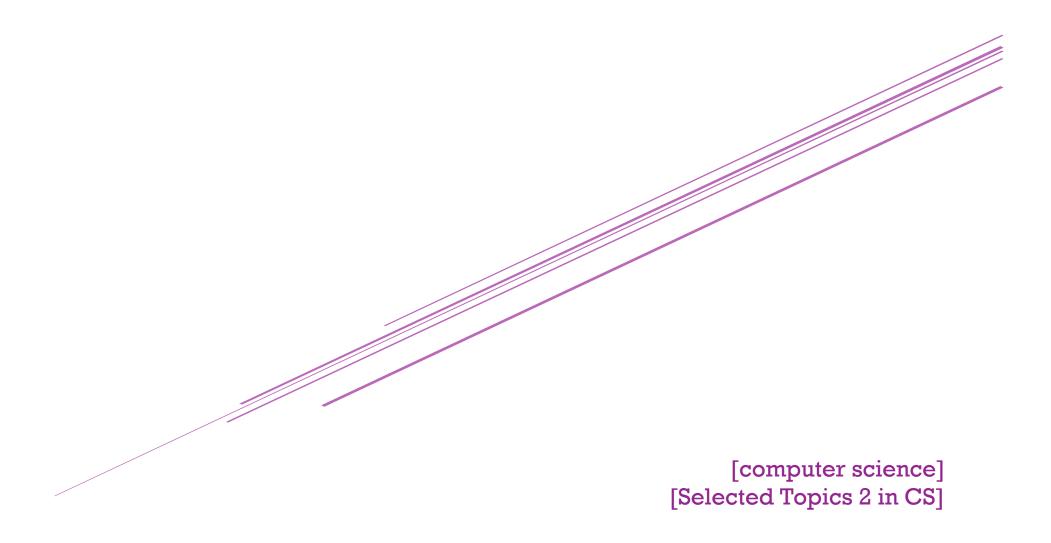
# [SELECTED PORJECT]



### 1)

### Team Number:5

Name	ID
Hana Mohamed Zein	202001039
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Emad Mostafa Serag Elden	202000580
Mohamed ALI Moslh	202000804
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### 2)Paper details:

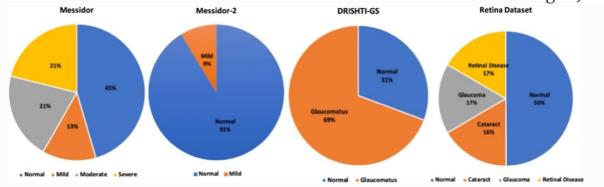
#### a)

- 1. Authors name (Rubina Sarki, Khandakar Ahmed, Hua Wang & Yanchun Zhang Corresponding author: Correspondence to Rubina Sarki).
- 2. paper name (Automated detection of mild and multi-class diabetic eye diseases using deep learning)
- 3. publisher name (Health Information Science and Systems)
- 4. year of publication (8, October (2020))

### b)

5. The dataset used: (Messidor dataset includes high fidelity images with reliable labeling despite its relatively small scale. Similarly, Messidor-2 is a public database used by other individual people to evaluate DED algorithm performance. The database consists of 1748

images of 874 subjects. Messidor-2 differs from the initial 1200 image Messidor set of data, and it has two images for each item, one for each eye. The Drishti-GS dataset contains 101 retinal images, with 31 normal images and 70 lesion images. Cataract dataset acquired from retina dataset GitHub. This dataset consists of 100 cataract images )



### 6. the implemented algorithms: (vgg16, InceptionV3)

### 7. result:

The two pretrained CNN models were compared with the yielded accuracy on the test dataset. Also, fine-tuning was used as a substitute for the default setting. After deletion and retraining of n layers (n was CNN-dependent), the efficiency acquired by each model was used for comparative purposes. The fine-tuning effect was evaluated in terms of Accuracy (%) increment or reduction. The highest accuracy was identified by each model (either through default or after fine-tuning) in four different optimizers. Finally, the top 1 CNN architectures + optimizers with the higher accuracy performance for the target task have been selected in

