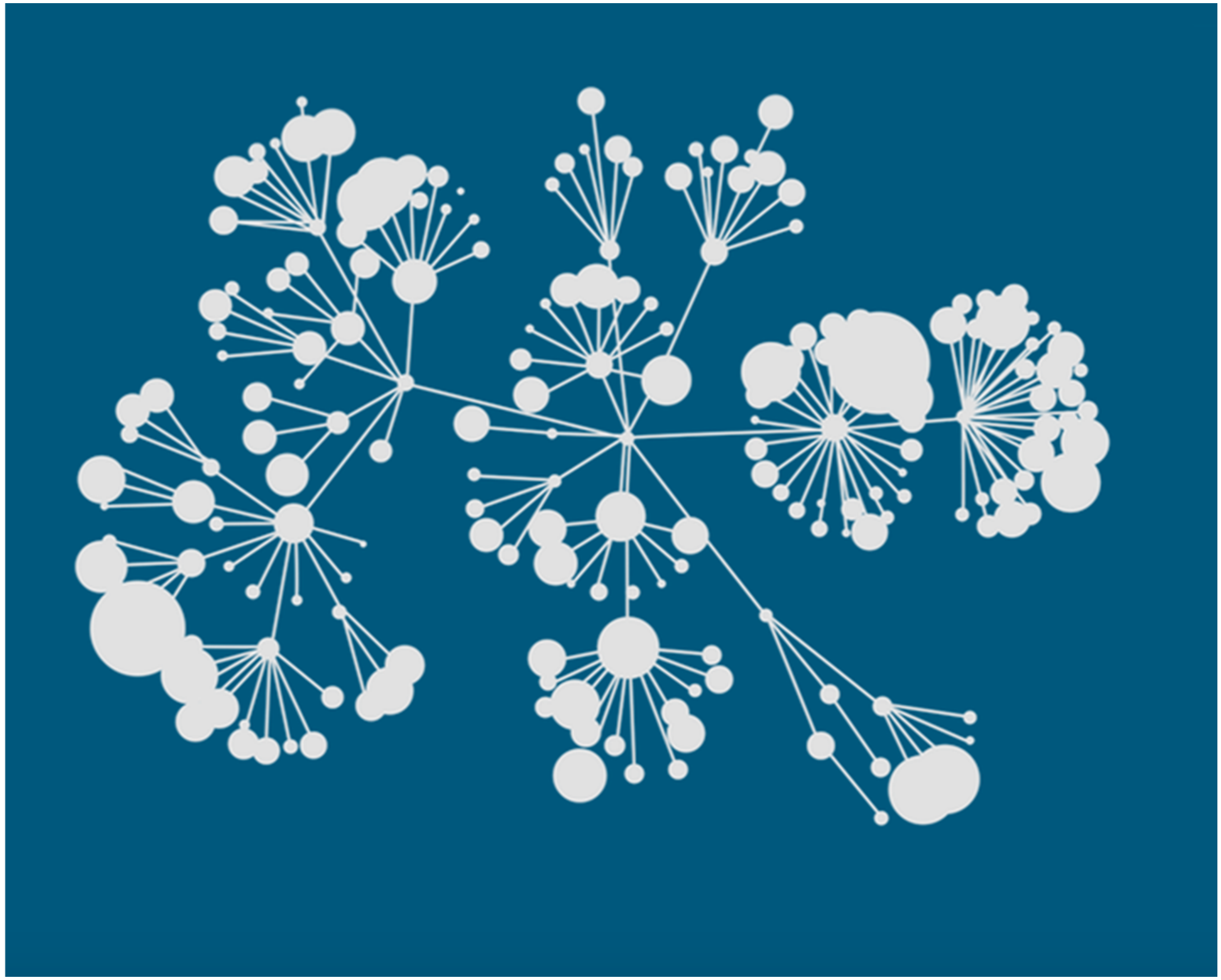
RSNA Intracranial Hemorrhage Detection

Keep Digging Gold
5th Place Solution
November 2019

kaggle



Team

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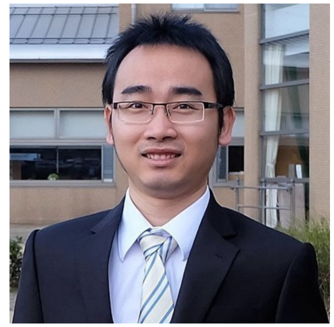

