Intracranial Hemorrhage Detection by Efficient Utilization of 3D CT Brain Images with Multimodal Labels

Mohan Rao Divate Kodandarama
University of Wisconsin-Madison
Madison, WI

Vivek Prabhakaran
Wisconsin Institute of Medical Research
Madison, WI

Vikas Singh
University of Wisconsin-Madison
Madison, WI

Abstract

Computerized tomography (CT) offers a useful and non-invasive means to gain insight into potential abnormalities present in tissue, bone or vascular components of the brain. However, unlike natural images, labeled CT (medical image) data is hard to acquire and the abnormalities such as Intracranial Hemorrhage are very rarely observed, resulting in a skewed dataset. Further, 3D CT Brain Image datasets are typically small compared to ImageNet. Hence, a traditional CNN easily overfits such small datasets. Furthermore, it is not practical to merge different 3D CT Brain Image datasets since the labels across the datasets are heterogeneous. In this work, we propose a Neural Network architecture capable of learning from a 3D CT Brain Images with heterogeneous labels. More formally, our network enforces custom loss criterion for each modality of label.

1. Related Work

[1] proposed a loss function for mitigating the effects of imbalance between background and object class in single stage object detectors. In this work we utilize [1] to deal with imbalanced distribution of labels.

[2] introduced triplet loss function for the task of face recognition. In this work we utilize triple loss to enforce the predicted labels for adjacent Image slices to be consistent.

2. Approach

Proposed model is show in the above diagram. Backbone model is based on resnet18, but process each slice independently. This enables us to use the same backbone for both 2d samples and 3D samples. In the diagram,

1. (x, y) is a labeled data
2. (U, Y) - U is an unlabeled set of 2D slices corresponding to and 3D scan and Y is the label for the 3D scan. $U = \{u_i\}_{i=1}^{N}$
3. **Output -** Model outputs six probability scores, one for the presence of Intracranial Hemorrhage, and the other five for each of the five hemorrhage subtypes.
4. **Proposed set based loss -** Let $P = \{p_i\}_{i=1}^{N}$ be the predicted probabilities for $U = \{u_i\}_{i=1}^{N}$

$$SetBasedLoss(Y, P) = CELoss(Y, \max_i p_i) \quad (1)$$

5. **Smoothness Constraint -** Let $E = \{e_i\}_{i=1}^{M}$ be the latent representations for $U = \{u_i\}_{i=1}^{N}$.

$$SC = \sum_{i=2}^{M-1} \max(d(e_{i+1}, e_i) - d(e_{i-1}, e_i) + margin, 0) \quad (2)$$

3. Experiments and Results

Dataset from released RSNA Intracranial Hemorrhage Detection Challenge is used in all experiments. Number of training samples - 387072. Number of samples in dev set 128000. Oversampling minority classes is used as a data augmentation technique.

4. Conclusion and Future Work

The architecture can further be improved by using a GAN based generator for unlabeled branch instead of the random shuffling.

5. Code

Code for all our experiments are available at GitHub.