## 1: Average performance of the models in mild DED classification (mild multi-classes):

Model	Optimiser	Learning rate	Accuracy* (%)	Accuracy** (%)
VGG16	Adam	1e-3	82.42	85.94
	RMSprop	1e-3	83.52	83.98
	SGD	1e-3	75	82.03
Adagra	Adagrad	1e-3	75	75.23
InceptionV3	Adam	1e-3	74	75
	RMSprop	1e-3	71	73
	SGD	1e-3	78.52	78.52
	Adagrad	1e-3	76	79.17

## 2: Average performance of the models in multi-class DED classification:

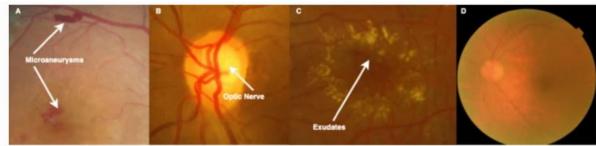
Model	Optimiser	Learning rate	Accuracy* (%)	Accuracy** (%)
VGG16	Adam	1e-3	84.88	88.3
	RMSprop	1e-3	74	80
	SGD	1e-3	80	80
	Adagrad	1e-3	79.95	80
InceptionV3	Adam	1e-3	79	81
	RMSprop	1e-3	65	78
	SGD	1e-3	63	63
	Adagrad	1e-3	58	64

This study is an investigation of mild and multi-class DL algorithms for automated detection of DED. As per the British Diabetic Association (BDA) standards, a minimum amount of 80% sensitivity and 95% specificity for sight-threatening DED detection must be achieved by any method [4]. After testing our approach in DED detection tasks, the scenario I achieved maximum sensitivity of 85% and a maximum specificity of 96%. Similarly, the sensitivity of 85% and specificity of 98% for scenario II, respectively. Thus, according to the BDA standards, mild and multi-class DED detection is sufficient, in terms of its sensitivity and specificity.

3)

#### General Information on the selected dataset:

- name of the dataset used: Retinal OCT Images (optical coherence tomography)
- the link of dataset: https://www.kaggle.com/datasets/paultimothymooney/kermany2018
- the total number of samples in the dataset:84452
- the dimension of images: (512,496)
- number of classes and their labels: labels = ['CNV', 'DME', 'DRUSEN', 'NORMAL'],4 classes



Complications of DED in fundus images; **a** Microaneurysms; narrow bulges in the side of the blood vessel (Diabetic Retinopathy). **b** Progressive damage of optic nerve damage(Glaucoma). **c** Exudates formation in macular region and thickening of macula(Diabetic Macular Edema). **d** Degeneration of lens (Cataract)

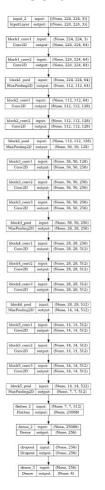
### b)

#### Implementation details:

1-Specify the ratio used for training, validation, and testing. Also, specify the number of images in each: (Train has 66787 images, Validation has: 1697 images, test has 968 images) (Train ratio:80%, validation Ratio:20%, test:100%

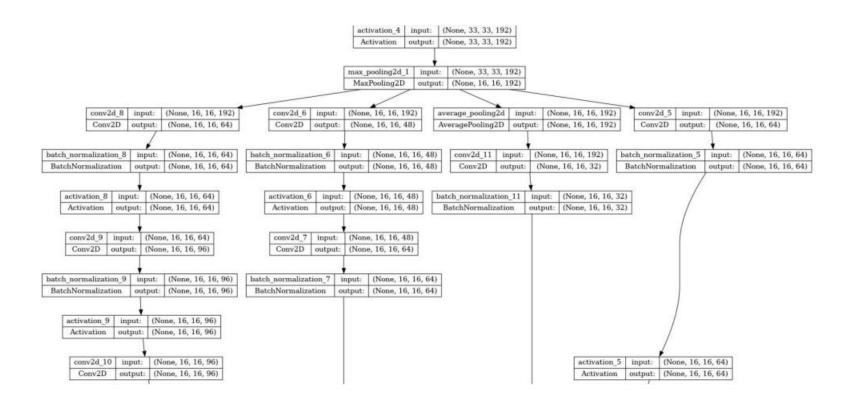
2- A block diagram of your implemented model to show the main steps, and specify in each block the used algorithm(s):

