

Assignment 4

MRNet Dataset

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Introduction

The MRNet dataset consists of 1,370 knee MRI exams performed at Stanford University Medical Center. The dataset contains 1,104 (80.6%) abnormal exams, with 319 (23.3%) ACL tears and 508 (37.1%) meniscal tears; labels were obtained through manual extraction from clinical reports.

We were asked to implement a CNN model to train the before mentioned data and see how accurately it predicted that the photo of the particular knee (given 3 different views of it) had any of the 3 labeled problems (Abnormality - ACL Tear - Meniscus Tear).

Step1: Download & Understand data:

We downloaded the dataset from the Stanford site and it contained the following:

6 CSV files , 3 for train and 3 for validation, containing the labels of the 3 different sicknesses in a single picture of a knee. 1 csv file for abnormal labels , 1 for acl tears and 1 for meniscus tears.

A train folder and a validate folder containing numpy files that contains the MRI of the knee in the form of slices , meaning that each numpy file has a particular number of slices representing the MRI of that specific knee for that specific view (Axial , Coronal , Sagittal) and it differs for each numpy file. However the pixels of each slice is the same [256,256] .

This concludes the step of downloading and understanding the dataset.

Step2: Pre-Processing:

We had to do some kind of pre-processing on the data after reading it.

We started by reading the data from google drive where we uploaded it, using panda frames we read all 3 csv label files and put them in dataframes and then we created a function that loops on the train folder directory and reading the numpy files into the shape (s,256,256) where s is the number of slices for the particular MRI.

The first pre processing thing we had to do was unite the s number for all the images and we did that using a function that finds the picture with the minimal number of slices and that the number we go with for all other pictures, we made a function that loops on all slices of each picture and choose a random combination of that same minimal number of slices previously decided.

The second pre processing step we had to was turn the 3 dimensional shape into a 4 dimensional shape because as we find out later the ResNet50 model only takes 4 dimensional shapes, so we did that by turning the 1 channel image or [grey scale] into a 3 channel image [RGB], turning it into the dimension (s,256,256,3) we did that using the CV2 resize function.

The third and last pre processing step we did was for the labels, the labels as we mentioned above were given for each picture not for each slice, so seeing that we decided to do our training on slice base information we had to enlarge the label data to be the same size and concept of the training data , so we made a function that repeated the label of each picture n times, n being the minimum number of slices in that entire MRI folder view. And that gave us our training labels.

This concludes the pre-processing part of our program.

Step3: Building The CNN Model:

We chose to use the ResNet50 architecture for our deep CNN model to perform the classification task.

We used 'imagenet' as pre-trained weights to help with the model building, the input_shape of our CNN is (256,256,3) the 3 channel (RGB) image.

Next we used GlobalAveragePooling2D() layer to help tune our model and for more efficient use of our RAM, followed by a dropout layer of 0.7 value, and a dense layer of a 'softmax' activation. We compiled using 'adam' optimization , categorical cross-entropy loss calculation and 'accuracy' metrics.

We then fit to our training data and training labels for the abnormal labels and we evaluate() on the test data and test abnormal labels we save the output of the evaluate() which is the loss and accuracy.

Followed by another model fit for the training data but with the ACL labels and evaluation on test data and ACL test labels. And ofcourse another fit with the Meniscus labels both train and test.

This is done using a function and the only thing that changes when we call it is the training and test data which each time is called using a different view (Axial,Coronal,Sagittal).

This way we end up with 9 accuracies , 3 for each view, 1 for each labeled sickness.

Results:

Step4: Combining Results:

To gather up the labels, we take the 3 Abnormal labels from all 3 models and append them in an array separately and the same goes for the 3 ACL labels and 3 Meniscus labels.

We then send each of these arrays to a function we made to combine all 3 labels into the final prediction :

If two of these abels is 0 , then the patient is considered to be healthy and doesn't have the disease.

If two of these labels is 1 , then the patient is considered to be sick.

We also provided another function that takes accuracies instead of the labels. And by the same concept calculates flags and returns average accuracy

Step5: Tuning:

We tried a few different but simple parameters to try and reach higher results and this is where we landed..

Epochs = 10

Batch size	Dropout ratio	Validation set
50	0.1	0.48288
50	0.7	0.5714
70	0.7	0.46433
80	0.7	0.56322
85	0.7	-
90	0.7	-

Step6: OUTPUT:

For a run with 3 epochs :

Epoch 1/3

10735/10735 [=====] - 191s 18ms/step - loss: 1.2091 - acc: 0.5046

Epoch 2/3

10735/10735 [=====] - 180s 17ms/step - loss: 1.1135 - acc: 0.4947

Epoch 3/3

10735/10735 [=====] - 181s 17ms/step - loss: 1.1119 - acc: 0.5081

1320/1320 [=====] - 10s 7ms/step

F-Scores for Axial-Abnormal:

[0.55882353 0.42307692]