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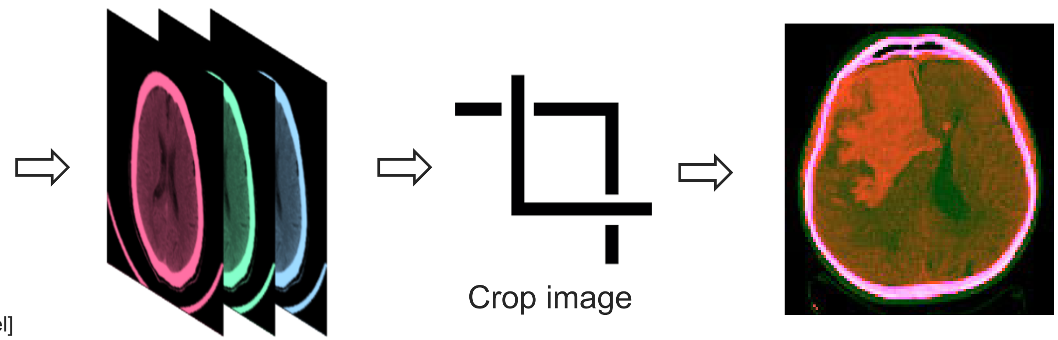
Preprocessing: Creating 3 color channels from DICOM images

#1: 3 CT Window Method

Brain window [40, 80]
Bone window [600, 2800]
Subdural window [75, 215]

Linear window parameters: [width, level]



#2: Adjacent Slice Method

Reconstruct 3D volume from study ID & patient position:
*n-1*th image
*n*th image
*n+1*th image
Apply subdural window

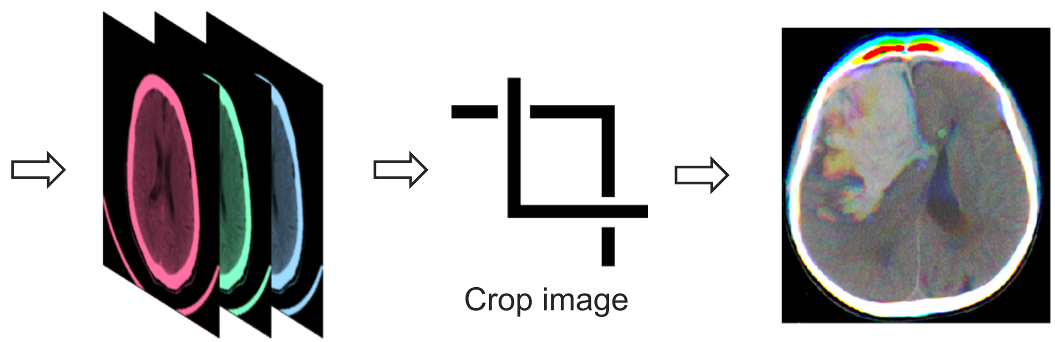


Image: ID_0fa314037, intraparenchymal

Overview of models used

Preprocessing Method	Network Architecture	Image Resolution	Score Before Post processing	Score After Post processing
1*	ResNet-18	512x512	0.060	0.054
1*	ResNet-34	512x512	0.058	0.052
1*	ResNet-50	512x512	0.058	0.052
1*	Inception-V3 & Deep Supervision	512x512	0.063	0.053
1	DenseNet-169	512x512	0.055	0.049
1	EfficientNet-B3	300x300	0.055	0.050
2	ResNet-50	512x512	0.054	0.051
2	EfficientNet-B0	224x224	0.054	0.051
2	EfficientNet-B5	456x456	0.048	0.048

* No cropping on the 3 window preprocessing

Final private leaderboard score: 0.04561

Training parameters

Cross validation scheme
- 5 fold CV grouped by Patient ID

Loss
- Weighted binary cross-entropy loss per class (weights = 2 for any and 1 for the other classes)