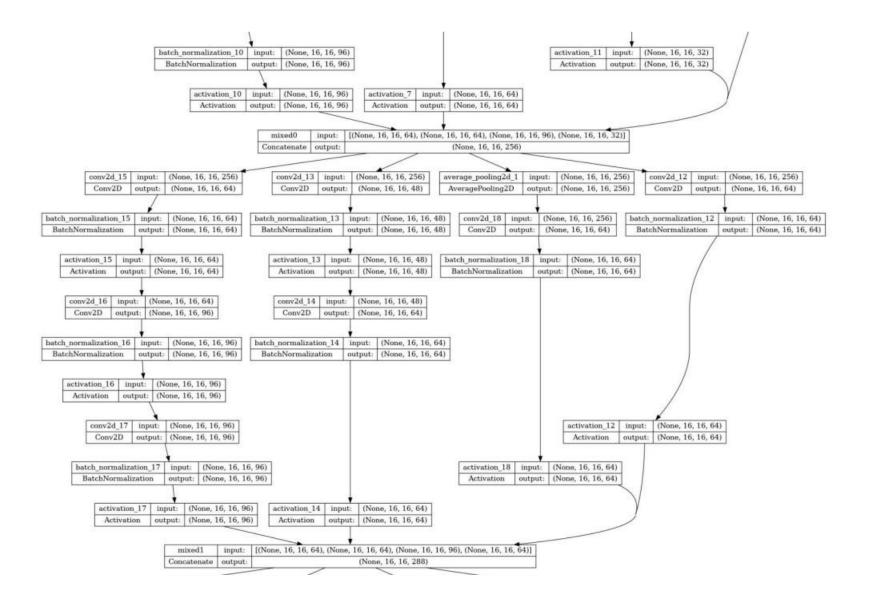
#### 1-VGG16

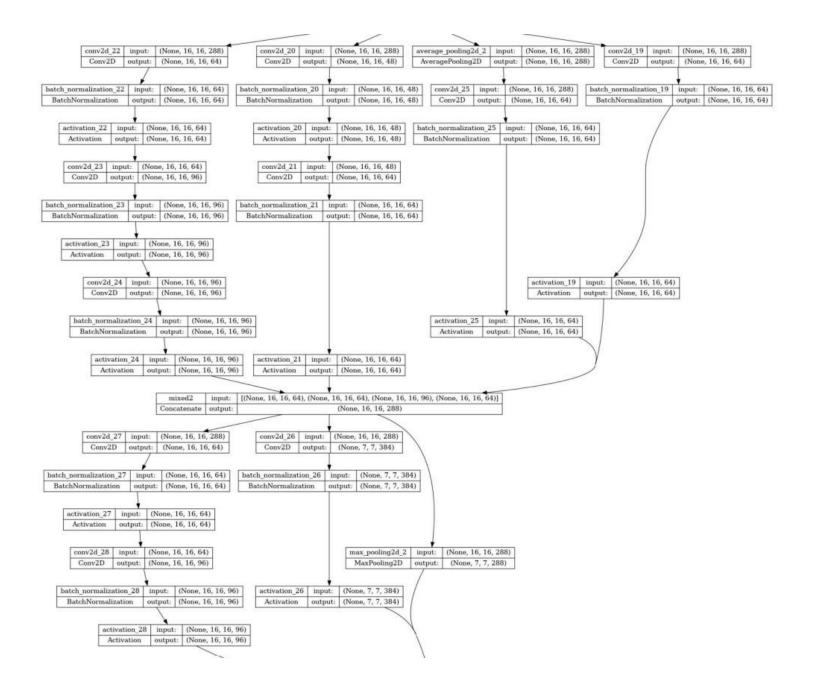


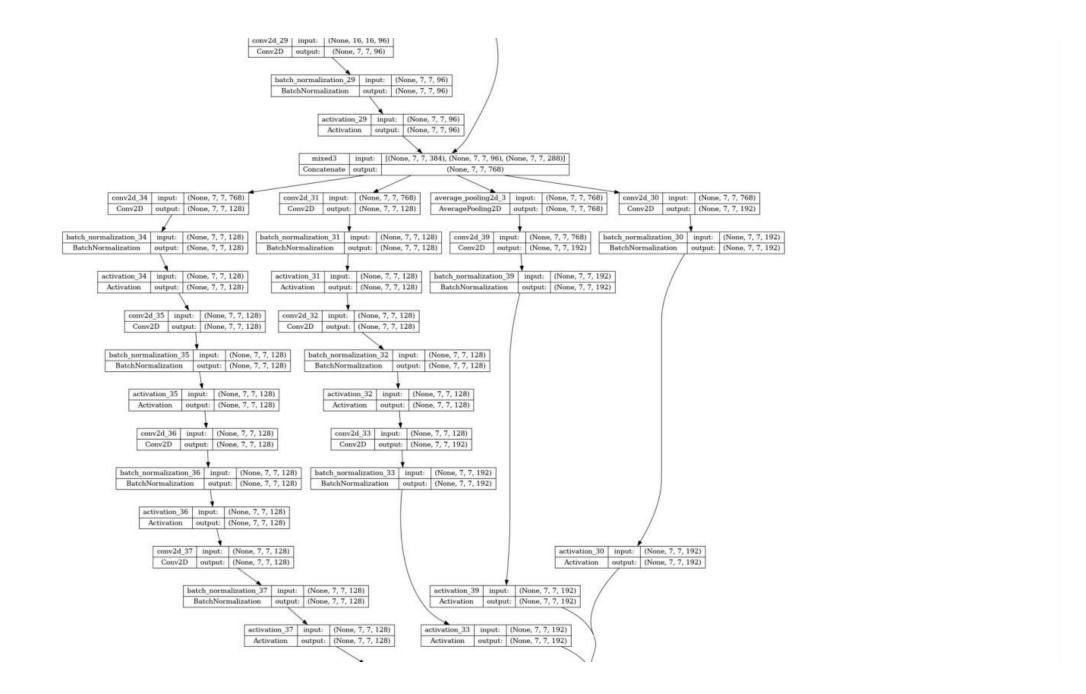
#### 2: InceptionV<sub>3</sub>

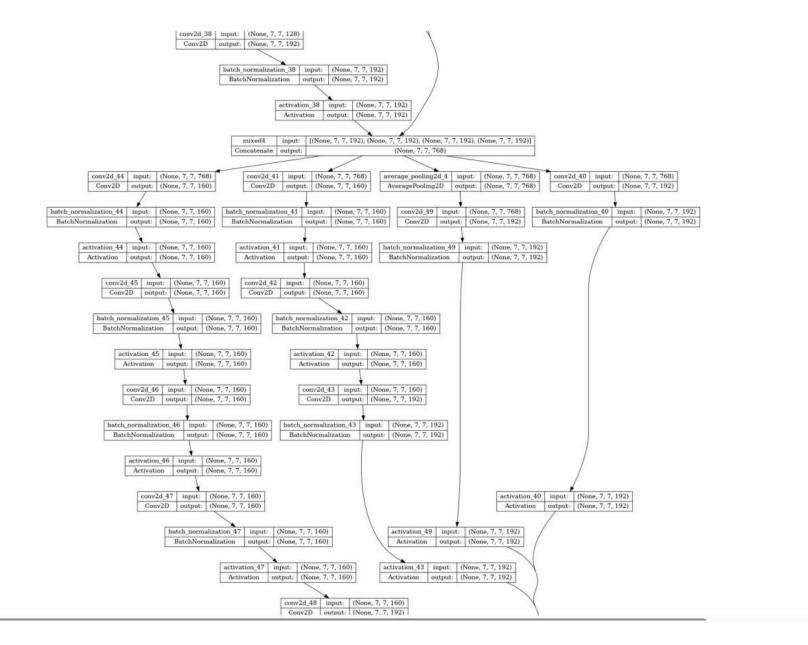
input_2 input: [(None, 150, 150, 3)] InputLayer output: [(None, 150, 150, 3)]  conv2d input: (None, 150, 150, 3)  Conv2D output: (None, 74, 74, 32)  batch_normalization input: (None, 74, 74, 32)  BatchNormalization output: (None, 74, 74, 32)
Conv2d   input:   (None, 150, 150, 3)   Conv2D   output:   (None, 74, 74, 32)
Conv2D output: (None, 74, 74, 32)  batch_normalization input: (None, 74, 74, 32)
Conv2D output: (None, 74, 74, 32)  batch_normalization input: (None, 74, 74, 32)
batch_normalization input: (None, 74, 74, 32)
BatchNormalization output: (None, 74, 74, 32)
•
<b>▼</b>
activation input: (None, 74, 74, 32)
Activation output: (None, 74, 74, 32)
conv2d_1 input: (None, 74, 74, 32)
Conv2D output: (None, 72, 72, 32)
batch_normalization_1 input: (None, 72, 72, 32)
BatchNormalization output: (None, 72, 72, 32)
activation 1 input: (None, 72, 72, 32)
Activation output: (None, 72, 72, 32)
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
<u> </u>
conv2d_2 input: (None, 72, 72, 32)
Conv2D output: (None, 72, 72, 64)
batch_normalization_2 input: (None, 72, 72, 64) BatchNormalization output: (None, 72, 72, 64)
<u> </u>
activation_2 input: (None, 72, 72, 64)
Activation output: (None, 72, 72, 64)
max_pooling2d   input: (None, 72, 72, 64)
MaxPooling2D output: (None, 35, 35, 64)
conv2d_3 input: (None, 35, 35, 64)
Conv2D output: (None, 35, 35, 80)
1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
batch_normalization_3 input: (None, 35, 35, 80)  BatchNormalization output: (None, 35, 35, 80)
Descrive industrial output: (Notice, 33, 33, 00)
activation_3 input: (None, 35, 35, 80)
Activation output: (None, 35, 35, 80)
- 100 P
conv2d 4 input: (None, 35, 35, 80)
Conv2D output: (None, 33, 33, 192)
hatch normalization 4 input. (Name 22 22 102)
Batch normalization 4 input: (None, 33, 33, 192)
batch_normalization_4 input: (None, 33, 33, 192) BatchNormalization output: (None, 33, 33, 192)