Layer (type)	Output Shape	Param #	Connected to
=====			
input_4 (InputLayer)	(None, 256, 256, 3)	0	
<hr/>			
conv1_pad (ZeroPadding2D)	(None, 262, 262, 3)	0	input_4[0][0]

conv1 (Conv2D)	(None, 128, 128, 64)	9472	conv1_pad[0][0]
bn_conv1 (BatchNormalization)	(None, 128, 128, 64)	256	conv1[0][0]
activation_135 (Activation)	(None, 128, 128, 64)	0	bn_conv1[0][0]
pool1_pad (ZeroPadding2D)	(None, 130, 130, 64)	0	activation_135[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 64, 64, 64)	0	pool1_pad[0][0]
res2a_branch2a (Conv2D)	(None, 64, 64, 64)	4160	max_pooling2d_4[0][0]
bn2a_branch2a (BatchNormalizati	(None, 64, 64, 64)	256	res2a_branch2a[0][0]
activation_136 (Activation)	(None, 64, 64, 64)	0	bn2a_branch2a[0][0]
res2a_branch2b (Conv2D)	(None, 64, 64, 64)	36928	activation_136[0][0]
bn2a_branch2b (BatchNormalizati	(None, 64, 64, 64)	256	res2a_branch2b[0][0]
activation_137 (Activation)	(None, 64, 64, 64)	0	bn2a_branch2b[0][0]
res2a_branch2c (Conv2D)	(None, 64, 64, 256)	16640	activation_137[0][0]
res2a_branch1 (Conv2D)	(None, 64, 64, 256)	16640	max_pooling2d_4[0][0]
bn2a_branch2c (BatchNormalizati	(None, 64, 64, 256)	1024	res2a_branch2c[0][0]
bn2a_branch1 (BatchNormalizatio	(None, 64, 64, 256)	1024	res2a_branch1[0][0]

add_44 (Add)	(None, 64, 64, 256)	0	bn2a_branch2c[0][0] bn2a_branch1[0][0]
activation_138 (Activation)	(None, 64, 64, 256)	0	add_44[0][0]
res2b_branch2a (Conv2D)	(None, 64, 64, 64)	16448	activation_138[0][0]
bn2b_branch2a (BatchNormalizati	(None, 64, 64, 64)	256	res2b_branch2a[0][0]
activation_139 (Activation)	(None, 64, 64, 64)	0	bn2b_branch2a[0][0]
res2b_branch2b (Conv2D)	(None, 64, 64, 64)	36928	activation_139[0][0]
bn2b_branch2b (BatchNormalizati	(None, 64, 64, 64)	256	res2b_branch2b[0][0]
activation_140 (Activation)	(None, 64, 64, 64)	0	bn2b_branch2b[0][0]
res2b_branch2c (Conv2D)	(None, 64, 64, 256)	16640	activation_140[0][0]
bn2b_branch2c (BatchNormalizati	(None, 64, 64, 256)	1024	res2b_branch2c[0][0]
add_45 (Add)	(None, 64, 64, 256)	0	bn2b_branch2c[0][0] activation_138[0][0]
activation_141 (Activation)	(None, 64, 64, 256)	0	add_45[0][0]
res2c_branch2a (Conv2D)	(None, 64, 64, 64)	16448	activation_141[0][0]

