Deep Learning Project Report

Blanca Bastardés Climent
blancabc@kth.se

Osheen Sharma
osheens@kth.se

1 Introduction

Radiography is an imaging technique which is widely used in medical applications for diagnosis and treatment of the diseases. The most commonly used radiographic technique is chest xray for screening and diagnosis of thoracic pathology. An algorithm which could mimic the human brain and predict the existence of the pathology as effectively as radiologist, will be beneficial in making clinical decisions and improve workflow in the radiology department. One such approach to make the clinical predictions and efficiently as radiologists is the implementation of deep learning algorithms on the medical images.

Deep learning has recently made a great success in the healthcare and is performing very well in prediction of different classes and making easier for clinicians to take decisions. It is not only helping to select and extract features but also construct new ones furthermore, it also measure predictive target and provides actionable prediction models to help physicians efficiently. This project focuses on prediction of pathalogies from a multi view chest radiographic images.

2 Methods

2.1 Dataset

The project is taken from the Grand-Challenge source and the name of the dataset is 'CheXpert'. The dataset consisted of 224,316 chest radiographs of 65,240 patient. The images involved 14 different studies for the patient with frontal and lateral view. The labels provided in the dataset were: blank for unmentioned (it was not studied), 0 for negative, -1 for uncertain (pathology is unknown), and 1 for positive. The main task of the project was to predict the probability of existence of 5 observations from the provided 14 different studies.

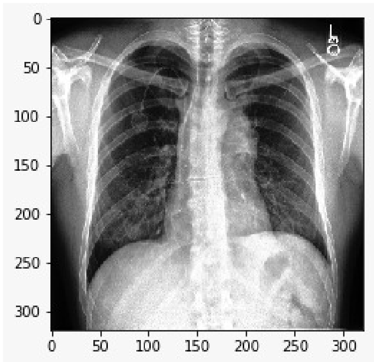

Figure 1: Frontal Chest Xray Image

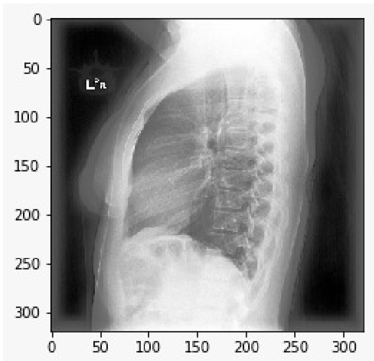

Figure 2: Lateral Chest Xray Image

2.2 Preprocessing Data

For loading and reading the data we first created the definition where we gave the 'path' and then converted the images into numpy array. Further, the policies were applied depending on the existence of the pathology to either map it to zero or to one which means U-Zeroes: We map all instances of the uncertain label to 0 and U-Ones: We map all instances of the uncertain label to 1.Then we created one-hot vector for the 5 labels. Finally, as shown in the Figure 3 the raw data was converted with only image path and the features as shown in Figure 4 that corresponded to the existence of the 5 different observations in the images.

	Path	Sex	Age	Frontal/Lateral	AP/PA	No Finding	Enlarged Cardiomediastinum	Cardiomegaly	Lung Opacity	Lung Lesion
0	CheXpert-v1.0-small/train/patient00001/study1/...	Female	68	Frontal	AP	1.0	NaN	NaN	NaN	NaN
1	CheXpert-v1.0-small/train/patient00002/study2/...	Female	87	Frontal	AP	NaN	NaN	-1.0	1.0	NaN
2	CheXpert-v1.0-small/train/patient00002/study1/...	Female	83	Frontal	AP	NaN	NaN	NaN	1.0	NaN
3	CheXpert-v1.0-small/train/patient00002/study1/...	Female	83	Lateral	NaN	NaN	NaN	NaN	1.0	NaN
4	CheXpert-v1.0-small/train/patient00003/study1/...	Male	41	Frontal	AP	NaN	NaN	NaN	NaN	NaN

Figure 3: Raw Data

	Path	feature_string
0	CheXpert-v1.0-small/train/patient00001/study1/...	
1	CheXpert-v1.0-small/train/patient00002/study2/...	Atelectasis;Edema
2	CheXpert-v1.0-small/train/patient00002/study1/...	
3	CheXpert-v1.0-small/train/patient00002/study1/...	
4	CheXpert-v1.0-small/train/patient00003/study1/...	Edema
5	CheXpert-v1.0-small/train/patient00004/study1/...	
6	CheXpert-v1.0-small/train/patient00004/study1/...	
7	CheXpert-v1.0-small/train/patient00005/study1/...	
8	CheXpert-v1.0-small/train/patient00005/study1/...	
9	CheXpert-v1.0-small/train/patient00005/study2/...	
10	CheXpert-v1.0-small/train/patient00005/study2/...	
11	CheXpert-v1.0-small/train/patient00006/study1/...	
12	CheXpert-v1.0-small/train/patient00007/study1/...	Atelectasis;Cardiomegaly
13	CheXpert-v1.0-small/train/patient00007/study2/...	Atelectasis
14	CheXpert-v1.0-small/train/patient00008/study1/...	Pleural Effusion
15	CheXpert-v1.0-small/train/patient00008/study2/...	Pleural Effusion
16	CheXpert-v1.0-small/train/patient00009/study1/...	Atelectasis;Cardiomegaly
17	CheXpert-v1.0-small/train/patient00009/study1/...	Atelectasis;Cardiomegaly

