Machine learning Engineer Nanodegree.

Capstone Report

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Domain background:

Musculoskeletal conditions affect more than 1.7 billion people worldwide, and are the most common cause of severe, long-term pain and disability, with 30 million emergency department visits annually and increasing. So, Stanford ML group has come up with a dataset MURA (**mu**sculoskeletal **ra**diographs), which is a large dataset of bone X-rays of finger, wrist, elbow, forearm, hand, humerus, and shoulder studies. (Ref0: https://arxiv.org/pdf/1712.06957.pdf).

My personal motivation is to build models to help in healthcare sector, which would identify most of false negatives which would remove untimely treatment and negligence out of the system. Accurately being able to predict the false positives would keep cost of health care down, by not subjecting the patients to a plethora of tests, which might not have been necessary to begin with and alleviate unnecessary stress on the patients.

Problem statement:

MURA, a large dataset of musculoskeletal radiographs containing 40,561 images from 14,863 studies, where each study is manually labeled by radiologists as either normal or abnormal. To evaluate models robustly and to get an estimate of radiologist performance, the Stanford group collected additional labels from six board-certified Stanford radiologists on the test set, consisting of 207 musculoskeletal studies. These 207 radiographs are considered as labeled data and will help in evaluating the performance of radiologist in labeling the rest of the radiographs. To keep the dataset manageable, we will consider the data for one study group, in my case -the wrist study.

Evaluation Metrics:

According to the MURA paper:

"We compare radiologists and our model on the Cohen's kappa statistic, which expresses the agreement of each radiologist/model with the gold standard, defined as the majority vote of a disjoint group of radiologists. "

"On finger studies and wrist studies, model performance is comparable to the best radiologist performance."

Radiologist 1	*Radiologist 2*	*Radiologist 3*	*MURA Model*

Wrist 0.791 (0.766, 0.817) 0.931 (0.922, 0.940) 0.931 (0.922, 0.940) 0.931 (0.922, 0.940)

Implementation:

I could not train my module with all the training data , which was 3000+ images. Due to the limitations on my personal laptop, the GPU could handle around 400 studys(views/radiographs). Beyond that I would get Out of Memory errors. Since there is no back propagation in the validation phase, I also made sure that we are not tracking the tensors for computing the gradients, as that was using up a lot of memory.

In the Mura paper, they had evaluated the model with Cohen-kappa statistic, as the imbalance in classes might be skewed with plain accuracy alone.
"Observed Accuracy** is simply the number of instances that were classified correctly throughout the entire confusion matrix. To calculate **Observed Accuracy**, we simply add the number of instances that the* machine learning classifier *agreed with the* ground truth *label and divide by the total number of instances**." – Ref1: https://stats.stackexchange.com/questions/82162/cohens-kappa-in-plain-english

Implementation:
I have derived the Observed accuracy by computing the number of predictions that were correct (running_corrects in train.py), both with abnormal and normal radiographs and then dividing it by the total data size.

"**The **Expected Accuracy** is directly related to the number of instances of each class (**class 1** and **class 2**), along with the number of instances that the* machine learning classifier *agreed with the* ground truth *label. To calculate **Expected Accuracy** for our confusion matrix, first multiply the* marginal frequency *of **class 1** for one "rater" by the* marginal frequency *of **class 1** for the second "rater" and divide by the total number of instances. The* marginal frequency *for a certain class by a certain "rater" is just the sum of all instances the "rater" indicated were that class**." – Ref1: above.

Implementation:
In my case I computed the abnormal_expected accuracy(class 1) by multiplying the abnormal label counts with abnormal predicted counts and dividing it by the total data size. Similarly computed the normal expected accuracy (class 2) by multiplying the normal label counts with normal predicted counts and dividing it by the total data size.
The expected accuracy for both classes was computed by adding the abnormal expected accuracy with normal expected accuracy and dividing it by the total size.
I then computed the Cohen's kappa statistic score, given by Kappa = (observed accuracy - expected accuracy)/(1 - expected accuracy).

Interpretation

***"**There is not a standardized interpretation of the kappa statistic. According to Wikipedia (citing their paper), Landis and Koch considers 0-0.20 as slight, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1 as almost perfect. Fleiss considers kappas > 0.75 as excellent, 0.40-0.75 as fair to good, and < 0.40 as poor**."* – Ref1: above*

Implementation:

Since I had run the code for 5 epochs only with a subset of training data, I got a kappa score of **`kappa: 0.3249,`** which is considered fair or poor(Interpretation above).

