Artivatic AI Labs **(Due: 6/9/19)**

Computer Vision Task

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1 Problem Statement:

Tuberculosis (TB) Detection in Chest Radiography Using Deep Learning. Given chest x-rays we have to classify whether a person is suffering from TB or not.

2 Resources Used:

- PyTorch 1.0
- Google Colab
- Jupyter Notebook
- scikit-learn
- matplotlib

3 Dataset Used:

ChinaSet [1],[2], it consists a total of 662 chest radiography images. The dataset is well balanced as it has almost equal number of positive and negative samples. The dataset consists of 326 images of normal people and 336 images of people suffering from TB. The images are of varying sizes and has an approximate resolution of $3K \times 3K$. Image file names are coded as CHNCXR_*****_0/1.png, where 0 represents the normal and 1 represents the abnormal lung.

4 Data Augmentation:

I have performed the following data augmentation :

- The images are resized to 128×128, to avoid difference in sizes and to ease the training process.
- The images are converted to grayscale.
- The images are randomly flipped horizontally.
- The images are normalized to [0,1].

5 Architecture and Training:

5.1 Architecture -

The architecture used in primarily a ResNet-18 [3] architecture. The Fully connected network is removed from the original model and another FC layer is attached to perform a binary classification. The images are first passed through a Convolutional architecture which converts 1-channel to 3-channel. The features are then passed through the modified ResNet-18 architecture.

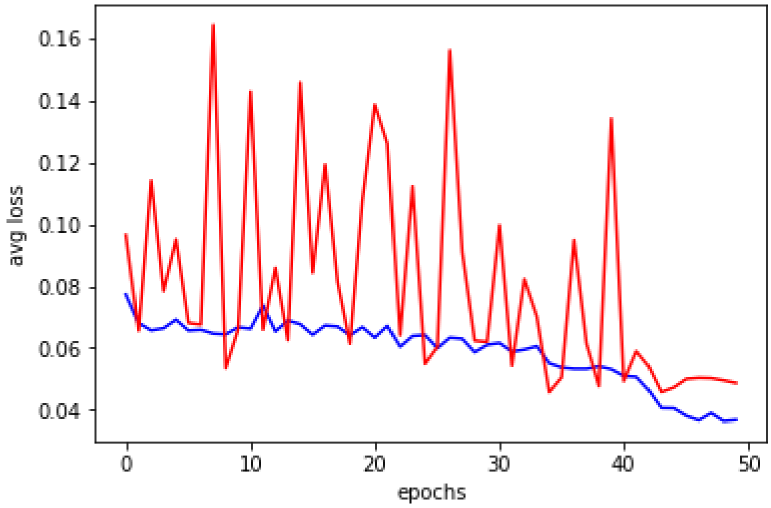
5.2 Training -

The model is trained for 50 epochs. Adam optimizer is used to update the weights. The loss function used is Cross Entropy Loss. The initial learning rate is set to 6E-4 and was exponentially reduced over the epochs.

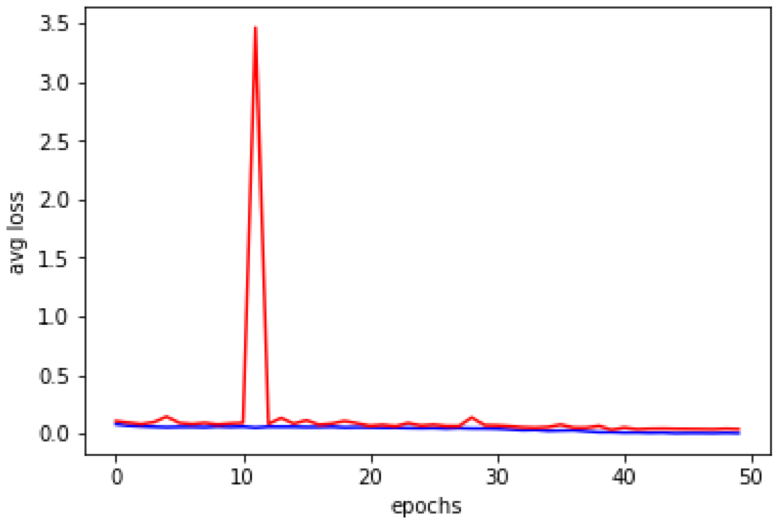
6 Results:

Two sets of experiments were performed. The first, in which the model is trained from scratch using ChinaSet dataset. In the second experiment, the pretrained weights of ResNet-18 model trained on ImageNet [4] dataset is used and further finetuned for ChinaSet dataset.

In Figure 1 the red line denotes the test loss and the blue line denotes the train loss. In both figures,namely, Figure 1a and Figure 1b the train loss is seen to be decreasing. However the test loss in Figure 1a is fluctuating compared to Figure 1b.



(a) Model from Scratch



(b) Model Finetuned

Figure 1: Loss Vs. Epoch Graph

The Figure 2 shows the classification report of both the experiments. The model with pretrained weights have an accuracy of 88% comapred to the model trained from scratch which has an accuracy of 85%.

The models are trained for 50 epochs only due to limited resources. The accuracy may increase if the model is trained for few more epochs. The hyperparameters can also be finetuned to achieve higher accuracy.

7 Conclusion:

On comparing Figure 1 and Figure 2, it is clear that pretrained model has better classification ability compared to a model trained from scratch. The models have a decent f1-score also which proves the model is able to predict both positive and negative classes fairly.

	precision	recall	f1-score	support
No TB	0.90	0.79	0.84	33
TB	0.81	0.91	0.86	33
accuracy			0.85	66
macro avg	0.85	0.85	0.85	66
weighted avg	0.85	0.85	0.85	66

(a) Model from Scratch

	precision	recall	f1-score	support
No TB	0.93	0.82	0.87	33
TB	0.84	0.94	0.89	33
accuracy			0.88	66
macro avg	0.88	0.88	0.88	66
weighted avg	0.88	0.88	0.88	66

(b) Model Finetuned

Figure 2: Classification Report

References

[1] Jaeger S, Karargyris A, Candemir S, Folio L, Siegelman J, Callaghan F, Xue Z, Palaniappan K, Singh RK, Antani S, Thoma G, Wang YX, Lu PX, McDonald CJ. Automatic tuberculosis screening using chest radiographs. IEEE Trans Med Imaging. 2014 Feb;33(2):233-45. doi: 10.1109/TMI.2013.2284099. PMID: 24108713

[2] Candemir S, Jaeger S, Palaniappan K, Musco JP, Singh RK, Xue Z, Karargyris A, Antani S, Thoma G, McDonald CJ. Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration. IEEE Trans Med Imaging. 2014 Feb;33(2):577-90. doi: 10.1109/TMI.2013.2290491. PMID: 24239990

[3] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[4] Deng, Jia, et al. "Imagenet: A large-scale hierarchical image database." 2009 IEEE conference on computer vision and pattern recognition. Ieee, 2009.