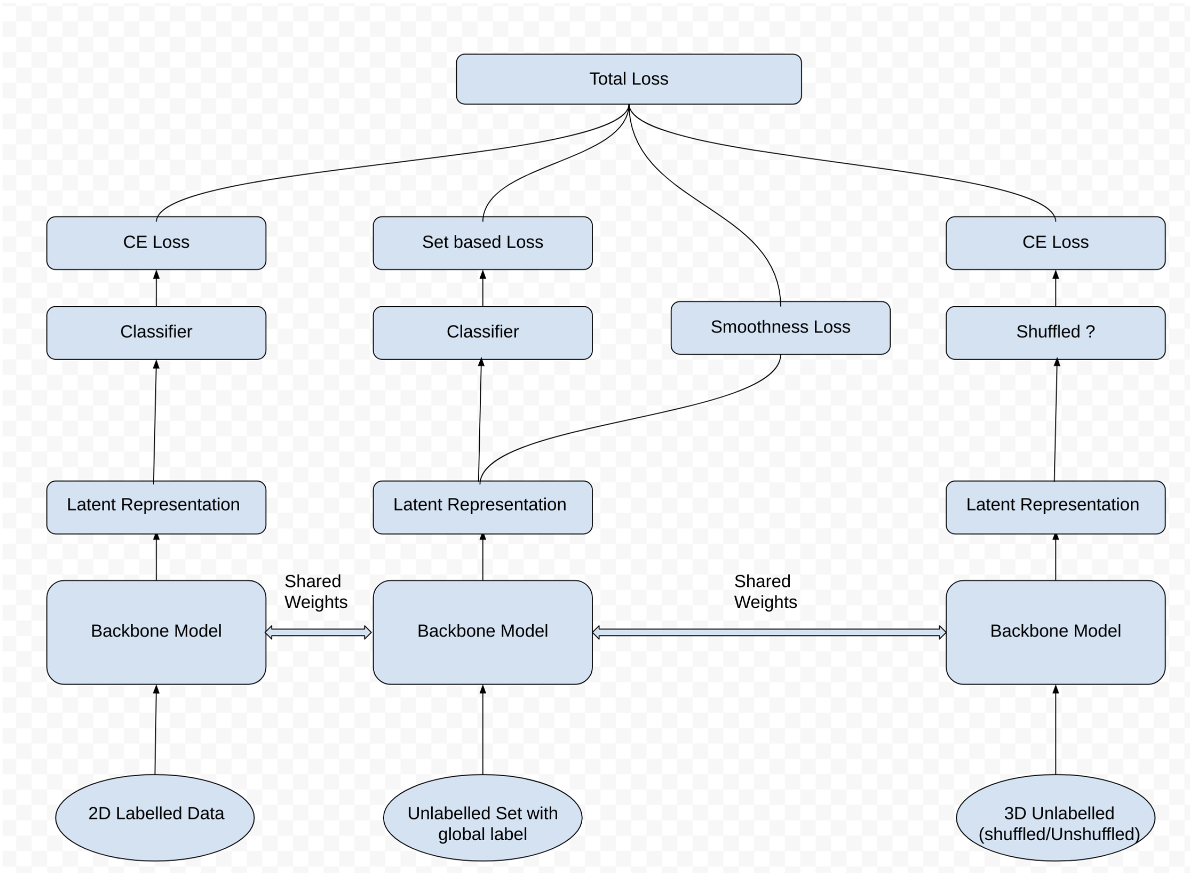

Figure 1. Proposed Model

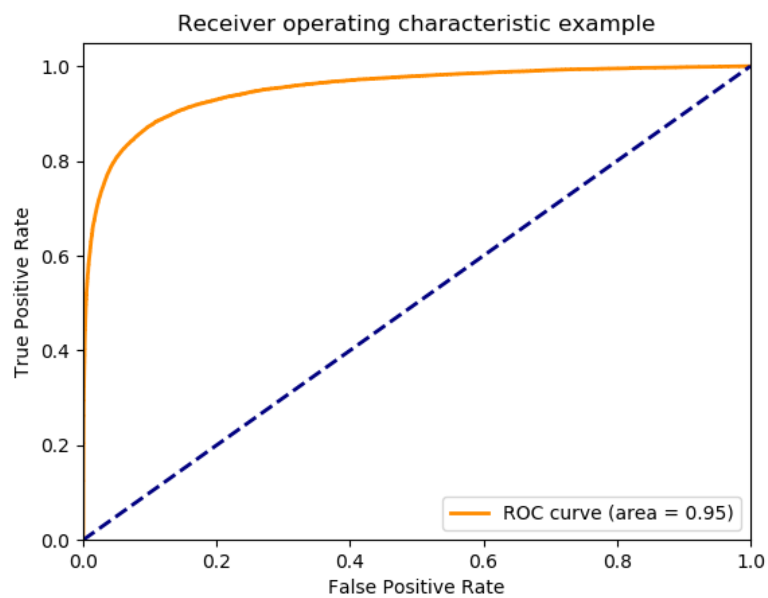

Figure 2. Results on RSNA Data - ROC (for any category)

