

# CLASSIFICATION OF OPTICAL COHERENCE TOMOGRAPHY (OCT) IMAGES

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## DO YOU KNOW?

- According to National Library of Medicine, 2.2 Million people<sup>[4,5,6]</sup> globally are suffering from Vision Impairments, can grow to 5.4 million by 2050
- Most cases can be prevented when treated at early stages.

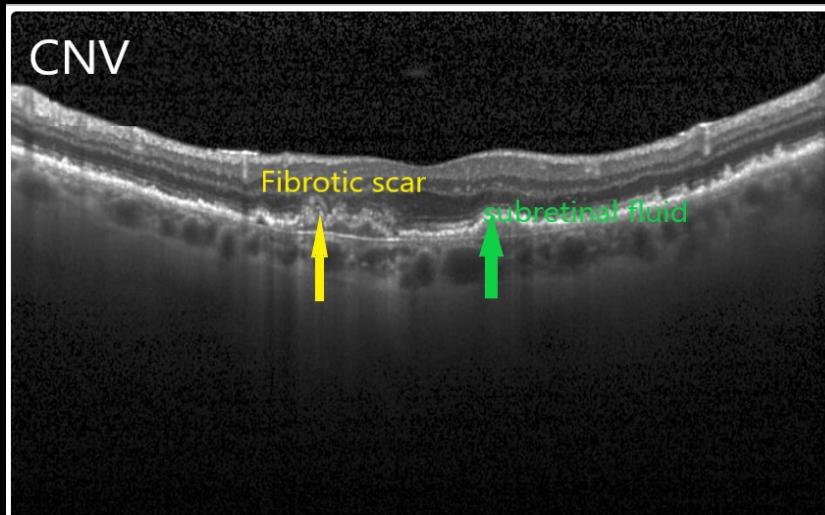
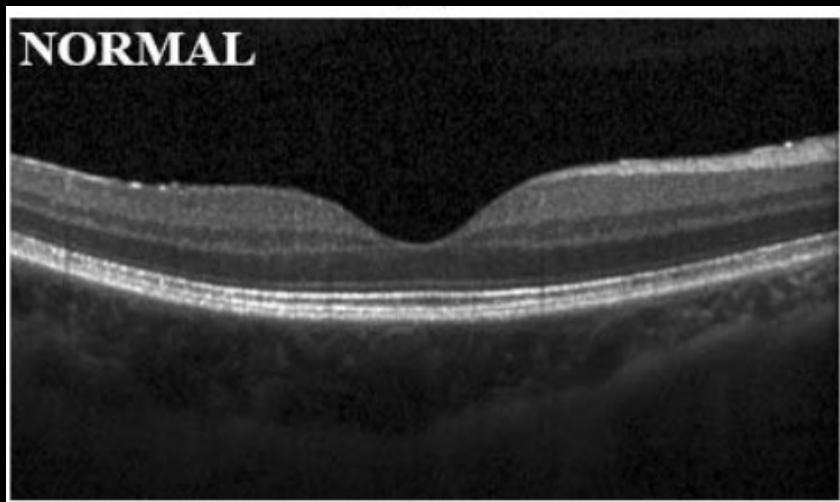
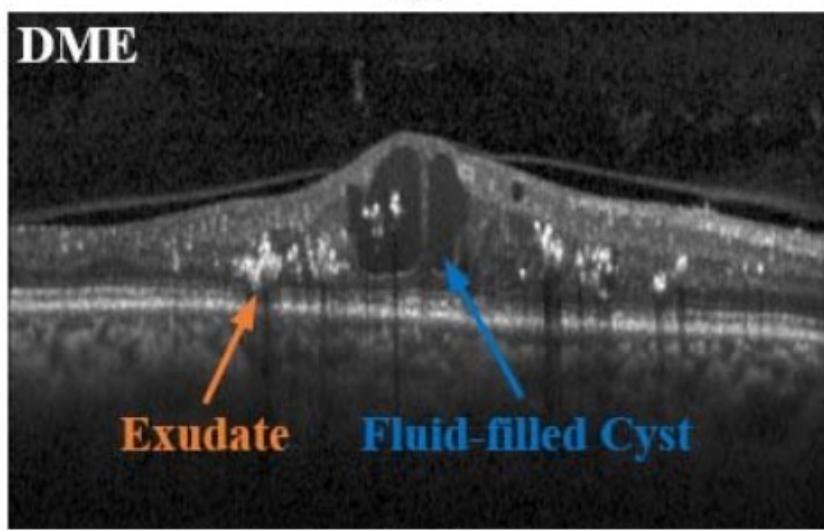
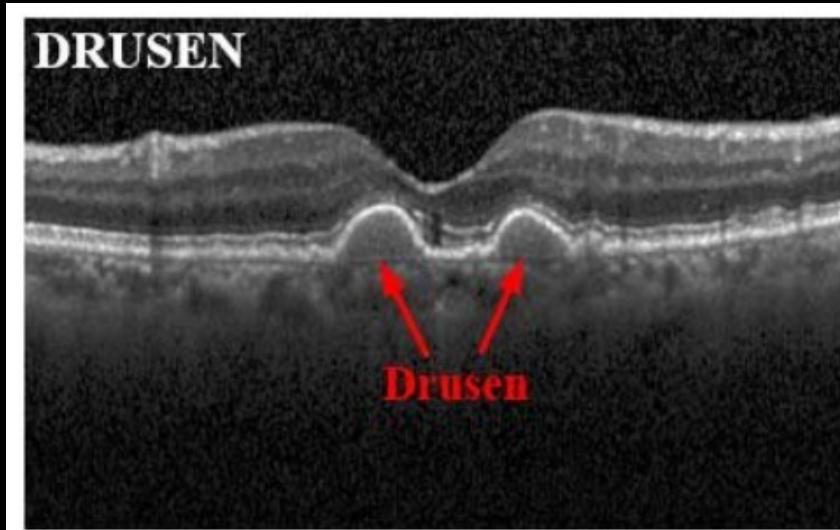
# OPTICAL COHERENCE TOMOGRAPHY

- Optical coherence tomography (OCT)<sup>[1]</sup> is a non-invasive imaging test. It 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.

## IMPORTANCE OF OCT IMAGES

- According to National Library of Medicine<sup>[2]</sup>, drusen, choroidal neovascularization (CNV), and diabetic macular edema (DME) are significant causes of visual impairment globally.  
Optical coherence tomography (OCT) imaging has emerged as a valuable diagnostic tool for these ocular conditions. However, subjective interpretation and inter-observer variability highlight the need for standardized diagnostic approaches.

# IN-DEPTH CLASSIFICATION OF EACH CONDITION:



# OBJECTIVES

- Develop deep learning models capable of accurately classifying retinal diseases such as CNV, DME, and Drusen based on OCT images.
- Evaluate the effectiveness of various deep learning architectures for OCT image classification.
- Investigate the impact of dataset size and diversity on model performance and generalization ability.
- Address class imbalance issues in the dataset, particularly for rare or underrepresented retinal diseases.
- Assess the influence of preprocessing techniques on model performance and interpretability.

## OUR RESEARCH QUESTIONS

- How effective are deep learning models in accurately classifying retinal diseases based on OCT images?
- Which deep learning architectures prove most effective for OCT image classification?
- How does the size and diversity of the training dataset impact model robustness and generalization ability?
- What strategies can be employed to address class imbalance issues in the OCT image dataset?
- How do preprocessing techniques such as denoising, image registration, and normalization impact model performance and interpretability?

# ABOUT THE DATASET

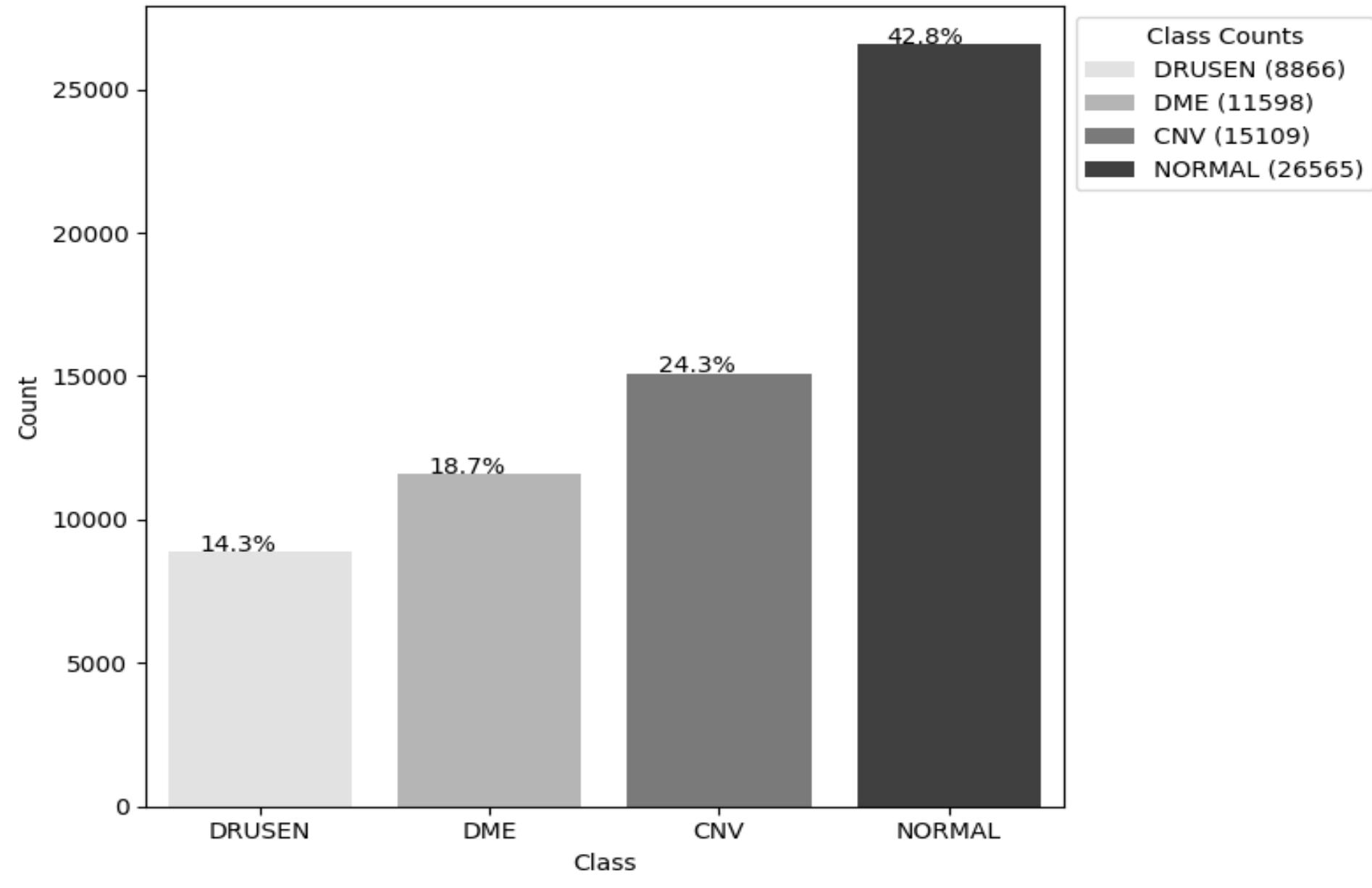
- Source:

Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), “Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification”, Mendeley Data, V2, doi: 10.17632/rscbjbr9sj.2<sup>[3]</sup>

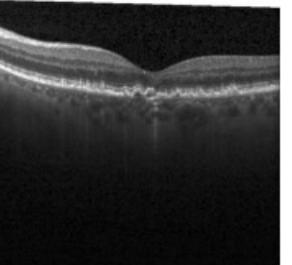
The dataset has 62,138 images of the following classes,

- CNV (Choroidal Neovascularization) – 15109 images
- DME (Diabetic Macular Edema) – 11598 images
- DRUSEN – 8866 images
- NORMAL – 26565 images

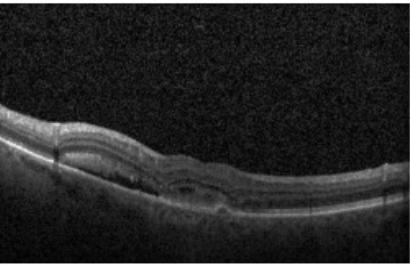
## Class Distribution



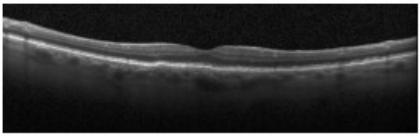
Class: CNV



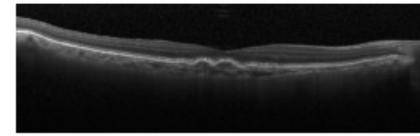
Class: CNV



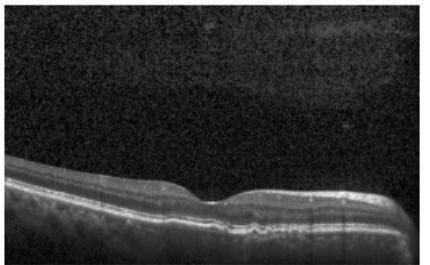
Class: CNV



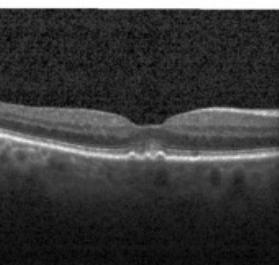
Class: CNV



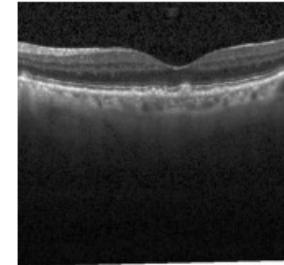
Class: DRUSEN



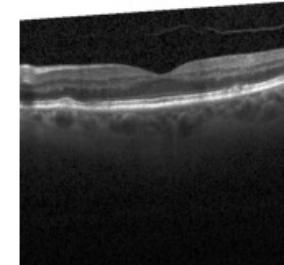
Class: DRUSEN



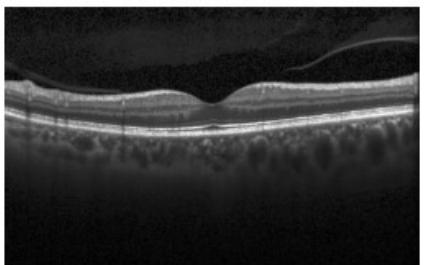
Class: DRUSEN



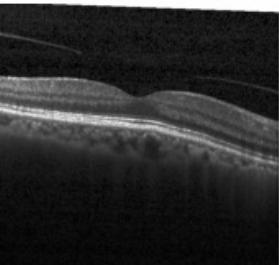
Class: DRUSEN



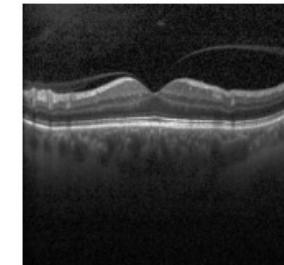
Class: NORMAL



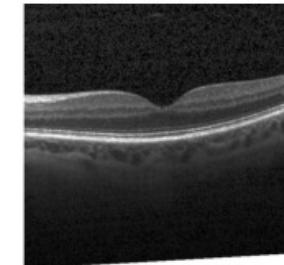
Class: NORMAL



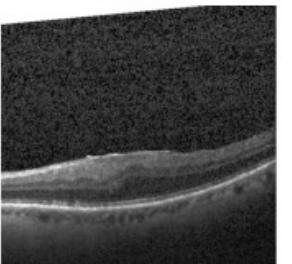
Class: NORMAL



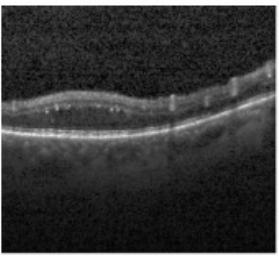