Analysis:

Datasets and inputs:

As defined above, MURA is a dataset of musculoskeletal radiographs consisting of 14,982 `studies` from 12,251 `patients`, with a total of 40,895 `multi-view radiographic images`. Each `study` belongs to one of seven standard upper extremity radiographic `study types`: elbow, finger, forearm, hand, humerus, shoulder and wrist.

MURA dataset comes with `train` and `valid` folders containing corresponding datasets, `train.csv` and `valid.csv` containing paths of `radiographic images` and their labels. Each image is labeled as 1 (abnormal) or 0 (normal) based on whether its corresponding study is negative or positive, respectively, by the radiologists. Sometimes, these radiographic images are also referred as `views`.

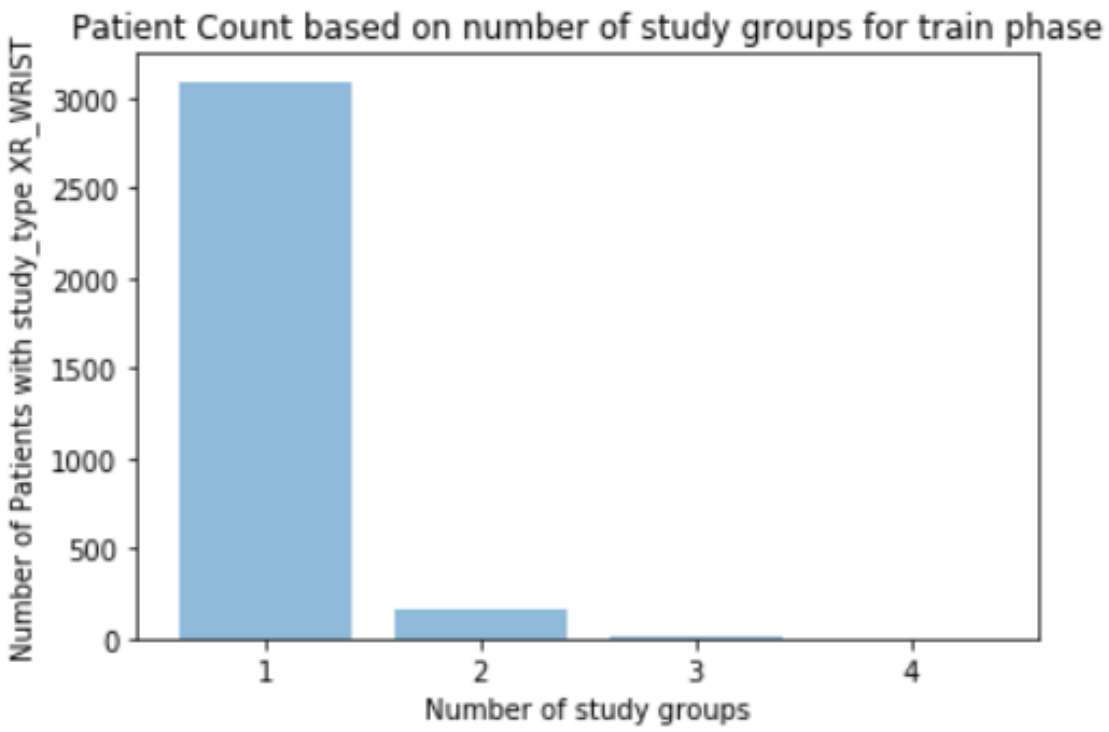
- The link to the data can be found at https://stanfordmlgroup.github.io/competitions/mura/
- There are 9751 views in training set of wrist images, with more than one image per patient. There are 3459 labeled data for patients in the training set. Off the 3459, there are 1325 abnormal (1) and 2134(normal).
  The validation set include 659 views, with more than one image per patient.
  There are 237 labeled data for patients in the validation set. Off the labeled data 97 are abnormal (1) and 140 normal (0).
  The test data set needs to be formulated using samples from the training data set.
- The images are gray scale (as it's a radiograph), but is of varying dimensions, with bounding Boxes also of varying dimensions. There is more than one view per patient.

