Computer-Aided Brain Abnormality Detection Using CAT Images of Brain

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Introduction

The abundance of medical imaging data as well as recent advances of deep learning models have enabled researcher to create models that can perform as good as radiologists. Disease detection using MR images and CT scans have attracted a lot of attention.
In this project, we study detection of three brain issues using head CT scans. We use real-world CT scans to detect hemorrhage, mass and chronic white matter loss.

Dataset

Dataset contains 970 brain CT scans. The data is split into:

- **Training set**: 675 images
- **Validation set**: 192 images
- **Test set**: 96 images

The data is split randomly. All the scans belonging to one patient lie in one of the sets.

- Number of slices: ~50-60 slices/scan
- Size of each slice: 512×512
- Pixels: single channel in Hounsfield Units(HU)

Labels:

- Acute, negative, and chronic
- White matter loss, Intraparenchymal hemorrhage, Extraaxial collection, Subarachnoid, Mass, Herniation

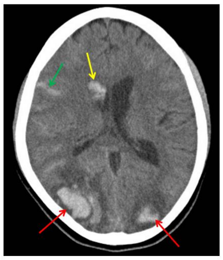
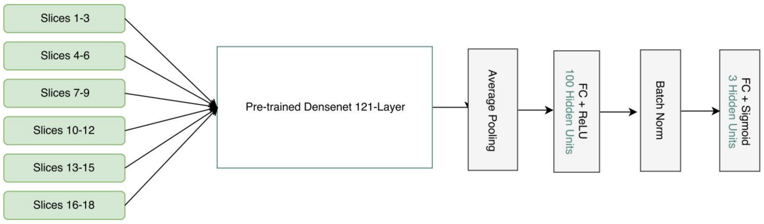


Figure 1: A sample brain CT with hemorrhage.



Architecture

- Group slices to get 3 channels
- Pick 6 images equidistantly
- Feed the images to the same Densenet
  - 121-layer Densenet
  - Pre-trained and frozen
- Average the output of the Densenet of all 6 images
- Fully connected + ReLU
  - 100 hidden units
- Batch normalization
- Fully connected + sigmoid
  - 3 hidden units

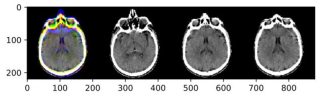


Figure 2: A sample image to feed the network.

Training

- Adam optimizer is used
  - $lr = 1e-4$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, decay $= 0.99$
- Batch size: 8
- Number of epochs: 100
- Data augmentation: random shift, flip and rotation

Results

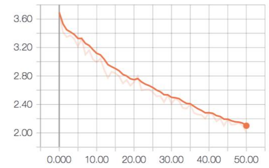


Figure 3: Training Loss

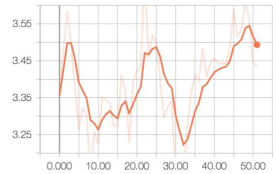


Figure 4: Validation Loss

Labels	Train acc.	Val acc.
White matter	0.680	0.788
Hemorrhage	0.696	0.833

Table 1: Accuracies

Challenges

- **Diverse labels:** Finding the most related, and informative labels and putting them in the same buckets
- **3D images:** Aggregating slice-level features using Average pooling
- **Small dataset:** Deploying methods such as data augmentation
- **Extremely imbalanced dataset:** Deploying methods such as weighted loss

Future Work

- **Collecting more data:** Working closely with our collaborating medical research group to label more positive images for each label at slice level with localization
- **Slice-level classification:** instead of scan-level and aggregating decisions for scan-level through methods such as random forest
- **Utilizing localization:** Enforcing network to identify the location of each label by defining loss based on localization, e.g., IOU loss

References

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[2] Gao Huang, Zhuang Liu, Kilian Q Weinberger, and Laurens van der Maaten. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, volume 1, page 3, 2017.

[3] Sasank Chilamkurthy, Rohit Ghosh, Swetha Tanamala, Mustafa Biviji, Norbert G Campeau, Vasantha Kumar Venugopal, Vidur Mahajan, Pooja Rao, and Prashant Warier. Development and validation of deep learning algorithms for detection of critical findings in head ct scans. *arXiv preprint arXiv:1803.05854*, 2018.