Class: NORMAL



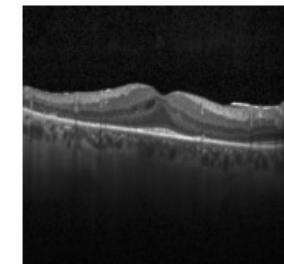
Class: DME



Class: DME



Class: DME



Class: DME

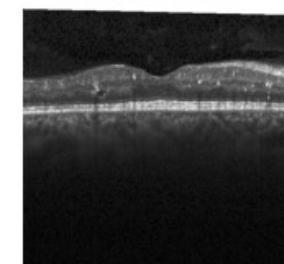


Image Size Distribution with Jitter

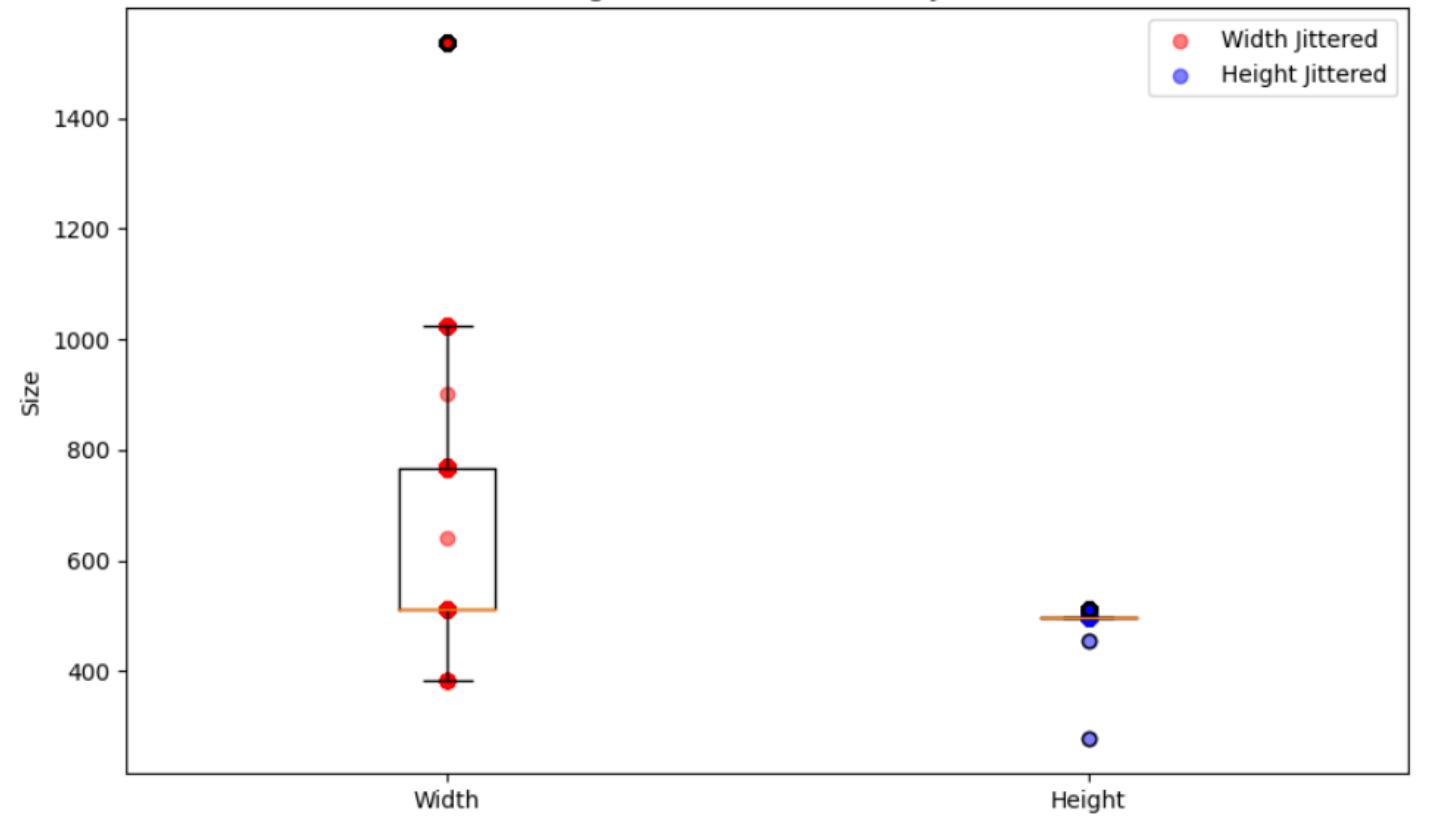


Image Size Statistics:

Minimum Width: 384

Maximum Width: 1536

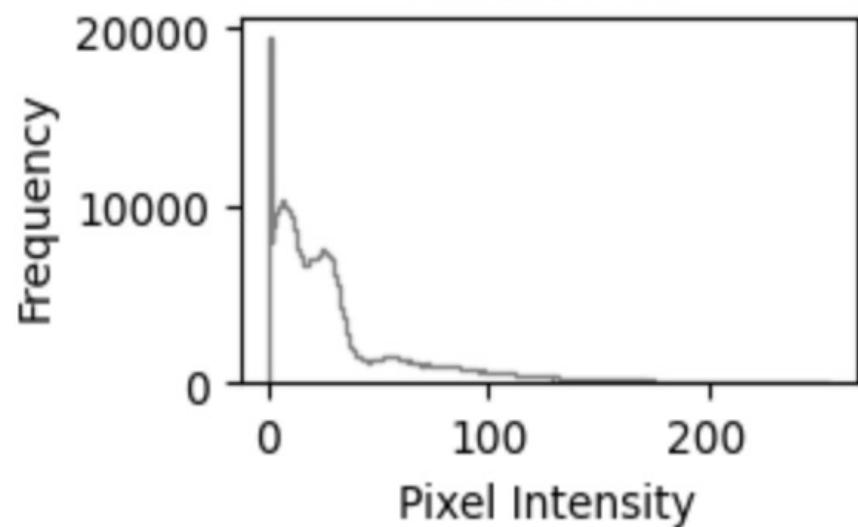
Average Width: 695.7205536598084

Minimum Height: 277

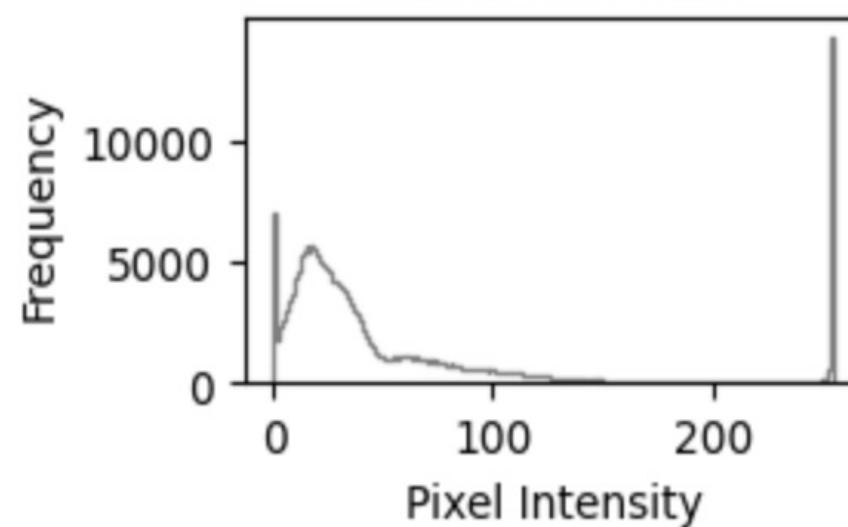
Maximum Height: 512

Average Height: 497.2650742390837

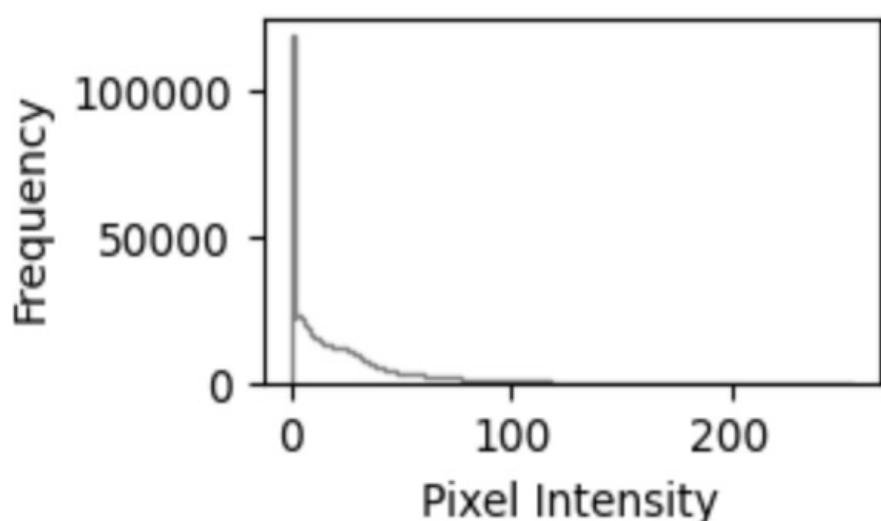
Class: CNV



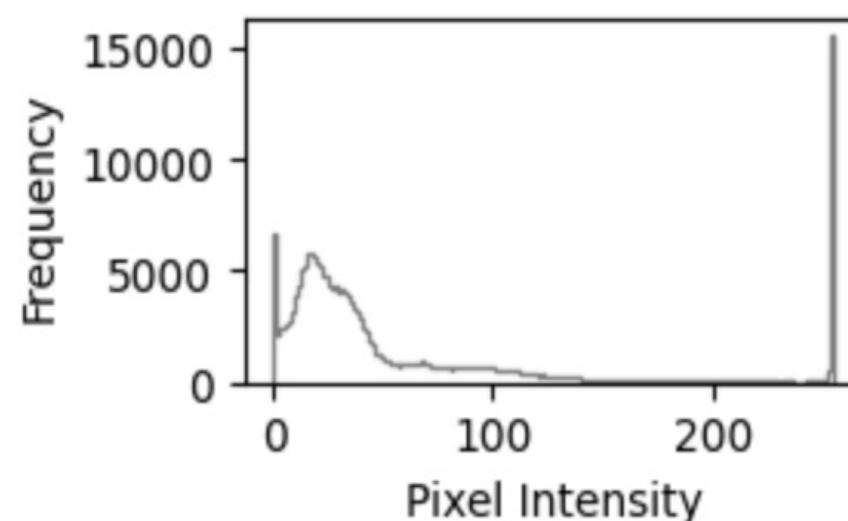
Class: DRUSEN



Class: NORMAL



Class: DME



## PREPROCESSING STEPS

- We resized the images to 256x256 and normalized the pixels using OpenCV library.
- We then stored the images in NumPy arrays and performed augmentation.
- We used data augmentation setup with Keras' ImageDataGenerator, which will generate augmented versions of the original images on-the-fly during training. Each batch of images fed into the model for training will be augmented differently, introducing variability and helping the model generalize better.