bn2c_branch2a	(BatchNormalizati	(None, 64, 64, 64)	256	res2c_branch2a[0][0]
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activation_142	(Activation)	(None, 64, 64, 64)	0	bn2c_branch2a[0][0]
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res2c_branch2b	(Conv2D)	(None, 64, 64, 64)	36928	activation_142[0][0]
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bn2c_branch2b	(BatchNormalizati	(None, 64, 64, 64)	256	res2c_branch2b[0][0]
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activation_143	(Activation)	(None, 64, 64, 64)	0	bn2c_branch2b[0][0]
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res2c_branch2c	(Conv2D)	(None, 64, 64, 256)	16640	activation_143[0][0]
<hr/>				
bn2c_branch2c	(BatchNormalizati	(None, 64, 64, 256)	1024	res2c_branch2c[0][0]
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add_46	(Add)	(None, 64, 64, 256)	0	bn2c_branch2c[0][0]
				activation_141[0][0]
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activation_144	(Activation)	(None, 64, 64, 256)	0	add_46[0][0]
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res3a_branch2a	(Conv2D)	(None, 32, 32, 128)	32896	activation_144[0][0]
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bn3a_branch2a	(BatchNormalizati	(None, 32, 32, 128)	512	res3a_branch2a[0][0]
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activation_145	(Activation)	(None, 32, 32, 128)	0	bn3a_branch2a[0][0]
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res3a_branch2b	(Conv2D)	(None, 32, 32, 128)	147584	activation_145[0][0]
<hr/>				
bn3a_branch2b	(BatchNormalizati	(None, 32, 32, 128)	512	res3a_branch2b[0][0]
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activation_146 (Activation)	(None, 32, 32, 128)	0	bn3a_branch2b[0][0]
<hr/>			
res3a_branch2c (Conv2D)	(None, 32, 32, 512)	66048	activation_146[0][0]
<hr/>			
res3a_branch1 (Conv2D)	(None, 32, 32, 512)	131584	activation_144[0][0]
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bn3a_branch2c (BatchNormalizati	(None, 32, 32, 512)	2048	res3a_branch2c[0][0]
<hr/>			
bn3a_branch1 (BatchNormalizatio	(None, 32, 32, 512)	2048	res3a_branch1[0][0]
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add_47 (Add)	(None, 32, 32, 512)	0	bn3a_branch2c[0][0] bn3a_branch1[0][0]
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activation_147 (Activation)	(None, 32, 32, 512)	0	add_47[0][0]
<hr/>			
res3b_branch2a (Conv2D)	(None, 32, 32, 128)	65664	activation_147[0][0]
<hr/>			
bn3b_branch2a (BatchNormalizati	(None, 32, 32, 128)	512	res3b_branch2a[0][0]
<hr/>			
activation_148 (Activation)	(None, 32, 32, 128)	0	bn3b_branch2a[0][0]
<hr/>			
res3b_branch2b (Conv2D)	(None, 32, 32, 128)	147584	activation_148[0][0]
<hr/>			
bn3b_branch2b (BatchNormalizati	(None, 32, 32, 128)	512	res3b_branch2b[0][0]
<hr/>			
activation_149 (Activation)	(None, 32, 32, 128)	0	bn3b_branch2b[0][0]
<hr/>			
res3b_branch2c (Conv2D)	(None, 32, 32, 512)	66048	activation_149[0][0]
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bn3b_branch2c (BatchNormalizati	(None, 32, 32, 512)	2048	res3b_branch2c[0][0]
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add_48 (Add)	(None, 32, 32, 512)	0	bn3b_branch2c[0][0] activation_147[0][0]
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activation_150 (Activation)	(None, 32, 32, 512)	0	add_48[0][0]
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res3c_branch2a (Conv2D)	(None, 32, 32, 128)	65664	activation_150[0][0]
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bn3c_branch2a (BatchNormalizati	(None, 32, 32, 128)	512	res3c_branch2a[0][0]
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activation_151 (Activation)	(None, 32, 32, 128)	0	bn3c_branch2a[0][0]
<hr/>			
res3c_branch2b (Conv2D)	(None, 32, 32, 128)	147584	activation_151[0][0]
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bn3c_branch2b (BatchNormalizati	(None, 32, 32, 128)	512	res3c_branch2b[0][0]
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activation_152 (Activation)	(None, 32, 32, 128)	0	bn3c_branch2b[0][0]
<hr/>			
res3c_branch2c (Conv2D)	(None, 32, 32, 512)	66048	activation_152[0][0]
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bn3c_branch2c (BatchNormalizati	(None, 32, 32, 512)	2048	res3c_branch2c[0][0]
<hr/>			
add_49 (Add)	(None, 32, 32, 512)	0	bn3c_branch2c[0][0] activation_150[0][0]
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activation_153 (Activation)	(None, 32, 32, 512)	0	add_49[0][0]
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res3d_branch2a (Conv2D)	(None, 32, 32, 128)	65664	activation_153[0][0]

bn3d_branch2a	(BatchNormalizati	(None, 32, 32, 128)	512	res3d_branch2a[0][0]
activation_154	(Activation)	(None, 32, 32, 128)	0	bn3d_branch2a[0][0]
res3d_branch2b	(Conv2D)	(None, 32, 32, 128)	147584	activation_154[0][0]
bn3d_branch2b	(BatchNormalizati	(None, 32, 32, 128)	512	res3d_branch2b[0][0]
activation_155	(Activation)	(None, 32, 32, 128)	0	bn3d_branch2b[0][0]
res3d_branch2c	(Conv2D)	(None, 32, 32, 512)	66048	activation_155[0][0]
bn3d_branch2c	(BatchNormalizati	(None, 32, 32, 512)	2048	res3d_branch2c[0][0]
add_50	(Add)	(None, 32, 32, 512)	0	bn3d_branch2c[0][0] activation_153[0][0]
activation_156	(Activation)	(None, 32, 32, 512)	0	add_50[0][0]
res4a_branch2a	(Conv2D)	(None, 16, 16, 256)	131328	activation_156[0][0]
bn4a_branch2a	(BatchNormalizati	(None, 16, 16, 256)	1024	res4a_branch2a[0][0]
activation_157	(Activation)	(None, 16, 16, 256)	0	bn4a_branch2a[0][0]
res4a_branch2b	(Conv2D)	(None, 16, 16, 256)	590080	activation_157[0][0]
bn4a_branch2b	(BatchNormalizati	(None, 16, 16, 256)	1024	res4a_branch2b[0][0]

activation_158 (Activation)	(None, 16, 16, 256)	0	bn4a_branch2b[0][0]
res4a_branch2c (Conv2D)	(None, 16, 16, 1024)	263168	activation_158[0][0]
res4a_branch1 (Conv2D)	(None, 16, 16, 1024)	525312	activation_156[0][0]
bn4a_branch2c (BatchNormalizati	(None, 16, 16, 1024)	4096	res4a_branch2c[0][0]
bn4a_branch1 (BatchNormalizatio	(None, 16, 16, 1024)	4096	res4a_branch1[0][0]
add_51 (Add)	(None, 16, 16, 1024)	0	bn4a_branch2c[0][0] bn4a_branch1[0][0]
activation_159 (Activation)	(None, 16, 16, 1024)	0	add_51[0][0]
res4b_branch2a (Conv2D)	(None, 16, 16, 256)	262400	activation_159[0][0]
bn4b_branch2a (BatchNormalizati	(None, 16, 16, 256)	1024	res4b_branch2a[0][0]
activation_160 (Activation)	(None, 16, 16, 256)	0	bn4b_branch2a[0][0]
res4b_branch2b (Conv2D)	(None, 16, 16, 256)	590080	activation_160[0][0]
bn4b_branch2b (BatchNormalizati	(None, 16, 16, 256)	1024	res4b_branch2b[0][0]
activation_161 (Activation)	(None, 16, 16, 256)	0	bn4b_branch2b[0][0]
res4b_branch2c (Conv2D)	(None, 16, 16, 1024)	263168	activation_161[0][0]