Implementation:

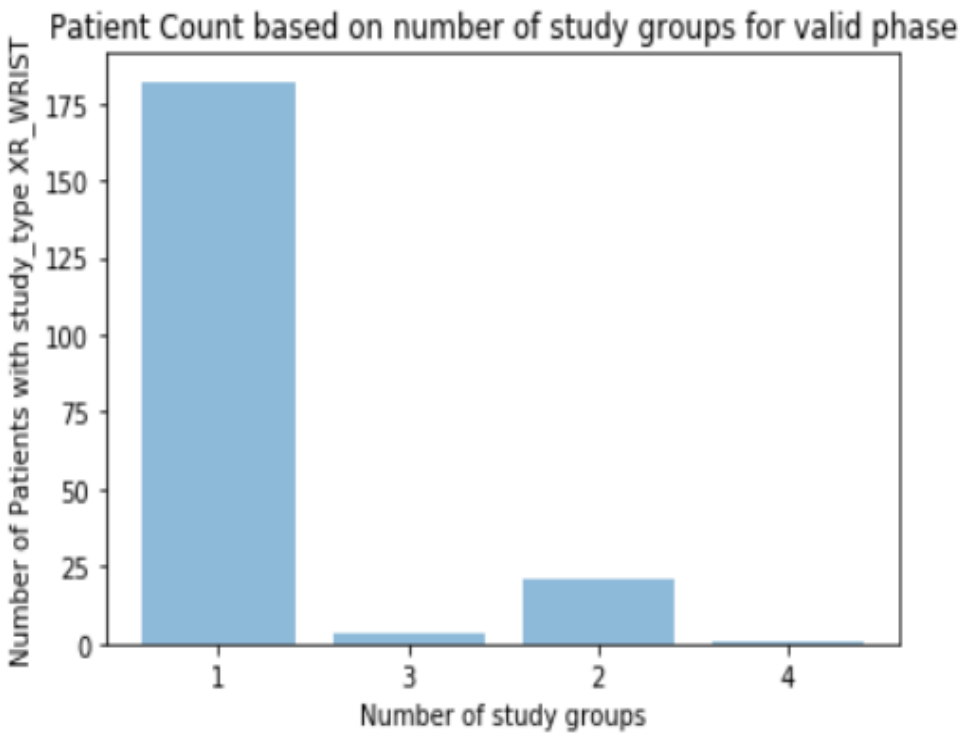
I used pytroch for reading the data pipeline, as it seemed fairly simple to read the data in the format I needed. get_path_imgCount_label function in mura.ipynb, reads the mura data set and dataframes them into paths ,counts and labels for each study. From the EDA I realized there could be more than one study group (positive or negative) per patient. Each study group could have more than one view or radiograph. So, the get_path_imgCount, looks into each study group for a patient and lists the path for each study group, with the total count of images for the study group and the label whether the prediction was abnormal (1) or normal (0).

	Path to study group/patient	Count	Label
0	./MURA-v1.1/train/XR_WRIST/patient00006/study1...	3	1
1	./MURA-v1.1/train/XR_WRIST/patient00012/study1...	4	0
2	./MURA-v1.1/train/XR_WRIST/patient00021/study1...	3	1
3	./MURA-v1.1/train/XR_WRIST/patient00021/study2...	3	1

Exploratory Data Analysis:



Train: **1: 3094, 2: 157, 3: 12, 4: 4**

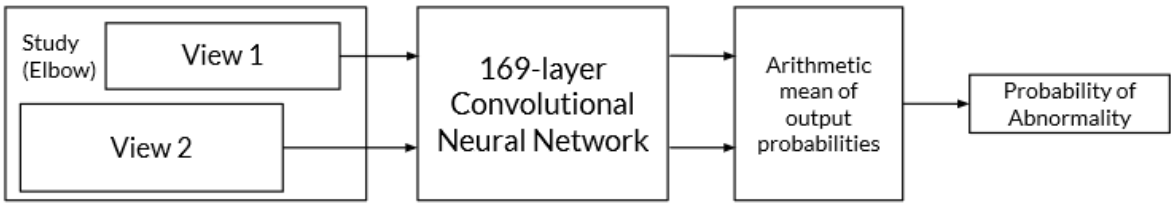



```
Valid: 1: 182, 2: 21, 3: 3, 4: 1
```

The above graphs give us the insight that the patient with the study type of XR_WRIST, could have more than one study group, meaning more than one set of x-rays taken. Each study group comes with the folder name like “study1_postive”, which I derive to get the label of normal or abnormal. Each of the study folder can contain more than one radiographs. So, in the graphs above we see that for training data, there were 157 patients with 2 views or radiographs and there was one patient in valid set that had 4 views.

Algorithms and techniques:

As the Mura paper (Ref0:) states that they have used the 169-layer convolutional neural network.