# MODELLING

# R A N D O M F O R E S T

- n\_estimators=20
- max\_depth = 10
- max\_features= "sqrt"

## Test Metrics:

Test Accuracy: 0.5794520547945206

Test Precision: 0.6612902812222957

Test Recall: 0.5794520547945206

Test F1-score: 0.5008363280543155

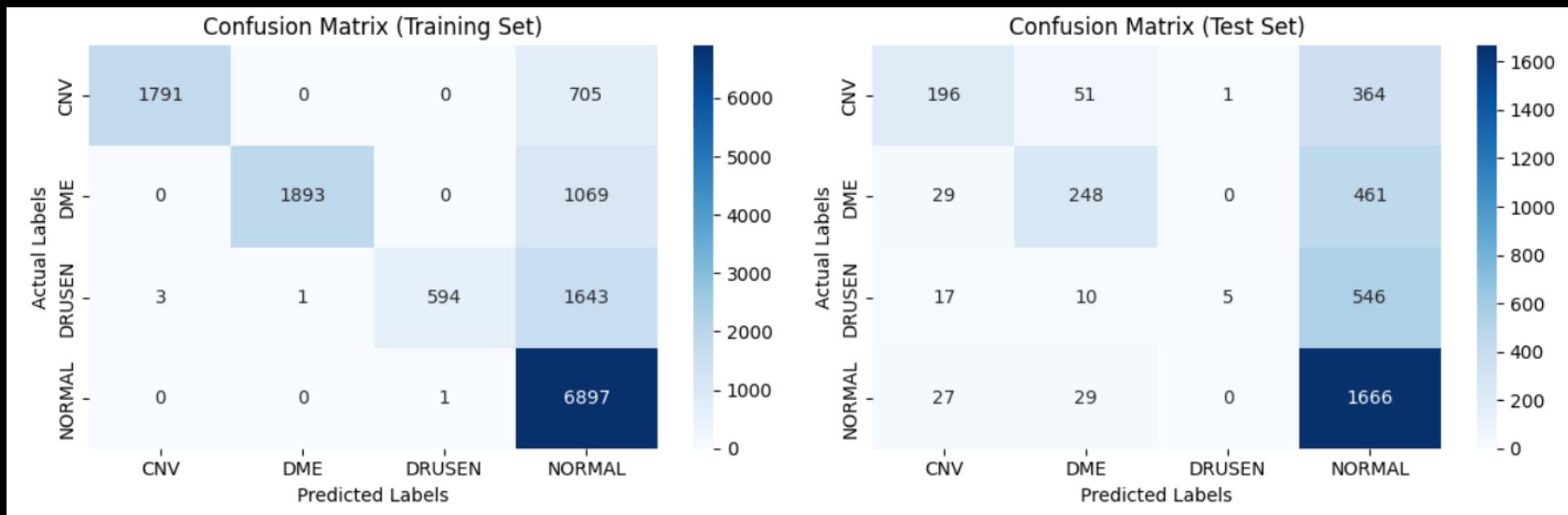
## Train Metrics:

Train Accuracy: 0.7655682674522162

Train Precision: 0.8427901126668152

Train Recall: 0.7655682674522162

Train F1-score: 0.7440118708689517



# K-NEAREST NEIGHBORS (KNN)

- algorithm='auto'
- n\_neighbors= 7
- p= 1

Classification Report (Training Set - KNN):				
	precision	recall	f1-score	support
CNV	0.63	0.49	0.55	791
DME	0.49	0.63	0.55	787
DRUSEN	0.53	0.53	0.53	806
NORMAL	0.57	0.54	0.56	816
accuracy			0.55	3200
macro avg	0.56	0.55	0.55	3200
weighted avg	0.56	0.55	0.55	3200

Classification Report (Testing Set - KNN):				
	precision	recall	f1-score	support
CNV	0.31	0.21	0.25	209
DME	0.38	0.42	0.40	213
DRUSEN	0.34	0.36	0.35	194
NORMAL	0.30	0.35	0.33	184
accuracy			0.34	800
macro avg	0.33	0.34	0.33	800
weighted avg	0.33	0.34	0.33	800

# SUPPORT VECTOR MACHINES (SVM)

- gamma='auto'
- C= 1
- kernel = 'rbf'

Classification Report (Training Set):				
	precision	recall	f1-score	support
CNV	0.56	0.48	0.51	791
DME	0.38	0.34	0.36	787
DRUSEN	0.39	0.33	0.36	806
NORMAL	0.42	0.58	0.49	816
accuracy			0.43	3200
macro avg	0.44	0.43	0.43	3200
weighted avg	0.44	0.43	0.43	3200

Classification Report (Testing Set):				
	precision	recall	f1-score	support
CNV	0.52	0.41	0.46	209
DME	0.35	0.29	0.32	213
DRUSEN	0.32	0.30	0.31	194
NORMAL	0.35	0.52	0.42	184
accuracy			0.38	800
macro avg	0.38	0.38	0.37	800
weighted avg	0.39	0.38	0.37	800

# ADABOOSTING

- n\_estimators=200
- learning\_rate=0.1

Train Metrics (200 Estimators):

Accuracy: 0.5746875  
Precision: 0.5774133546676918  
Recall: 0.5745430636476441  
F1-score: 0.5751545273760863

Test Metrics (200 Estimators):

Accuracy: 0.44125  
Precision: 0.4484732334907211  
Recall: 0.4410732462642231  
F1-score: 0.4424190224086838

Classification Report (Training Set - 200 Estimators):

	precision	recall	f1-score	support
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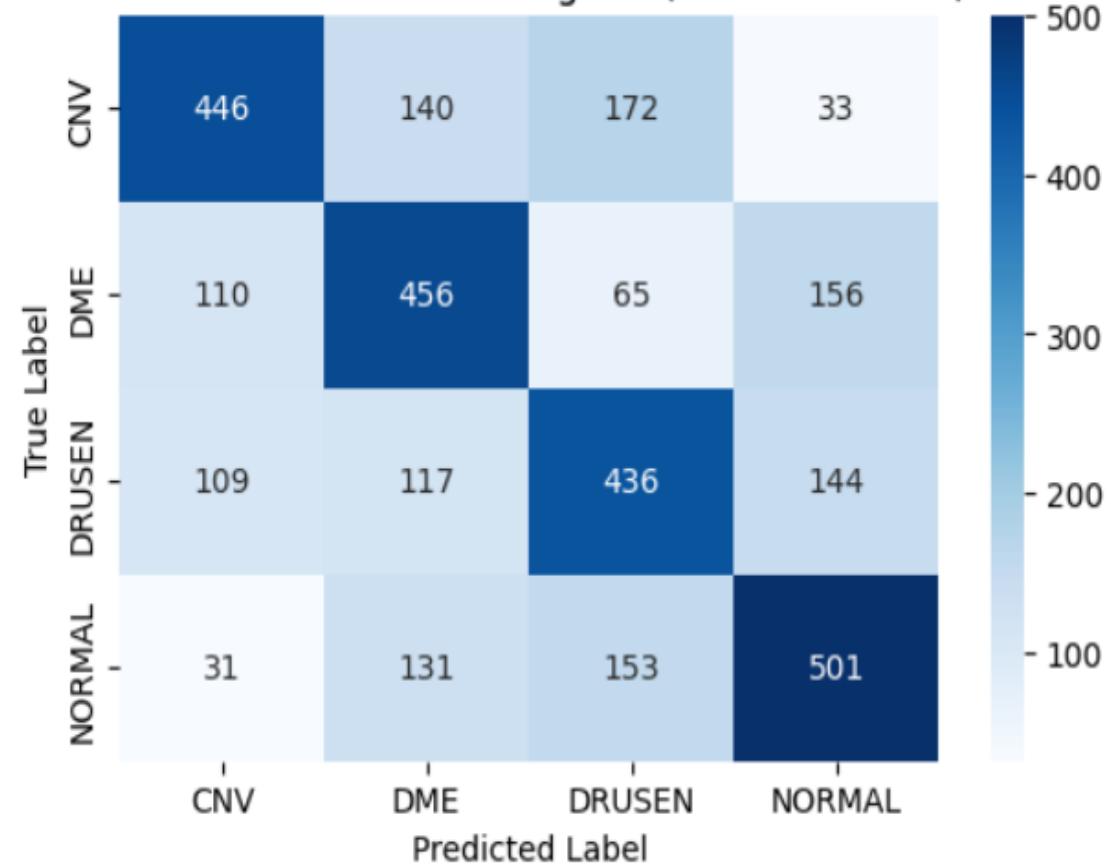
CNV	0.64	0.56	0.60	791
DME	0.54	0.58	0.56	787
DRUSEN	0.53	0.54	0.53	806
NORMAL	0.60	0.61	0.61	816
accuracy			0.57	3200
macro avg	0.58	0.57	0.58	3200
weighted avg	0.58	0.57	0.58	3200

Classification Report (Testing Set - 200 Estimators):

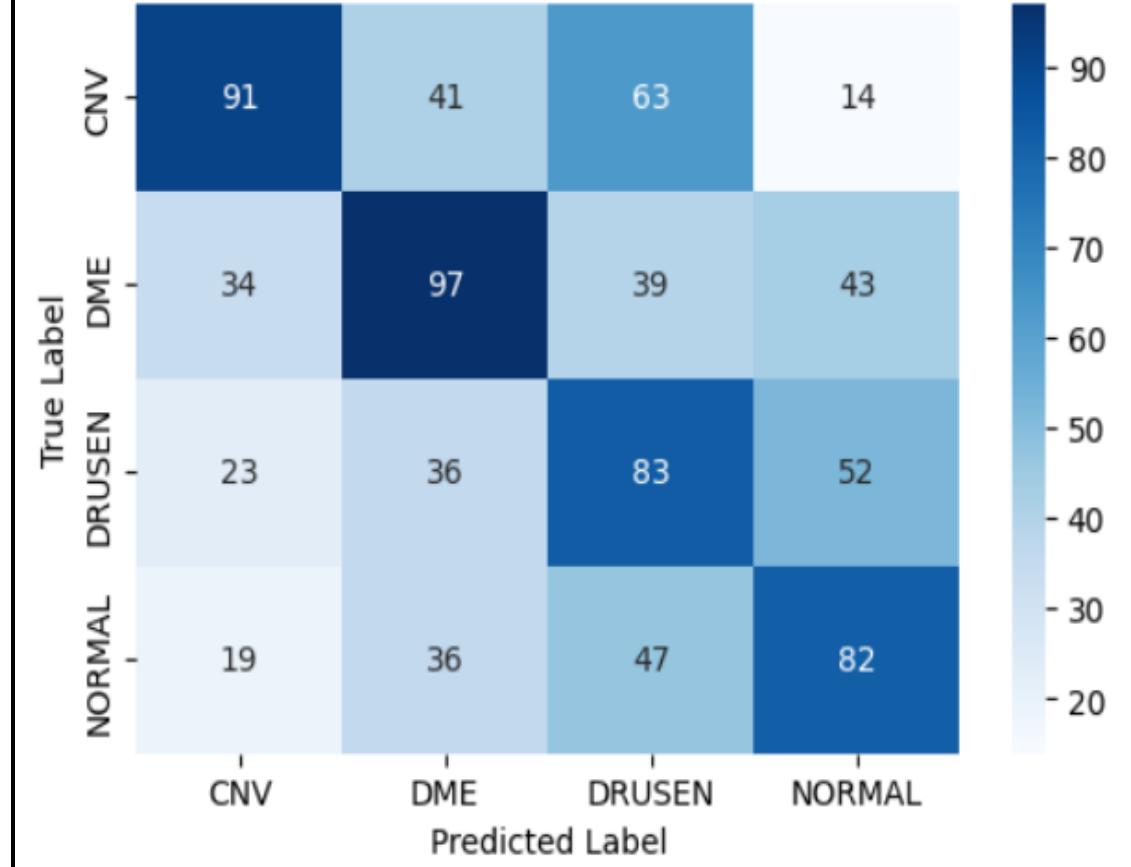
	precision	recall	f1-score	support
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CNV	0.54	0.44	0.48	209
DME	0.46	0.46	0.46	213
DRUSEN	0.36	0.43	0.39	194
NORMAL	0.43	0.45	0.44	184
accuracy			0.44	800
macro avg	0.45	0.44	0.44	800
weighted avg	0.45	0.44	0.44	800