bn4b_branch2c (BatchNormalizati	(None, 16, 16, 1024) 4096	res4b_branch2c[0][0]
add_52 (Add)	(None, 16, 16, 1024) 0	bn4b_branch2c[0][0] activation_159[0][0]
activation_162 (Activation)	(None, 16, 16, 1024) 0	add_52[0][0]
res4c_branch2a (Conv2D)	(None, 16, 16, 256) 262400	activation_162[0][0]
bn4c_branch2a (BatchNormalizati	(None, 16, 16, 256) 1024	res4c_branch2a[0][0]
activation_163 (Activation)	(None, 16, 16, 256) 0	bn4c_branch2a[0][0]
res4c_branch2b (Conv2D)	(None, 16, 16, 256) 590080	activation_163[0][0]
bn4c_branch2b (BatchNormalizati	(None, 16, 16, 256) 1024	res4c_branch2b[0][0]
activation_164 (Activation)	(None, 16, 16, 256) 0	bn4c_branch2b[0][0]
res4c_branch2c (Conv2D)	(None, 16, 16, 1024) 263168	activation_164[0][0]
bn4c_branch2c (BatchNormalizati	(None, 16, 16, 1024) 4096	res4c_branch2c[0][0]
add_53 (Add)	(None, 16, 16, 1024) 0	bn4c_branch2c[0][0] activation_162[0][0]
activation_165 (Activation)	(None, 16, 16, 1024) 0	add_53[0][0]

res4d_branch2a (Conv2D)	(None, 16, 16, 256)	262400	activation_165[0][0]
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bn4d_branch2a (BatchNormalizati	(None, 16, 16, 256)	1024	res4d_branch2a[0][0]
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activation_166 (Activation)	(None, 16, 16, 256)	0	bn4d_branch2a[0][0]
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res4d_branch2b (Conv2D)	(None, 16, 16, 256)	590080	activation_166[0][0]
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bn4d_branch2b (BatchNormalizati	(None, 16, 16, 256)	1024	res4d_branch2b[0][0]
<hr/>			
activation_167 (Activation)	(None, 16, 16, 256)	0	bn4d_branch2b[0][0]
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res4d_branch2c (Conv2D)	(None, 16, 16, 1024)	263168	activation_167[0][0]
<hr/>			
bn4d_branch2c (BatchNormalizati	(None, 16, 16, 1024)	4096	res4d_branch2c[0][0]
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add_54 (Add)	(None, 16, 16, 1024)	0	bn4d_branch2c[0][0]
			activation_165[0][0]
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activation_168 (Activation)	(None, 16, 16, 1024)	0	add_54[0][0]
<hr/>			
res4e_branch2a (Conv2D)	(None, 16, 16, 256)	262400	activation_168[0][0]
<hr/>			
bn4e_branch2a (BatchNormalizati	(None, 16, 16, 256)	1024	res4e_branch2a[0][0]
<hr/>			
activation_169 (Activation)	(None, 16, 16, 256)	0	bn4e_branch2a[0][0]
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res4e_branch2b (Conv2D)	(None, 16, 16, 256)	590080	activation_169[0][0]
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bn4e_branch2b (BatchNormalizati	(None, 16, 16, 256)	1024	res4e_branch2b[0][0]
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activation_170 (Activation)	(None, 16, 16, 256)	0	bn4e_branch2b[0][0]
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res4e_branch2c (Conv2D)	(None, 16, 16, 1024)	263168	activation_170[0][0]
<hr/>			
bn4e_branch2c (BatchNormalizati	(None, 16, 16, 1024)	4096	res4e_branch2c[0][0]
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add_55 (Add)	(None, 16, 16, 1024)	0	bn4e_branch2c[0][0]
			activation_168[0][0]
<hr/>			
activation_171 (Activation)	(None, 16, 16, 1024)	0	add_55[0][0]
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res4f_branch2a (Conv2D)	(None, 16, 16, 256)	262400	activation_171[0][0]
<hr/>			
bn4f_branch2a (BatchNormalizati	(None, 16, 16, 256)	1024	res4f_branch2a[0][0]
<hr/>			
activation_172 (Activation)	(None, 16, 16, 256)	0	bn4f_branch2a[0][0]
<hr/>			
res4f_branch2b (Conv2D)	(None, 16, 16, 256)	590080	activation_172[0][0]
<hr/>			
bn4f_branch2b (BatchNormalizati	(None, 16, 16, 256)	1024	res4f_branch2b[0][0]
<hr/>			
activation_173 (Activation)	(None, 16, 16, 256)	0	bn4f_branch2b[0][0]
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res4f_branch2c (Conv2D)	(None, 16, 16, 1024)	263168	activation_173[0][0]
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bn4f_branch2c (BatchNormalizati	(None, 16, 16, 1024)	4096	res4f_branch2c[0][0]
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add_56 (Add)	(None, 16, 16, 1024)	0	bn4f_branch2c[0][0] activation_171[0][0]
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activation_174 (Activation)	(None, 16, 16, 1024)	0	add_56[0][0]
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res5a_branch2a (Conv2D)	(None, 8, 8, 512)	524800	activation_174[0][0]
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bn5a_branch2a (BatchNormalizati	(None, 8, 8, 512)	2048	res5a_branch2a[0][0]
<hr/>			
activation_175 (Activation)	(None, 8, 8, 512)	0	bn5a_branch2a[0][0]
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res5a_branch2b (Conv2D)	(None, 8, 8, 512)	2359808	activation_175[0][0]
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bn5a_branch2b (BatchNormalizati	(None, 8, 8, 512)	2048	res5a_branch2b[0][0]
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activation_176 (Activation)	(None, 8, 8, 512)	0	bn5a_branch2b[0][0]
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res5a_branch2c (Conv2D)	(None, 8, 8, 2048)	1050624	activation_176[0][0]
<hr/>			
res5a_branch1 (Conv2D)	(None, 8, 8, 2048)	2099200	activation_174[0][0]
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bn5a_branch2c (BatchNormalizati	(None, 8, 8, 2048)	8192	res5a_branch2c[0][0]
<hr/>			
bn5a_branch1 (BatchNormalizatio	(None, 8, 8, 2048)	8192	res5a_branch1[0][0]
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add_57 (Add)	(None, 8, 8, 2048)	0	bn5a_branch2c[0][0] bn5a_branch1[0][0]
<hr/>			
activation_177 (Activation)	(None, 8, 8, 2048)	0	add_57[0][0]