“*We used a 169-layer convolutional neural network to predict the probability of abnormality for each image in a study. The network uses a Dense Convolutional Network architecture – detailed in Huang et al. (2016) – which connects each layer to every other layer in a feed-forward fashion to make the*

optimization of deep networks tractable. We replaced the final fully connected layer with one that has a single output, after which we applied a sigmoid nonlinearity" - Ref0:

Implementation:

DenseNet-169 is defined by the paper, Ref2: https://arxiv.org/abs/1608.06993

"The weights of the network were initialized with weights from a model pretrained on ImageNet." Ref0*:*

I used the available densenet-169 implementation
Ref3: https://pytorch.org/docs/master/_modules/torchvision/models/densenet.html, with a pretrained value of true, which initialized the weights from a model pretrained on imageNet.

"*For each image X of study type T in the training set, we optimized the weighted binary cross entropy loss*."- Ref0:
I used the Weighted Binary cross entropy loss function, given by the formula -
(wt1*y*log(p)+wt0*(1−y)log(1−p)). Where wt1 is the weight of abnormal class and wt0, is the weight of the normal class, y is the target labels and p is the input predictions. I had to normalize the weights for any skewing.

"The network was trained end-to-end using Adam with default parameters
We trained the model using minibatches of size 8. We used an initial learning rate of 0.0001that is decayed by a factor of 10 each time the validation loss plateaus after an epoch." – Ref0:
I used Adam for my optimizer with a learning rate of 0.0001. I also used the scheduler, lr_scheduler.reducelronplateau, which allows dynamic learning rate reducing based on validation measurements.
I ran it on one device (cuda0:) meaning one GPU, as my computer could not really use the parallelization given by using multiple GPUs at the same.

Benchmark :

The one advantage of this data set is, it is baselined against a 169-layer convolutional neural network to detect and localize abnormalities. MURA paper states that:

"Our baseline uses a 169-layer convolutional neural network to detect and localize abnormalities. The model takes as input one or more views for a study of an upper extremity. On each view, our 169-layer convolutional neural network predicts the probability of abnormality."

Though for the XR_WRIST study, the paper states a very high accuracy of prediction, mine was fair at best, because I used a very small data set to train the model and do the validations.

Data Preprocessing:

MURA paper states that:

"Before feeding images into the network, we normalized each image to have the same mean and standard deviation of images in the ImageNet training set. We then scaled the variable-sized images to

224×224. We augmented the data during training by applying random lateral inversions and rotations." - Ref0:

Implementation:

The data or the images/views/radiographs came in different sizes and needs to be normalized. I used pytorch dataloaders(https://www.sanyamkapoor.com/machine-learning/pytorch-data-loaders/) to load data. With dataloaders, it's fairly simple to implement transforms. I used the transforms.Resize, to size the data to 224X224. I used the RandomFilp, RandomRotation and Normalize the data to the imageNet mean and standard deviation for the training data set.

On the validation set Resized to (224X224) and normalized to the imageNet's mean and standard deviation.

Implementation of metrics, algorithms and techniques:

I have used implementation sections throughout the paper to explain how a topic was implemented in the code.

Complications and issues:

I primarily used pytorch, because the data pipelines with transformation could be easily created and had examples and tutorials everywhere. But then I did not know how to implement the denseNet model. I did not have an architectural blue print like proposed in the dog-project. So, thought of turning back to keras and OpenCV. But then the data manipulation seemed a lot harder and I needed to come up with my own model for denseNet as well. So, reverted back to pytorch. My Python knowledge is a "java to python translation", which does not work too well with Data manipulations and python classes. Just got to know how much I do not know☺

The one of Problems I faced was running Out of Memory every so often. I then realized by trial and error that it died on 423 items of my training data. So, I limited my training to a dataset of 400. Then on validation set it would die randomly. I then used the no_grad option which would not cache all the tensor Variables(parameters) as back propagation was not needed.

Another problem I faced was there was dimensionality difference when one of the core modules was comparing labels with inputs. I knew they were of the same dimension. But then figured out after a while that the input was a tensor Variable of the format tensor ([1.0], device='cuda:0') and the label was a plain old int of value 1.

Refinement:

I used the weighted Binary cross entropy loss function instead of the plain Binary cross entropy function so if there were any class imbalances between the normal and abnormal radiographs could be addressed.

I also used a scheduler, lr_scheduler.reducelronplateau , which allows dynamic learning rate reducing based on validation measurements.

If I could use a cloud-based GPU, I probably could have trained the model with all of the 3400+ training data and could have had a better kappa score, which would have implied a better accuracy in prediction.