Confusion Matrix - Training Set (200 Estimators)



Confusion Matrix - Testing Set (200 Estimators)



# GRADIENT BOOSTING

- n\_estimators=50
- learning\_rate=0.1

Classification Report (Training Set - Gradient Boosting - 50 Estimators):				
	precision	recall	f1-score	support
CNV	0.93	0.90	0.92	791
DME	0.89	0.93	0.91	787
DRUSEN	0.94	0.90	0.92	806
NORMAL	0.90	0.93	0.91	816
accuracy			0.92	3200
macro avg	0.92	0.92	0.92	3200
weighted avg	0.92	0.92	0.92	3200

Classification Report (Testing Set - Gradient Boosting - 50 Estimators):				
	precision	recall	f1-score	support
CNV	0.57	0.55	0.56	209
DME	0.50	0.47	0.49	213
DRUSEN	0.38	0.38	0.38	194
NORMAL	0.42	0.47	0.45	184
accuracy			0.47	800
macro avg	0.47	0.47	0.47	800
weighted avg	0.47	0.47	0.47	800

#### Training Metrics (Gradient Boosting - 50 Estimators):

Accuracy: 0.915625

Precision: 0.9163691947675392

Recall: 0.9155879442208441

F1-score: 0.9156745173100541

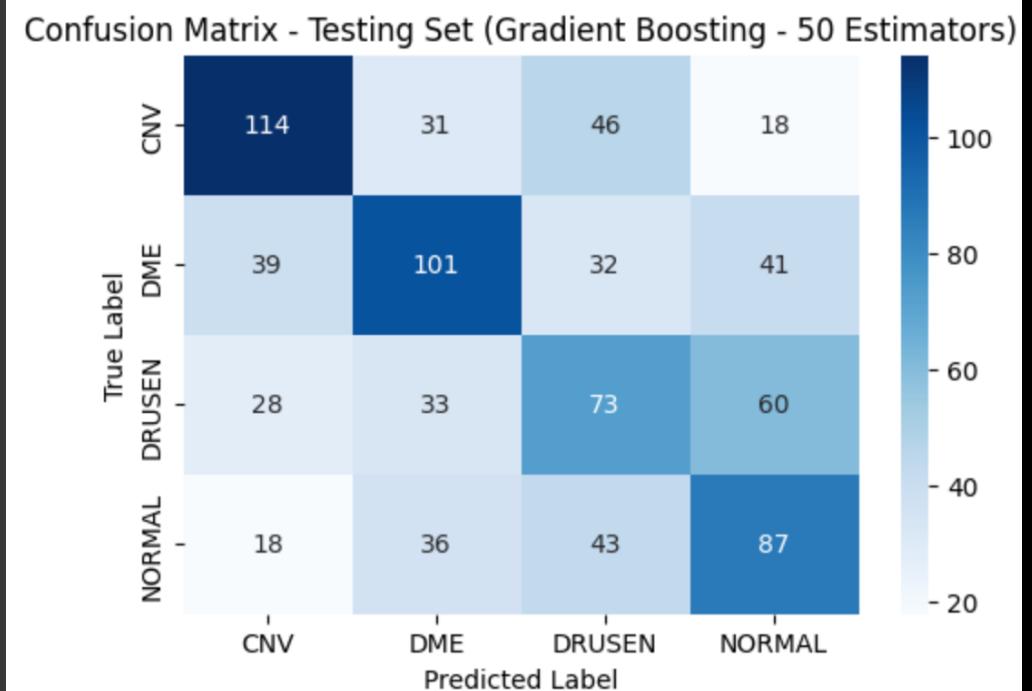
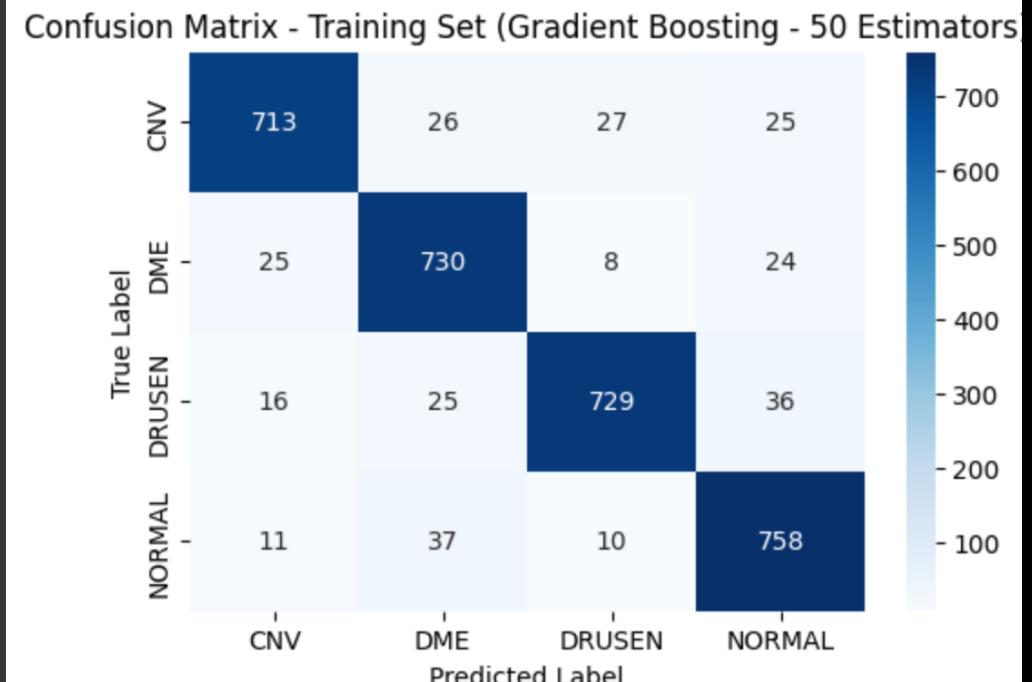
#### Testing Metrics (Gradient Boosting - 50 Estimators):

Accuracy: 0.46875

Precision: 0.46849266016957203

Recall: 0.4671869239901875

F1-score: 0.4672971851683588



# XGBOOSTING:

n\_estimators=200, learning\_rate=0.01, max\_depth = 5)

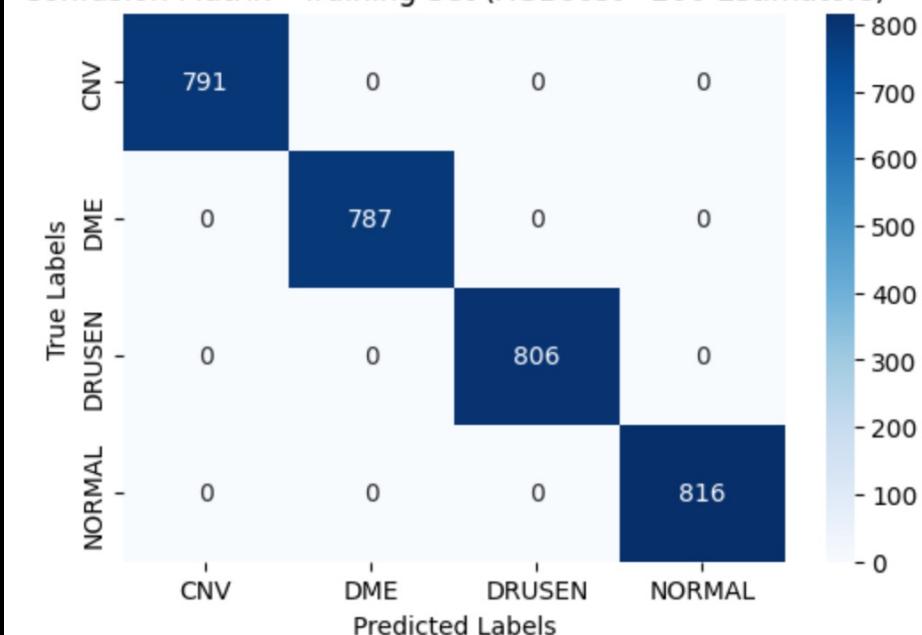
Classification Report (Training Set - XGBoost - 200 Estimators):

	precision	recall	f1-score	support
CNV	0.99	0.95	0.97	791
DME	0.95	0.94	0.95	787
DRUSEN	0.98	0.95	0.97	806
NORMAL	0.91	0.98	0.94	816
accuracy			0.96	3200
macro avg	0.96	0.96	0.96	3200
weighted avg	0.96	0.96	0.96	3200