res5b_branch2a (Conv2D)	(None, 8, 8, 512)	1049088	activation_177[0][0]
bn5b_branch2a (BatchNormalizati	(None, 8, 8, 512)	2048	res5b_branch2a[0][0]
activation_178 (Activation)	(None, 8, 8, 512)	0	bn5b_branch2a[0][0]
res5b_branch2b (Conv2D)	(None, 8, 8, 512)	2359808	activation_178[0][0]
bn5b_branch2b (BatchNormalizati	(None, 8, 8, 512)	2048	res5b_branch2b[0][0]
activation_179 (Activation)	(None, 8, 8, 512)	0	bn5b_branch2b[0][0]
res5b_branch2c (Conv2D)	(None, 8, 8, 2048)	1050624	activation_179[0][0]
bn5b_branch2c (BatchNormalizati	(None, 8, 8, 2048)	8192	res5b_branch2c[0][0]
add_58 (Add)	(None, 8, 8, 2048)	0	bn5b_branch2c[0][0] activation_177[0][0]
activation_180 (Activation)	(None, 8, 8, 2048)	0	add_58[0][0]
res5c_branch2a (Conv2D)	(None, 8, 8, 512)	1049088	activation_180[0][0]
bn5c_branch2a (BatchNormalizati	(None, 8, 8, 512)	2048	res5c_branch2a[0][0]
activation_181 (Activation)	(None, 8, 8, 512)	0	bn5c_branch2a[0][0]
res5c_branch2b (Conv2D)	(None, 8, 8, 512)	2359808	activation_181[0][0]

bn5c_branch2b	(BatchNormalizati	(None, 8, 8, 512)	2048	res5c_branch2b[0][0]
activation_182	(Activation)	(None, 8, 8, 512)	0	bn5c_branch2b[0][0]
res5c_branch2c	(Conv2D)	(None, 8, 8, 2048)	1050624	activation_182[0][0]
bn5c_branch2c	(BatchNormalizati	(None, 8, 8, 2048)	8192	res5c_branch2c[0][0]
add_59	(Add)	(None, 8, 8, 2048)	0	bn5c_branch2c[0][0] activation_180[0][0]
activation_183	(Activation)	(None, 8, 8, 2048)	0	add_59[0][0]
global_average_pooling2d_3	(Glo	(None, 2048)	0	activation_183[0][0]
dropout_3	(Dropout)	(None, 2048)	0	global_average_pooling2d_3[0][0]
dense_3	(Dense)	(None, 2)	4098	dropout_3[0][0]

=====

Total params: 23,591,810

Trainable params: 23,538,690

Non-trainable params: 53,120

Epoch 1/3

10735/10735 [=====] - 181s 17ms/step - loss: 0.2773 - acc: 0.5058

Epoch 2/3

10735/10735 [=====] - 181s 17ms/step - loss: 0.2773 - acc: 0.4873

Epoch 3/3

10735/10735 [=====] - 181s 17ms/step - loss: 0.2773 - acc: 0.4875

1320/1320 [=====] - 7s 5ms/step

F-Scores for Axial-ACL:

[0.60273973 0.38297872]