Results:

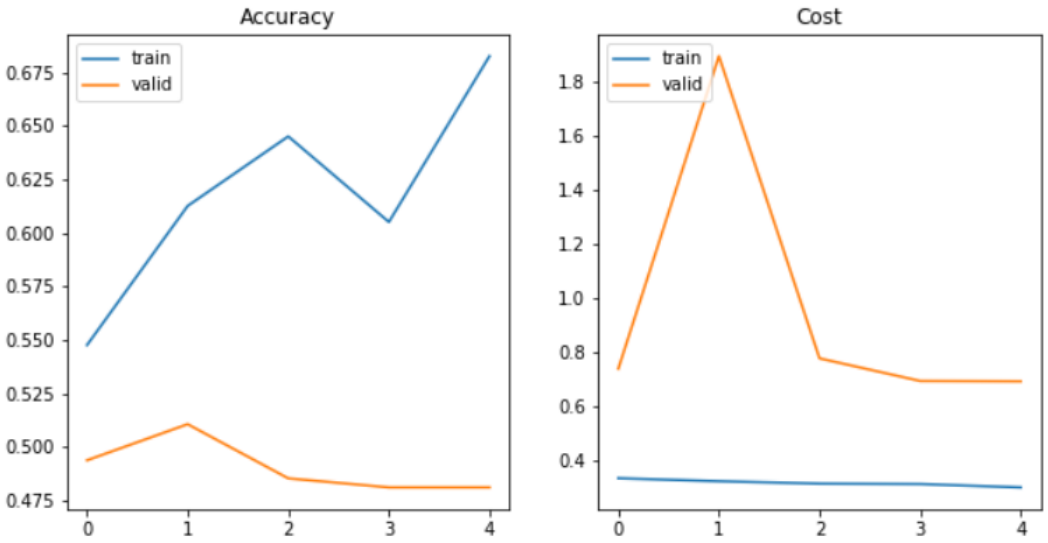
Model Evaluation and Validation:

I have evaluated the model for loss and absolute accuracy for the training set. The code is also printing the confusion matrix for the model for each epoch for both validation and training sets.

```
Train batches: 400
Valid batches: 237

Epoch 1/5
----------
Train:
train Loss: 0.3354 Acc: 0.5475
Confusion Meter:
 [[0.6487603  0.35123968]
 [0.6075949  0.39240506]]

Valid:
valid Loss: 0.7390 Acc: 0.4937
Confusion Meter:
 [[0.43571427 0.5642857 ]
 [0.4226804  0.57731956]]
Time elapsed: 4m 26s

Epoch 2/5
----------
Train:
train Loss: 0.3244 Acc: 0.6125
Confusion Meter:
 [[0.677686   0.32231405]
 [0.48734176 0.51265824]]
Valid:
valid Loss: 1.8916 Acc: 0.5105
Confusion Meter:
 [[0.6357143 0.3642857]
 [0.6701031 0.3298969]]
Time elapsed: 8m 45s

Epoch 3/5
----------
Train:
train Loss: 0.3156 Acc: 0.6450
Confusion Meter:
 [[0.7066116  0.29338843]
 [0.44936708 0.5506329 ]]
Valid:
valid Loss: 0.7773 Acc: 0.4852
Confusion Meter:
 [[0.54285717 0.45714286]
 [0.5979381  0.40206185]]
Epoch     2: reducing learning rate of group 0 to 1.0000e-05.
Time elapsed: 12m 48s

Epoch 4/5
----------
Train:
train Loss: 0.3140 Acc: 0.6050
```

```
Confusion Meter:
 [[0.45454547 0.54545456]
 [0.16455697 0.835443  ]]
Valid:
valid Loss: 0.6940 Acc: 0.4810
Confusion Meter:
 [[0.49285713 0.50714284]
 [0.53608245 0.46391752]]
Time elapsed: 16m 46s

Epoch 5/5
----------
Train:
train Loss: 0.3017 Acc: 0.6825
Confusion Meter:
 [[0.75206614 0.24793388]
 [0.42405063 0.5759494 ]]
Valid:
valid Loss: 0.6928 Acc: 0.4810
Confusion Meter:
 [[0.49285713 0.50714284]
 [0.53608245 0.46391752]]
```

The training loss seems to decrease over the epochs, but the validation loss jumps up in the second epoch and then goes down. The observed accuracy seems to vary from epoch to epoch. The confusion matrix is printed for every epoch.



Justification:

For the XR_WRIST study type the model had a kappa of 0.931 (0.922, 0.940), where as I had a kappa of 0.3249(0.535, 0.3112) for a data set of 400 images from the training set of 3459 images. So, my justification is that had I more processing power I probably could have done lot better with more training data than the 400 images I trained with.