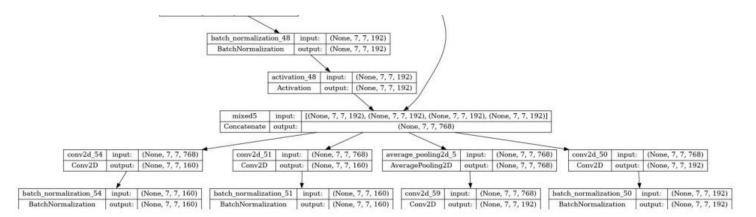






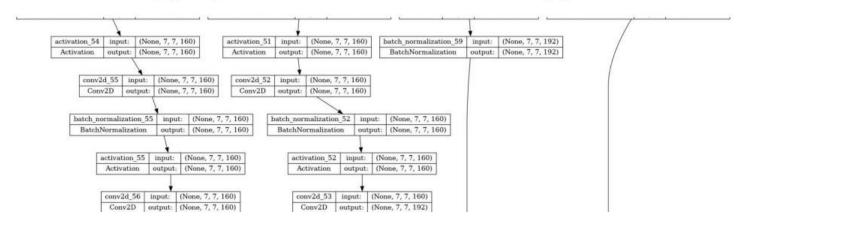


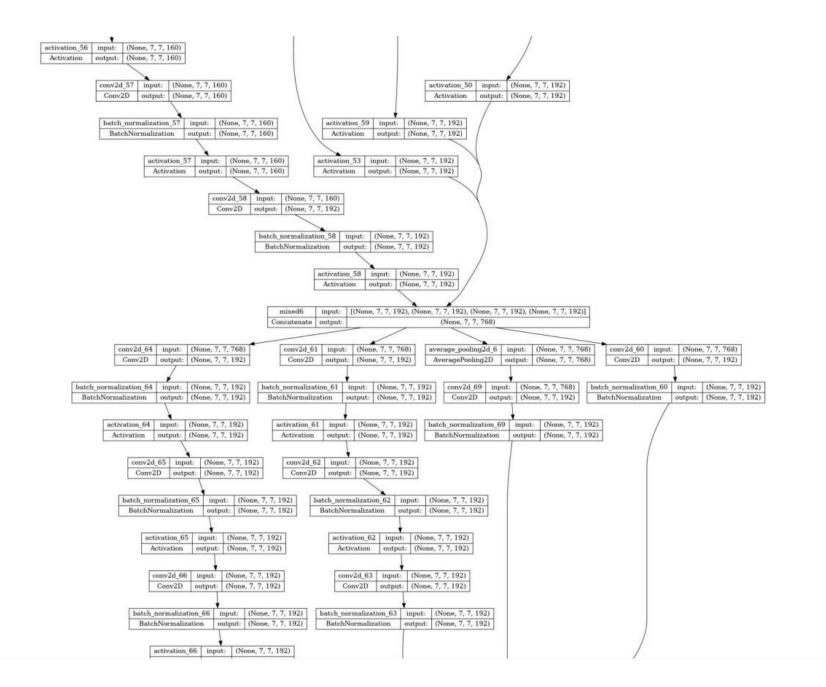