Epoch 1/3

10735/10735 [=====] - 182s 17ms/step - loss: 0.5079 - acc: 0.5031

Epoch 2/3

10735/10735 [=====] - 182s 17ms/step - loss: 0.5079 - acc: 0.5086

Epoch 3/3

10735/10735 [=====] - 181s 17ms/step - loss: 0.5079 - acc: 0.5060

printaya le mennaya eval 2

1320/1320 [=====] - 7s 5ms/step

F-Scores for Axial-Meniscus:

[0.52631579 0.18181818]

Loss = 0.8318139567519679

Test Accuracy = 0.5787878784266385

Loss = 0.3696857517415827

Test Accuracy = 0.4492424249649048

Loss = 0.1617361494989106

Test Accuracy = 0.4340909087296688

CORONAL:

Epoch 1/3

9605/9605 [=====] - 185s 19ms/step - loss: 1.2095 - acc: 0.4999

Epoch 2/3

9605/9605 [=====] - 167s 17ms/step - loss: 1.1128 - acc: 0.4913

Epoch 3/3

9605/9605 [=====] - 167s 17ms/step - loss: 1.1118 - acc: 0.4826

printaya le mennaya eval 0

1020/1020 [=====] - 12s 12ms/step

F-Scores for Coronal-Abnormal:

[0.27906977 0.5974026]

Epoch 1/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.2773 - acc:
0.4658

Epoch 2/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.2773 - acc: 0.4804

Epoch 3/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.2773 - acc: 0.4811

printaya le mennaya eval 1

1020/1020 [=====] - 5s 5ms/step

F-Scores for Coronal-ACL:

[0.46376812 0.2745098]

Epoch 1/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.5079 - acc: 0.4734

Epoch 2/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.5079 - acc: 0.4918

Epoch 3/3

9605/9605 [=====] - 167s 17ms/step - loss: 0.5079 - acc: 0.4965

printaya le mennaya eval 2

1020/1020 [=====] - 5s 5ms/step

F-Scores for Coronal-Meniscus:

[0.63414634 0.21052632]

Loss = 0.8317977049771477

Test Accuracy = 0.39901960854436835

Loss = 0.3696818092290093

Test Accuracy = 0.4411764707051071

Loss = 0.1617348264245426

Test Accuracy = 0.4833333334502052

Epoch 1/3

9605/9605 [=====] - 174s 18ms/step - loss: 1.2174 - acc: 0.5028

Epoch 2/3

9605/9605 [=====] - 165s 17ms/step - loss: 1.1139 - acc: 0.4994

Epoch 3/3

9605/9605 [=====] - 165s 17ms/step - loss: 1.1120 - acc: 0.5049

1260/1260 [=====] - 11s 8ms/step

F-Scores for sagittal-Abnormal:

[0.51724138 0.5483871]

Epoch 1/3

9605/9605 [=====] - 169s 18ms/step - loss: 0.2773 - acc: 0.5071

Epoch 2/3

9605/9605 [=====] - 169s 18ms/step - loss: 0.2773 - acc: 0.5085

Epoch 3/3

9605/9605 [=====] - 169s 18ms/step - loss: 0.2773 - acc: 0.5027

1260/1260 [=====] - 6s 5ms/step

F-Scores for Sagittal-ACL:

[0.30188679 0.44776119]

Epoch 1/3

9605/9605 [=====] - 170s 18ms/step - loss: 0.5079 - acc: 0.5044

Epoch 2/3

9605/9605 [=====] - 170s 18ms/step - loss: 0.5079 - acc: 0.5044

Epoch 3/3

9605/9605 [=====] - 169s 18ms/step - loss: 0.5079 - acc: 0.5095

1260/1260 [=====] - 6s 5ms/step

F-Scores for Sagittal-Meniscus:

[0.41791045 0.26415094]

Loss = 0.8318177465408567

Test Accuracy = 0.5420634918742709

Loss = 0.36969071134688364

Test Accuracy = 0.3650793651739756

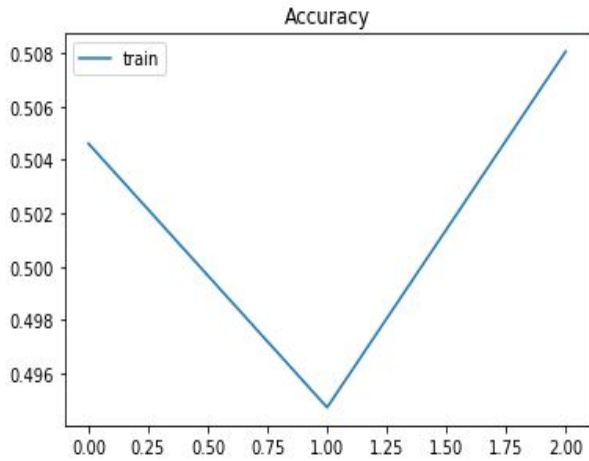
Loss = 0.161735363044436

Test Accuracy = 0.4063492062545958

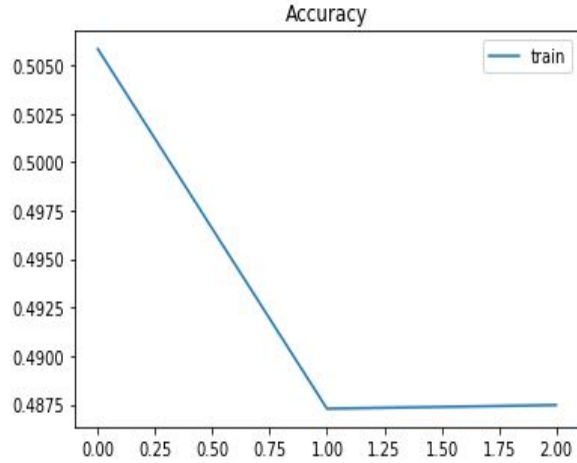
Big Picture:

AXIAL:

Abnormal F-score & Accuracy:



ACL F-score & Accuracy:



F-score:

[0.55882353 0.42307692]

Loss = 0.8318139567519679

Test Accuracy = 0.5787878784266385

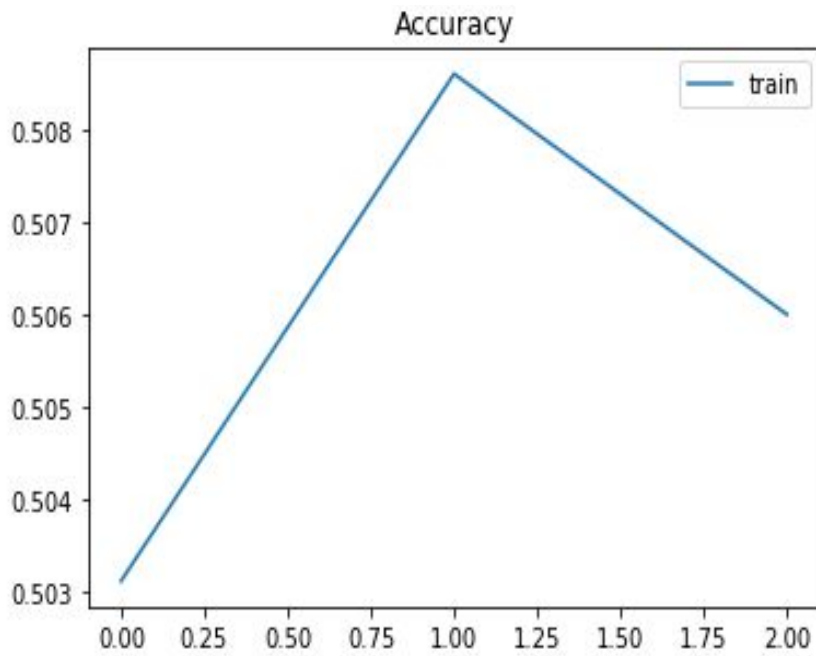
F-score:

[0.60273973 0.38297872]

Loss = 0.3696857517415827

Test Accuracy = 0.4492424249649048

Meniscus F-score & Accuracy:



F-score:

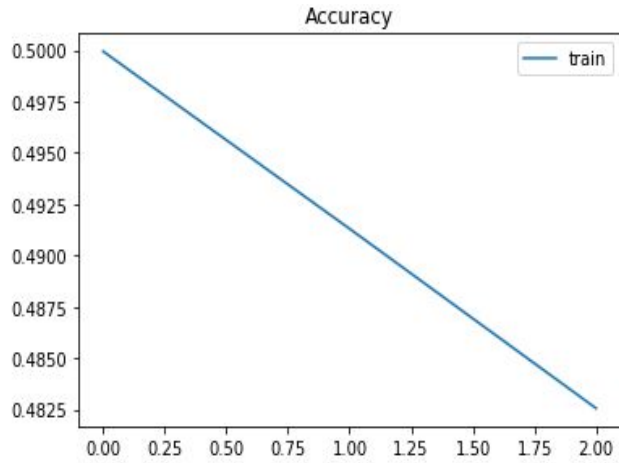
[0.52631579 0.18181818]

Loss = 0.1617361494989106

Test Accuracy = 0.4340909087296688

CORONAL:

Abnormal F-score & Accuracy:



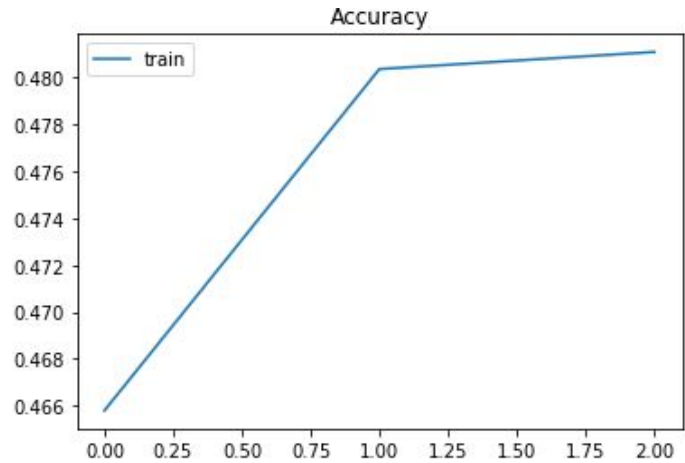
F-score:

[0.27906977 0.5974026]

Loss = 0.8317977049771477

Test Accuracy = 0.39901960854436835

ACL F-score & Accuracy:



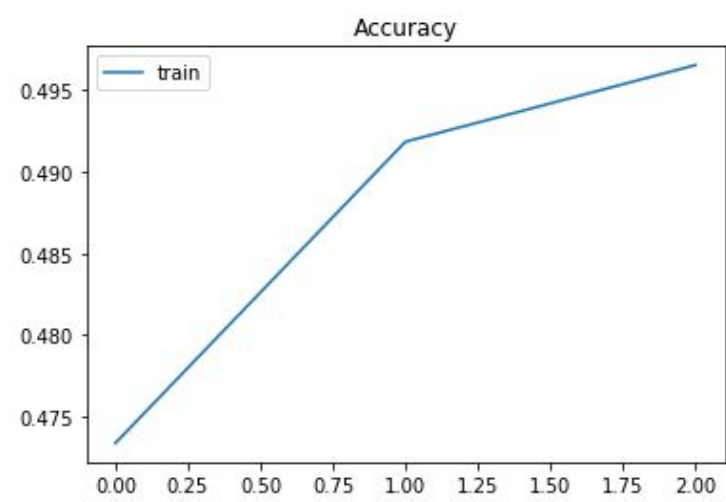
F-score:

[0.46376812 0.2745098]

Loss = 0.3696818092290093

Test Accuracy = 0.4411764707051071

Meniscus F-score & Accuracy:



F-Score:

[0.63414634 0.21052632]

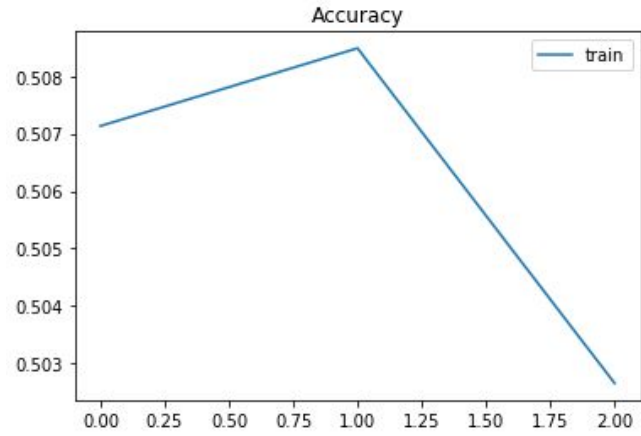
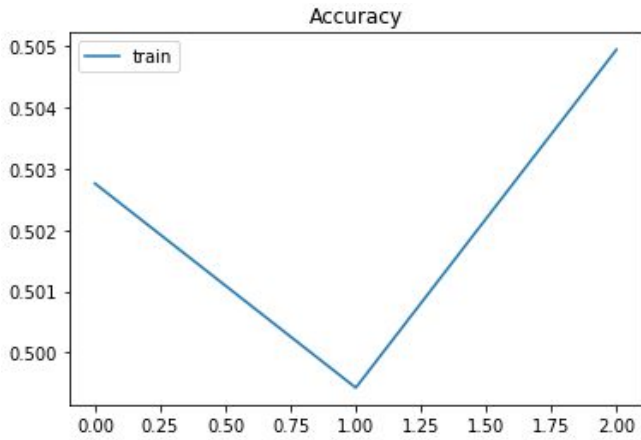
Loss = 0.1617348264245426

Test Accuracy = 0.4833333334502052

Sagittal:

Abnormal F-score & Accuracy:

ACL F-score & Accuracy:



F-score:

[0.51724138 0.5483871]

Loss = 0.8318177465408567

Test Accuracy = 0.5420634918742709

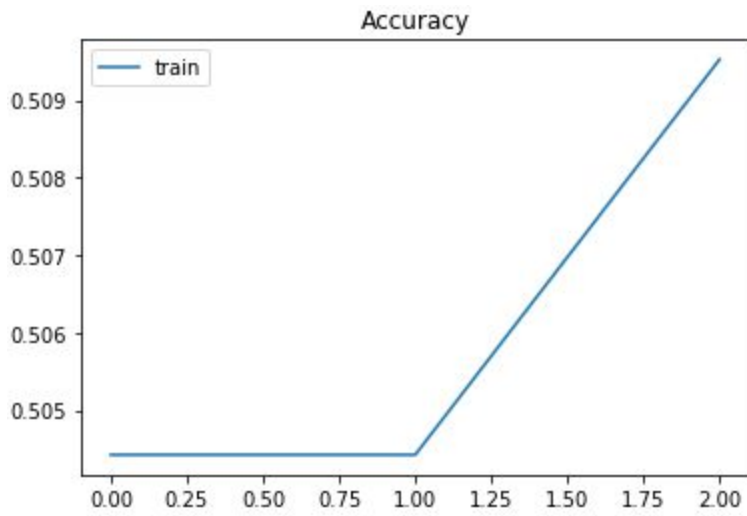
F-score:

[0.30188679 0.44776119]

Loss = 0.36969071134688364

Test Accuracy = 0.3650793651739756

Meniscus F-score & Accuracy:



F-Score:

[0.41791045 0.26415094]

Loss = 0.161735363044436

Test Accuracy = 0.4063492062545958