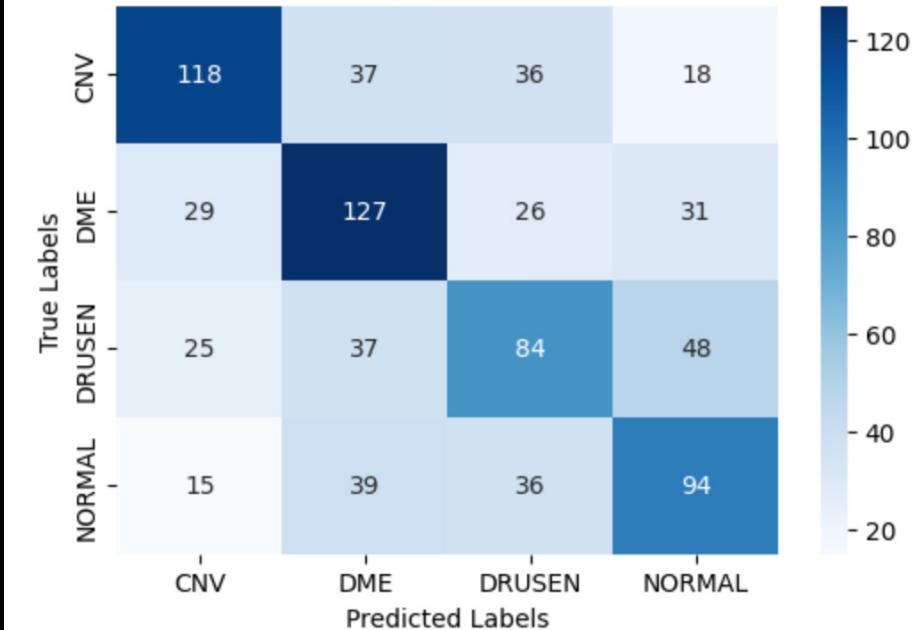
Classification Report (Testing Set - XGBoost - 200 Estimators):

	precision	recall	f1-score	support
CNV	0.57	0.60	0.58	209
DME	0.55	0.50	0.52	213
DRUSEN	0.41	0.34	0.37	194
NORMAL	0.47	0.57	0.51	184
accuracy			0.50	800
macro avg	0.50	0.50	0.50	800
weighted avg	0.50	0.50	0.50	800

Confusion Matrix - Training Set (XGBoost - 200 Estimators)



Confusion Matrix - Testing Set (XGBoost - 200 Estimators)



## VGG-16

- optimizer=Adam(lr=0.001),
- loss='sparse\_categorical\_crossentropy'

Classification Report for Training Data:				
	precision	recall	f1-score	support
0	0.87	0.99	0.92	3898
1	0.98	0.81	0.89	2942
2	0.86	0.82	0.84	2247
3	0.94	0.96	0.95	6912
accuracy			0.92	15999
macro avg	0.91	0.89	0.90	15999
weighted avg	0.92	0.92	0.92	15999

Classification Report:				
	precision	recall	f1-score	support
0	0.77	0.94	0.85	962
1	0.91	0.70	0.79	758
2	0.70	0.62	0.66	572
3	0.89	0.90	0.90	1708
accuracy			0.83	4000
macro avg	0.82	0.79	0.80	4000
weighted avg	0.84	0.83	0.83	4000

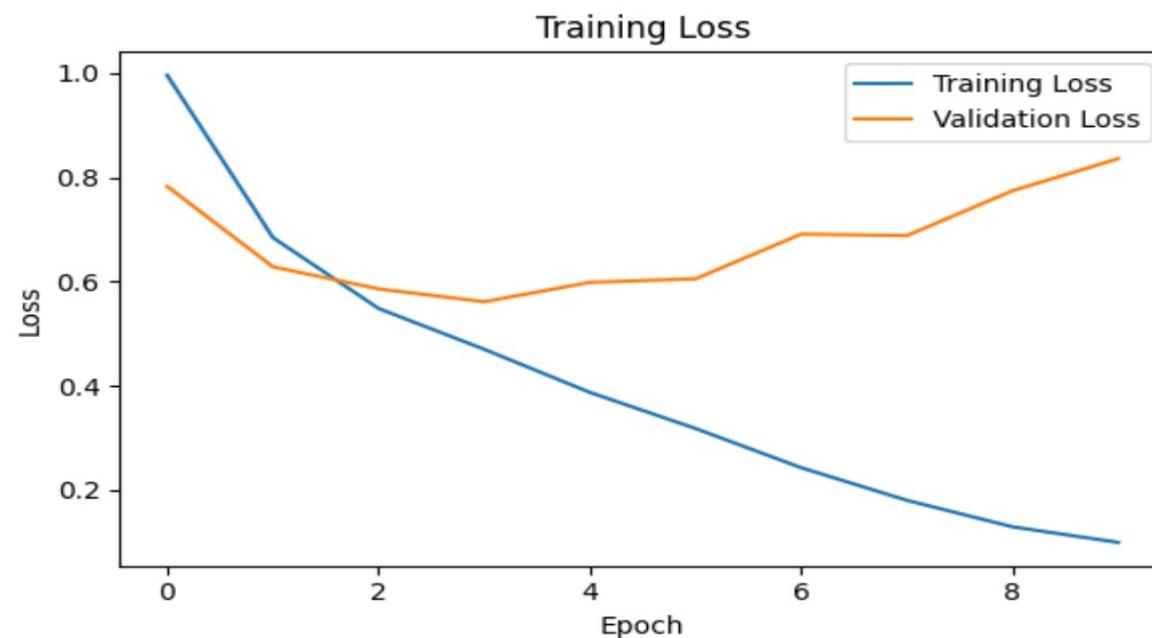


# LE-NET MODEL

- optimizer='adam',
- loss='sparse\_categorical\_crossentropy'

Model: "sequential_8"		
Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 124, 124, 6)	156
max_pooling2d_16 (MaxPooling2D)	(None, 62, 62, 6)	0
conv2d_17 (Conv2D)	(None, 58, 58, 16)	2416
max_pooling2d_17 (MaxPooling2D)	(None, 29, 29, 16)	0
flatten_9 (Flatten)	(None, 13456)	0
dense_26 (Dense)	(None, 120)	1614840
dense_27 (Dense)	(None, 84)	10164
dense_28 (Dense)	(None, 4)	340
<hr/>		
Total params: 1627916 (6.21 MB)		
Trainable params: 1627916 (6.21 MB)		
Non-trainable params: 0 (0.00 Byte)		

Classification Report for Train Set:					Classification Report for Test Set:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
CNV	1.00	0.98	0.99	3898	CNV	0.85	0.82	0.84	962
DME	0.99	0.98	0.98	2942	DME	0.76	0.69	0.73	758
DRUSEN	0.97	0.95	0.96	2247	DRUSEN	0.58	0.58	0.58	572
NORMAL	0.98	1.00	0.99	6912	NORMAL	0.84	0.89	0.86	1708
accuracy			0.98	15999	accuracy			0.79	4000
macro avg	0.98	0.98	0.98	15999	macro avg	0.76	0.75	0.75	4000
weighted avg	0.98	0.98	0.98	15999	weighted avg	0.79	0.79	0.79	4000



# CONVOLUTION NEURAL NETWORKS

- 3 Convolutional layers (conv2d)
- 3 Pooling layers  
(max\_pooling2d)
- 1 Flatten layer
- 3 Dense layers (dense)

Model: "sequential_2"		
Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 254, 254, 32)	320
max_pooling2d_6 (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_7 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_7 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_8 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_8 (MaxPooling2D)	(None, 30, 30, 128)	0
flatten_2 (Flatten)	(None, 115200)	0
dense_6 (Dense)	(None, 128)	14745728
dense_7 (Dense)	(None, 64)	8256
dense_8 (Dense)	(None, 4)	260
<hr/>		
Total params: 14846916 (56.64 MB)		
Trainable params: 14846916 (56.64 MB)		
Non-trainable params: 0 (0.00 Byte)		