Any Category	Actual Positive	Actual Negative
Predicted Positive	13266	2461
Predicted Negative	5341	106932

Figure 3. Results on RSNA Data - Confusion Matrix (for any category)

Metric	**Value**
Precision (Any category)	0.84
Recall	0.71
F1	0.77
Accuracy	93.9
AUC	0.95

Figure 4. Results on RSNA Data - Metrics (for any category)

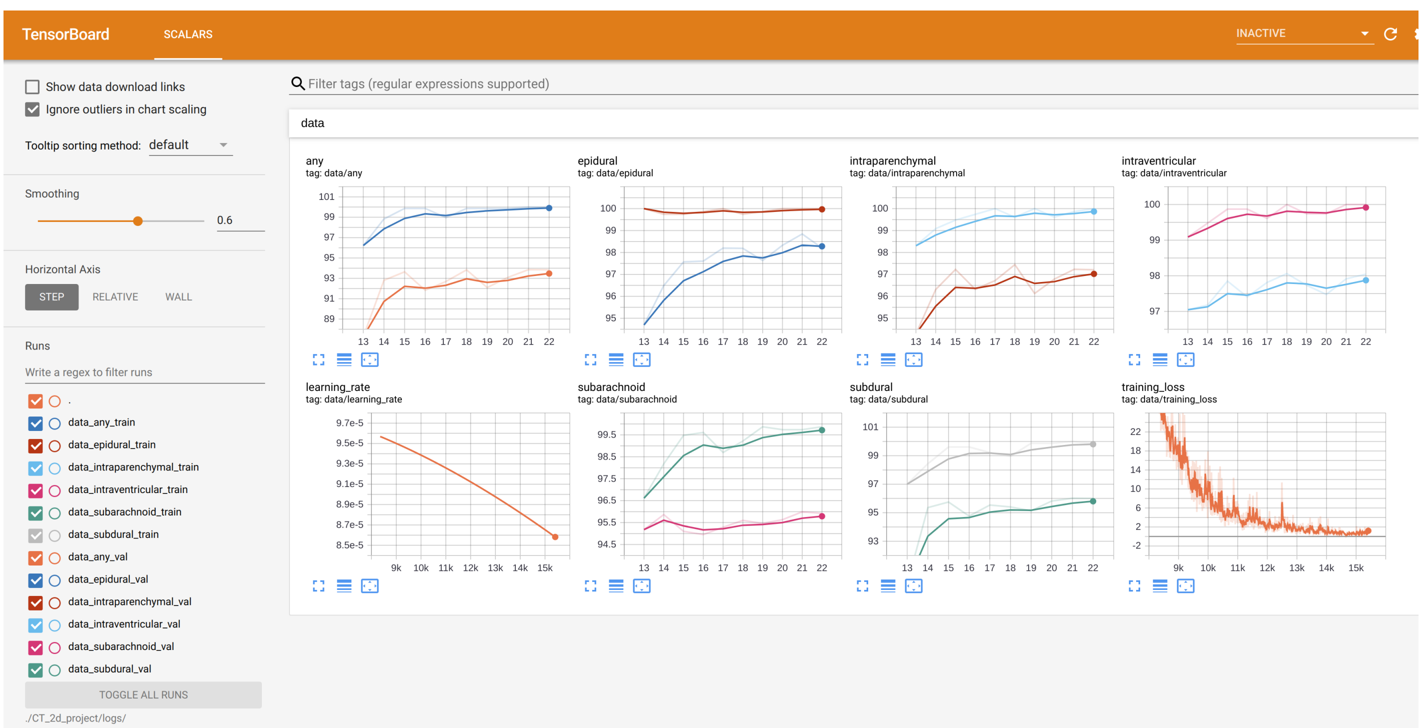

Figure 5. Results on RSNA Data - Train and Val Accuracy across Epochs

References

[1] Tsung-Yi Lin, Priya Goyal, Ross B. Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. *CoRR*, abs/1708.02002, 2017.

[2] Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. *CoRR*, abs/1503.03832, 2015.