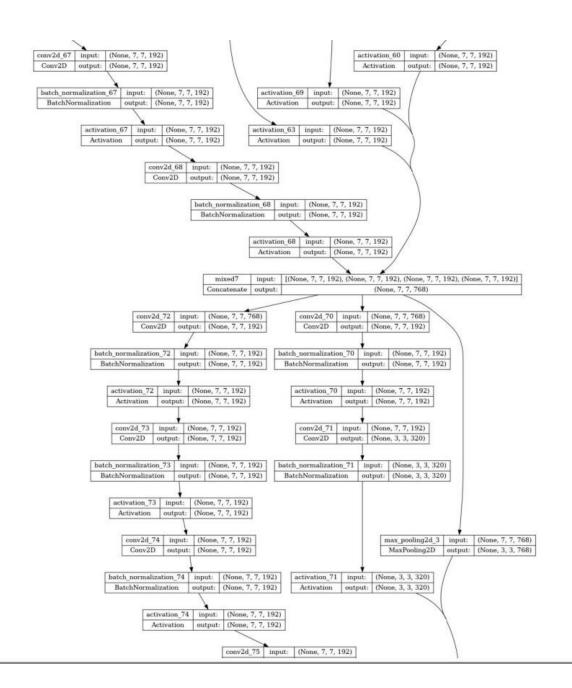


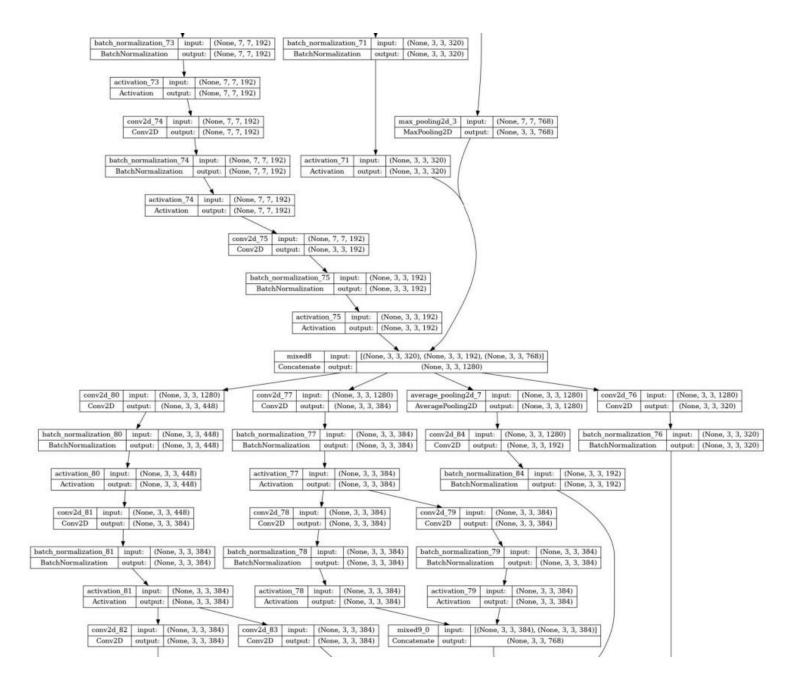
# a/selected\_project/blob/main/notebookbf55995721.ipynb