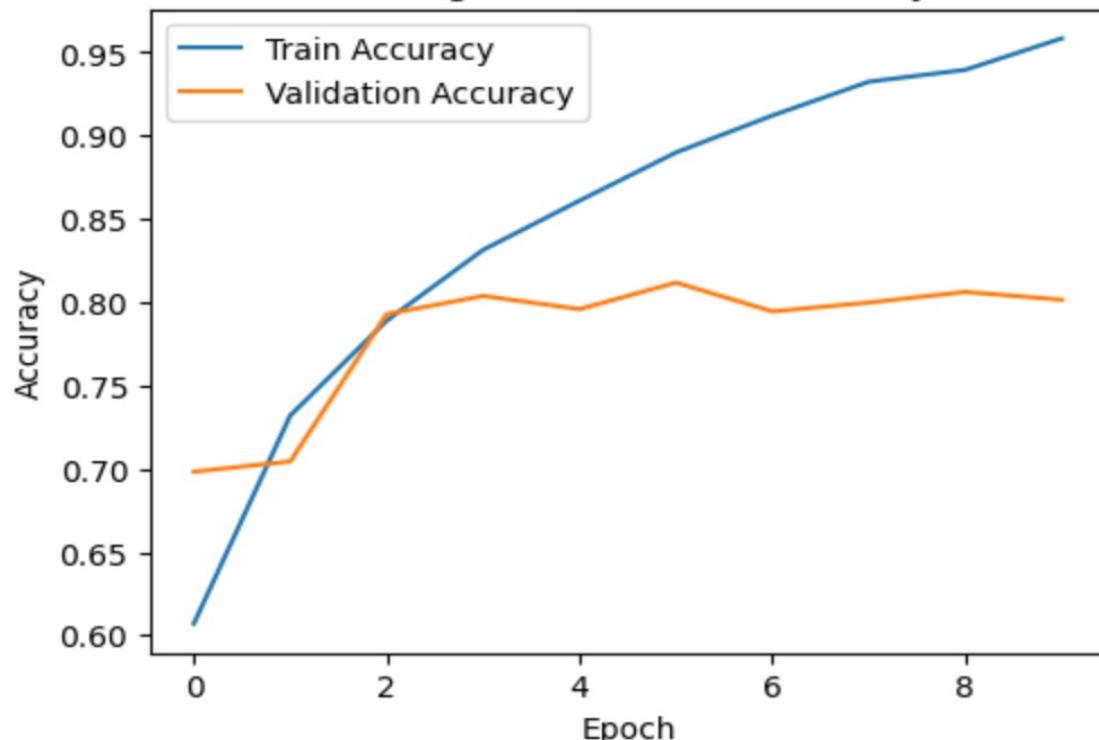
Train Classification Report:

	precision	recall	f1-score	support
CNV	0.98	0.98	0.98	10380
DME	0.98	0.95	0.96	7443
DRUSEN	0.90	0.95	0.92	6031
NORMAL	0.98	0.97	0.97	18420
accuracy			0.97	42274
macro avg	0.96	0.96	0.96	42274
weighted avg	0.97	0.97	0.97	42274

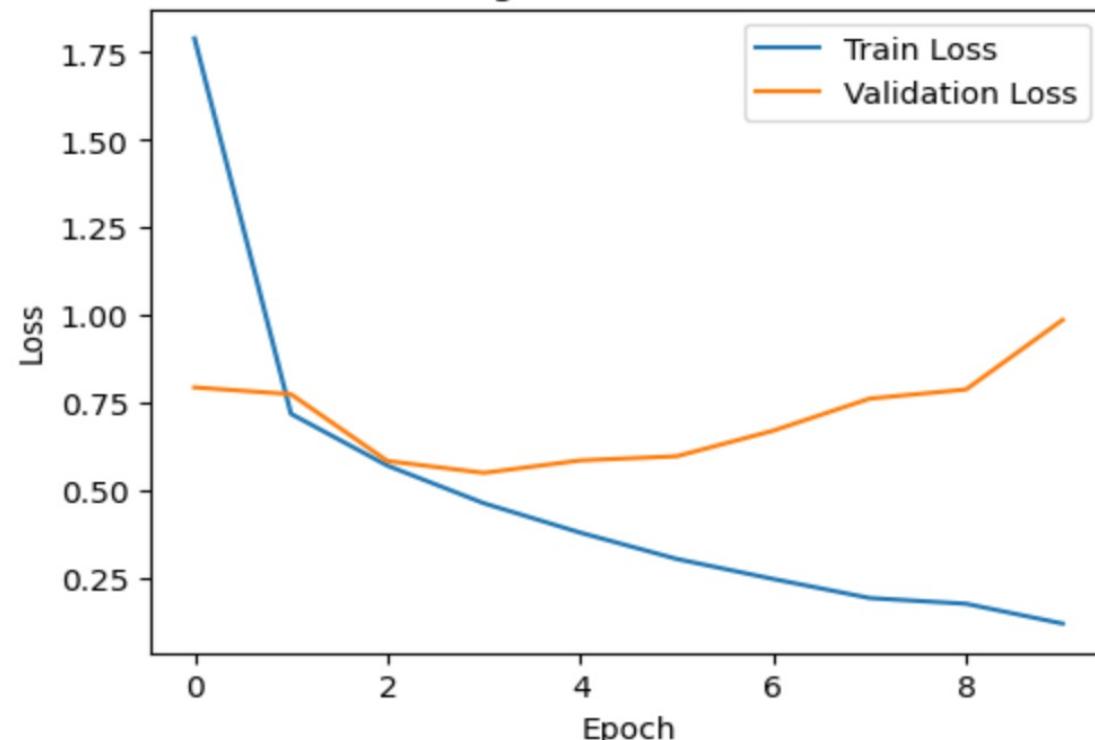
Test Classification Report:

	precision	recall	f1-score	support
CNV	0.81	0.83	0.82	4449
DME	0.81	0.73	0.77	3189
DRUSEN	0.57	0.59	0.58	2585
NORMAL	0.87	0.88	0.87	7895
accuracy				0.80
macro avg			0.77	0.76
weighted avg			0.80	0.80

Training and Validation Accuracy



Training and Validation Loss



# CONVOLUTION NEURAL NETWORKS

- 4 Convolutional layers (conv2d)
  - Shape of X\_train: (42274, 256, 256)
- 4 Pooling layers (max\_pooling2d)
  - Shape of y\_train: (42274,)
- 1 Flatten layer
  - Shape of X\_test: (18118, 256, 256)
- 3 Dense layers (dense)
  - Shape of y\_test: (18118,)

Model: "sequential_19"		
Layer (type)	Output Shape	Param #
conv2d_91 (Conv2D)	(None, 256, 256, 32)	320
max_pooling2d_41 (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_92 (Conv2D)	(None, 128, 128, 64)	18496
max_pooling2d_42 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_93 (Conv2D)	(None, 64, 64, 128)	73856
max_pooling2d_43 (MaxPooling2D)	(None, 32, 32, 128)	0
conv2d_94 (Conv2D)	(None, 32, 32, 256)	295168
max_pooling2d_44 (MaxPooling2D)	(None, 16, 16, 256)	0
flatten_19 (Flatten)	(None, 65536)	0
dense_55 (Dense)	(None, 512)	33554944
dropout_1 (Dropout)	(None, 512)	0
dense_56 (Dense)	(None, 4)	2052

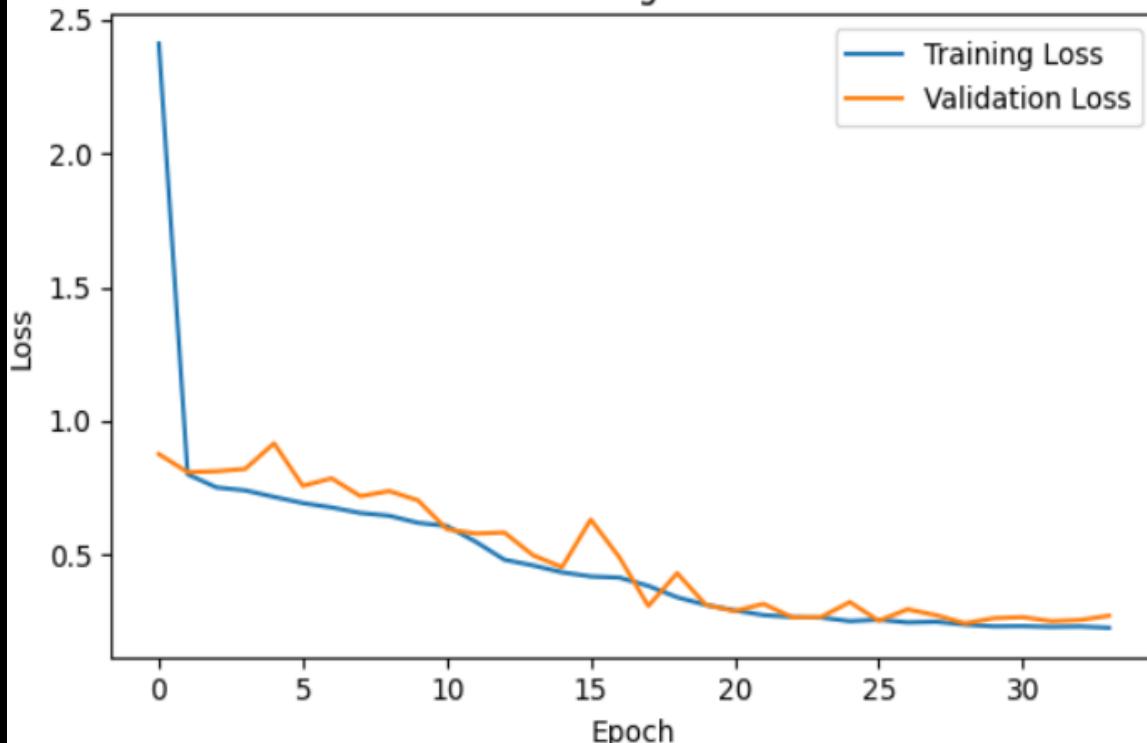
Train Classification Report:

	precision	recall	f1-score	support
0	0.88	0.96	0.92	9341
1	0.98	0.79	0.87	6680
2	0.93	0.78	0.84	5427
3	0.92	0.99	0.95	16598
accuracy			0.92	38046
macro avg	0.92	0.88	0.90	38046
weighted avg	0.92	0.92	0.91	38046

