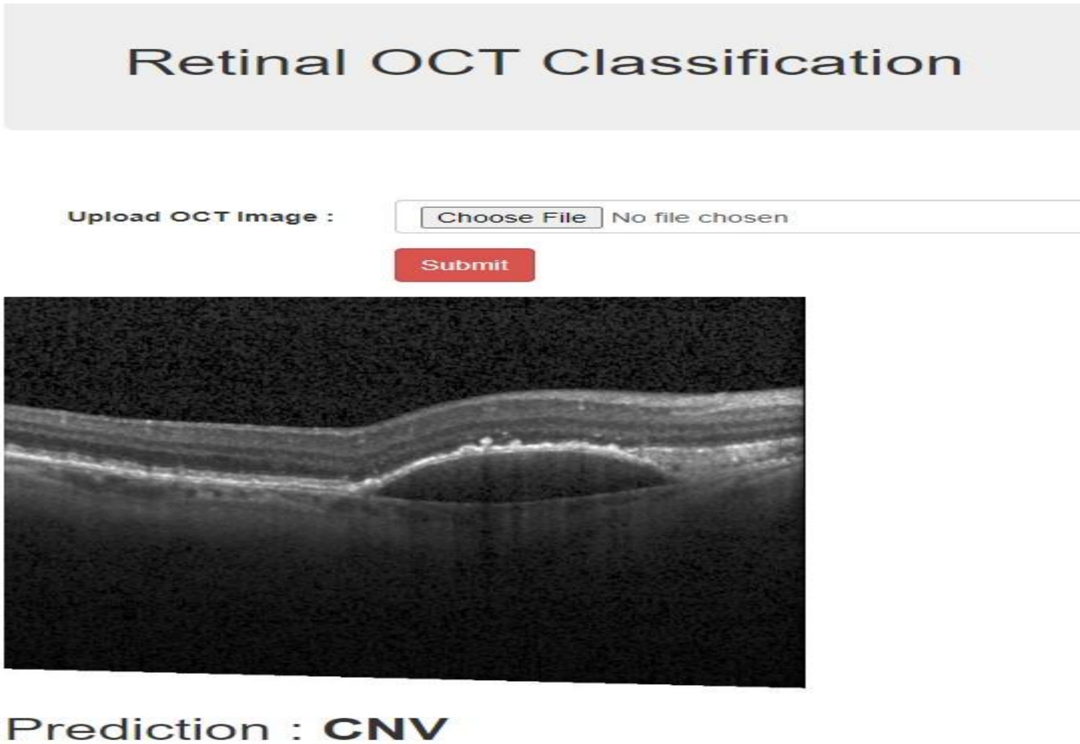
Loss

## Accuracy vs Loss




Validation Loss

Loss


Retinal OCT Classification
Upload OCT Image :
Choose File No file chosen
Submit
Prediction : CNV


Retinal OCT Classification
Upload OCT Image :
Choose File No file chosen
Submit
Prediction : DME


Retinal OCT Classification
Upload OCT Image :
Choose File
No file chosen
Submit
Prediction : DRUSEN


Retinal OCT Classification
Upload OCT Image :
Choose File
No file chosen
Submit
Prediction : NORMAL

# Chapter 7
# Bibliography

# Bibliography

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