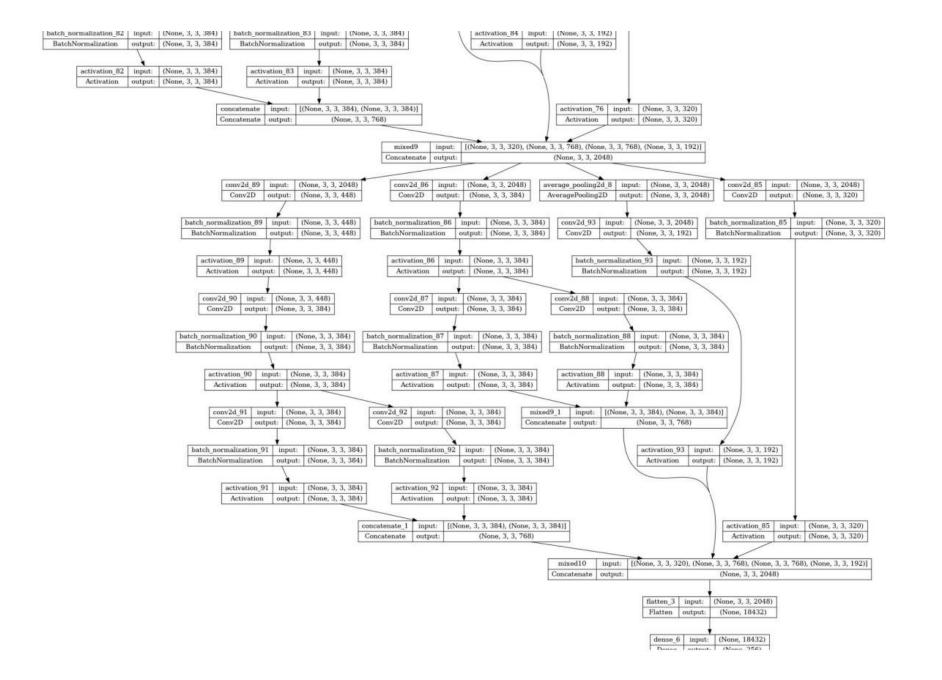
# selected\_project/notebookbf55995721.ipynb at main · 3madMos











3: Specify any hyperparameters used in your model:

1: vgg16:(optimizer: ADAM, Learning Rate:0.0001, Drop out:0.5,epoch size=30,batch-size=32,early\_stop=15, input(224,224))

2: InceptionV<sub>3</sub>:(optimizer: ADAM, Learning Rate: 0.0001, Drop out: 0.5, epochs = 30, batch\_size=32, input(224,224))

c)

1:data Augmentation, making data balanced by using different weights,

# 1: vgg16:

	precision	recall	f1-score	support
CNV	0.98	0.97	0.98	7477
DME	0.94	0.96	0.95	2239
DRUSEN	0.89	0.90	0.89	1704
NORMAL	0.97	0.97	0.97	5277
accuracy			0.96	16697
macro avg	0.94	0.95	0.95	16697
weighted avg	0.96	0.96	0.96	16697

Test accuracy: 0.9948347210884094

Test loss: 0.01875172182917595

#### 2: InceptionV3:

	precision	recall	f1-score	support
CNV	0.93	0.95	0.94	7477
DME	0.86	0.83	0.84	2239
DRUSEN	0.77	0.65	0.70	1704
NORMAL	0.92	0.96	0.94	5277
accuracy			0.90	16697
macro avg	0.87	0.84	0.86	16697
weighted avg	0.90	0.90	0.90	16697

Test accuracy: 0.9545454382896423

Test loss: 0.12928970158100128