Figure 4: Frontal Chest Xray Image

2.3 Implemented Models

The model we implemented for training the images were basic CNN, ResNet and DenseNet.The performance of all the three models was compared and DenseNet was the final model which we selected for our results. The convolutional neural network with 5 layers was implemented with filter size of 3 and pooling size of (2,2). Second, standard Resnet and Densenet were also implemented. The densenet had the depth of 4 as the training images given to the model were less so we reduced the number of layers to reduce the complexity. The hyper-parameters were chosen as Loss = binary_crossentropy, Optimizer = Adam, metric = 'accuracy'. We chose to have activation function as sigmoid because we were interested in predicting the probability of existence of the pathology independent of each other. The use of softmax was not appropriate for this particular problem as softmax only predicts the highest probability of existence of a class and that was not our intention. For Densenet Batch normalization and dropout was implemented to prevent the model from learning minute details.

3 Results

For training our models we split the data into training and validation set with 12000 images for training and 3000 images for validation, both consisting of frontal and lateral images.

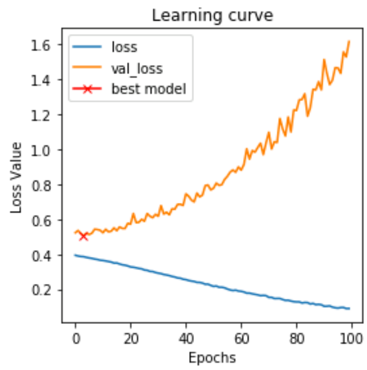

Figure 5: CNN Loss Plot

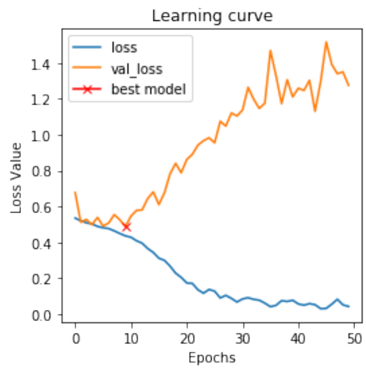

Figure 6: ResNet Loss Plot

In the beginning our models were having overfiting which is clearly seen in the loss plots. To overcome with this issue we added l1, l2 and l1_l2 regularization term in all our models. For L2 regularizer our model performed the best loss curve. L2 regularizer is the sum of the square of

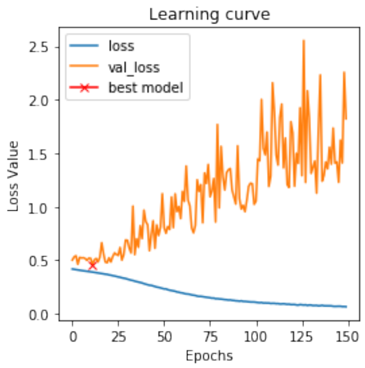

Figure 7: DenseNet Loss Plot

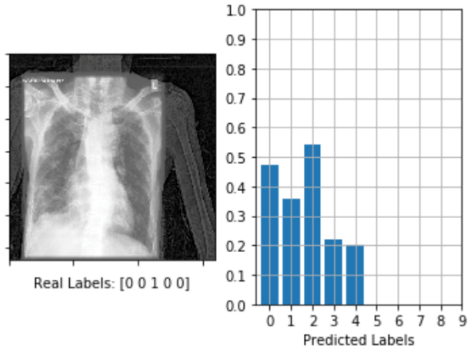

Figure 10: Probability: Edema

the weights, which improved our loss plots for all our models.

Further we tested the accuracy of the models with 20 test images and predicted the existence if the 5 observations in the images.

Figure 8: Loss plot after l2 regularizer

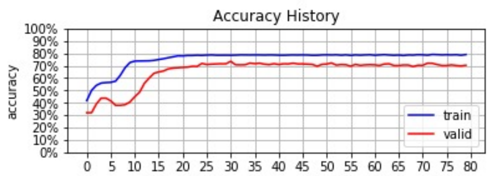

Figure 9: Accuracy plot after l2 regularizer

4 Conclusions

Finally, the presence of the pathology was compared with the real one hot vector label and was displayed in the form of probability vector. Figure shows the presence of Edema in the image

The accuracy from our model was 78% and that of the cheXpert challenge participating team was 92.6%. With the implementation of all the models we learnt the difference between the models, their performance and the importance of hyper parameters an their effect on the training.We think regularization was the outmost important in our case because it prevented over fitting. However, we would like to change the problem as it was very challenging to work with 14 labels and large dataset. We would like to focus only on one pathology and train the model to observe the accuracy and loss and gradually add pathologies and see the effect.