Test Classification Report:

	precision	recall	f1-score	support
0	0.87	0.96	0.91	4449
1	0.97	0.79	0.87	3189
2	0.93	0.77	0.84	2585
3	0.92	0.99	0.95	7895
accuracy			0.91	18118
macro avg	0.92	0.88	0.89	18118
weighted avg	0.92	0.91	0.91	18118

Training Loss



Training Accuracy



# BEST PERFORMING MODEL- CNN

- 5 Convolutional layers (conv2d).
- 5 Pooling layers (max\_pooling2d).
- 1 Flatten layer.
- 2 Dense layers (dense, dense\_1)
- 1 Dropout layer

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	320
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 32, 32, 128)	0
conv2d_3 (Conv2D)	(None, 32, 32, 256)	295168
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 256)	0
conv2d_4 (Conv2D)	(None, 16, 16, 512)	1180160
max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 512)	0
flatten (Flatten)	(None, 32768)	0
dense (Dense)	(None, 512)	16777728
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 4)	2052
<hr/>		
Total params: 18347780 (69.99 MB)		
Trainable params: 18347780 (69.99 MB)		
Non-trainable params: 0 (0.00 Byte)		

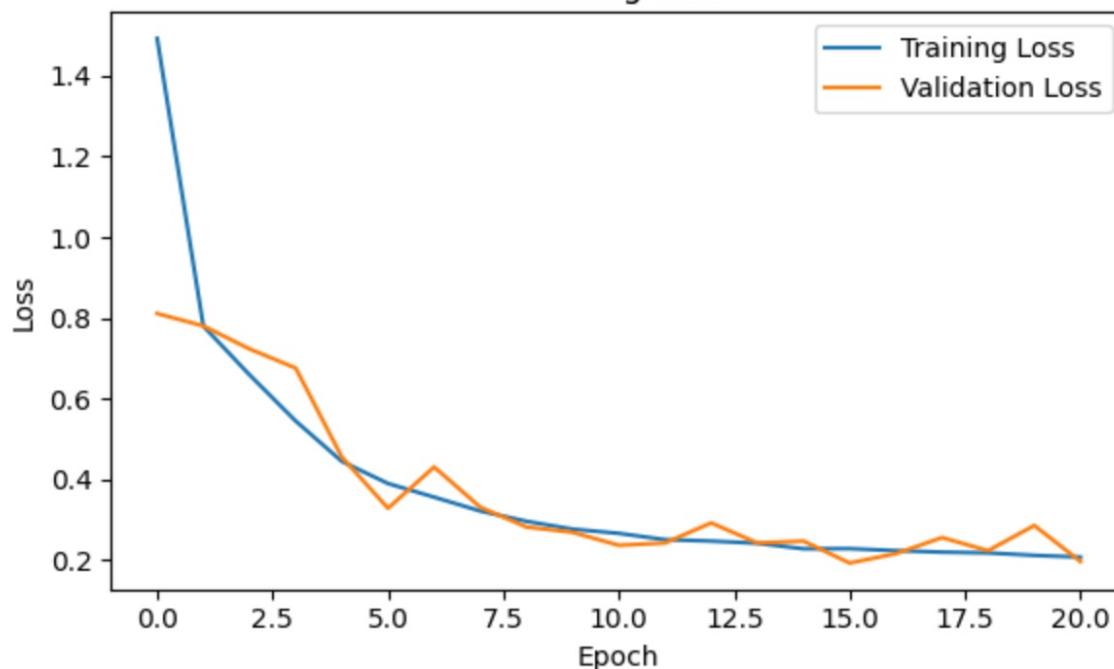
Train Classification Report:

	precision	recall	f1-score	support
0	0.93	0.93	0.93	9341
1	0.95	0.88	0.91	6680
2	0.89	0.86	0.88	5427
3	0.94	0.98	0.96	16598
accuracy			0.93	38046
macro avg	0.93	0.91	0.92	38046
weighted avg	0.93	0.93	0.93	38046

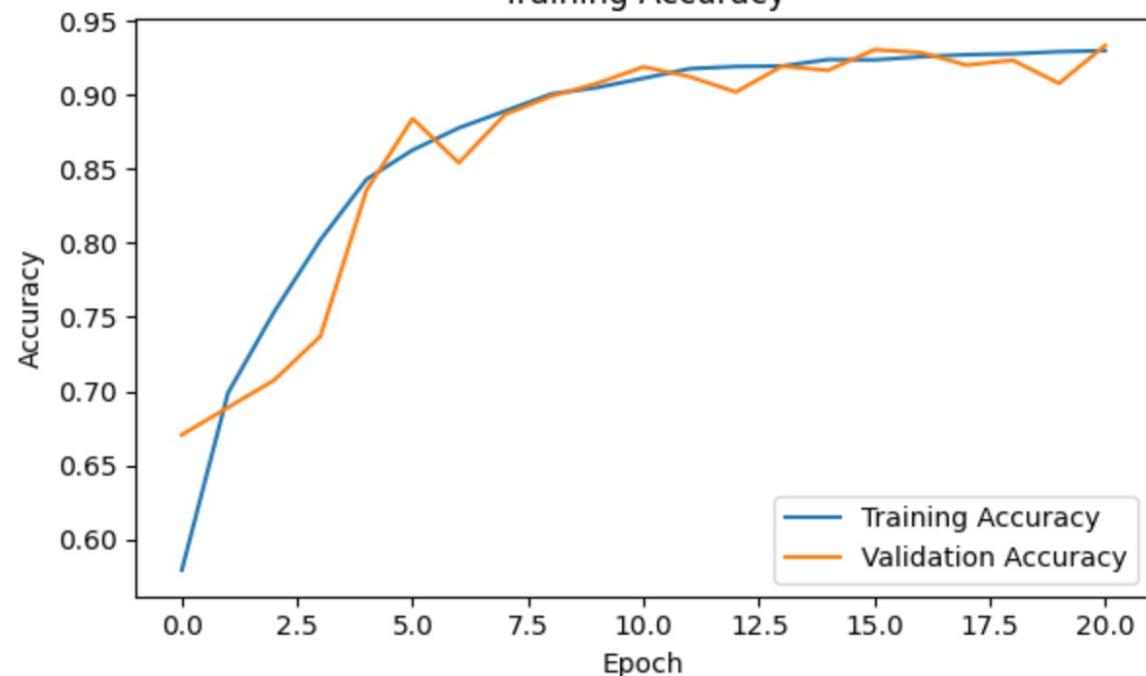
Test Classification Report:

	precision	recall	f1-score	support
0	0	0.93	0.92	4449
1	0.94	0.87	0.91	3189
2	0.88	0.86	0.87	2585
3	0.94	0.98	0.96	7895
accuracy			0.93	18118
macro avg	0.92	0.91	0.92	18118
weighted avg	0.93	0.93	0.93	18118

Training Loss



Training Accuracy



	<b>CNV</b>	<b>DME</b>	<b>DRUSEN</b>	<b>NORMAL</b>	<b>Overall F-1 Score</b>
<b>XGBoosting (n_estimators=200, learning_rate=0.01, max_depth = 5)</b>					
Train	0.97	0.95	0.97	0.94	0.95
Test	0.58	0.52	0.37	0.51	0.5
<b>Gradient Boosting (n_estimators=50, learning_rate=0.1)</b>					
Train	0.92	0.91	0.92	0.91	0.91
Test	0.56	0.49	0.38	0.45	0.46
<b>AdaBoosting (n_estimators=200,learning_rate=0.1)</b>					
Train	0.6	0.56	0.53	0.61	0.57
Test	0.48	0.46	0.39	0.44	0.44
<b>K-Nearest Neighbors (n_neigbors=7, p=1)</b>					
Train	0.55	0.55	0.53	0.56	0.54
Test	0.25	0.4	0.35	0.33	0.33
<b>VGG16 (optimizer='Adam( lr =0.001), loss='sparse categorical cross-entropy')</b>					
Train	0.92	0.89	0.84	0.95	0.9
Test	0.85	0.79	0.66	0.9	0.8
<b>LeNet (optimizer='adam', loss='sparse categorical cross-entropy')</b>					
Train	0.99	0.98	0.96	0.99	0.98
Test	0.82	0.69	0.58	0.86	0.73
<b>CNN</b>					
( 3 Convolutional layers (conv2d), 3 Pooling layers (max_pooling2d), 1 Flatten layer, 3 Dense layers (dense))					
Train	0.98	0.96	0.92	0.97	0.95
Test	0.82	0.77	0.58	0.87	0.76
<b>CNN</b>					
( 5 Convolutional layers (conv2d), 5 Pooling layers (max_pooling2d), 1 Flatten layer, 2 Dense layers (dense, dense_1), 1Dropout layer)					
Train	0.93	0.91	0.88	0.96	0.92
Test	0.93	0.91	0.87	0.96	0.92

Number of images  
= 20,000

Number of images  
= 62,138  
(Entire Dataset)

## ADDRESSING OUR RESEARCH QUESTIONS

- How effective are deep learning models in accurately classifying retinal diseases based on OCT images?
- Which deep learning architectures prove most effective for OCT image classification?
- How does the size and diversity of the training dataset impact model robustness and generalization ability?
- What strategies can be employed to address class imbalance issues in the OCT image dataset?
- How do preprocessing techniques such as denoising, image registration, and normalization impact model performance and interpretability?

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