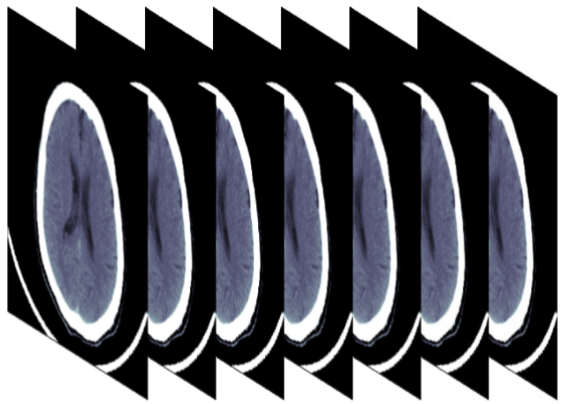
Image augmentation
- Horizontal flip, elastic transform, grid distortion, optical distortion, shift-scale-rotate, random resized crop, random rotation

Optimizers & learning rate:
- AdamW optimizer, initial learning rate: 0.01 or 0.001, weight decay: 0.01
- ReduceLROnPlateau or Cosine annealing, both with early stopping (patience=3)

Test time augmentation (TTA):
- Identity, horizontal flip, rotate +/- 10 degrees

Postprocessing

Reconstruct 3D volume from
study ID & patient position



Target	0	0	1	1	1	1	0
Prediction	0.08	0.12	0.58	0.65	0.78	0.65	0.20
Final	0.02	0.08	0.70	0.80	0.85	0.90	0.05

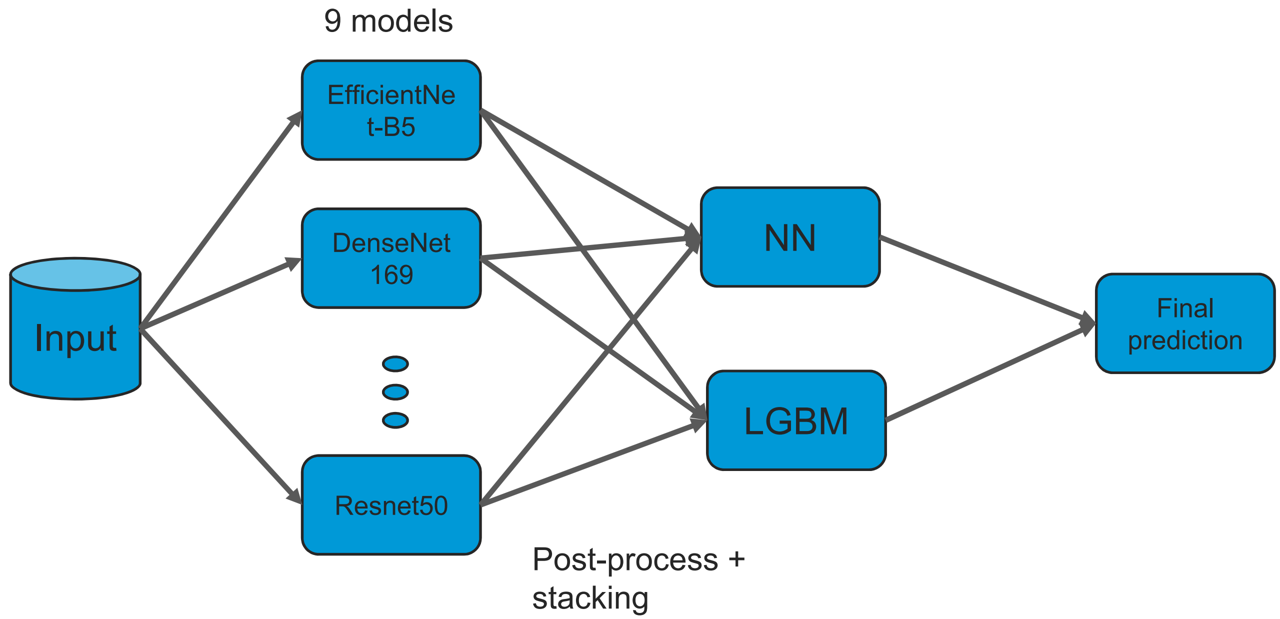
Final probabilities per
axial slice

Create a binary classifier for each of the 6 classes using the following features:

- The original prediction p0
- The predictions of the previous image p_prev and the next image p_next
- The statistical features for all images before and all the images after the image in the same studyID: number of images, mean/std/skew of the original predictions.

Binary classifiers built using H2O AutoML & OOF predictions

Model Stacking



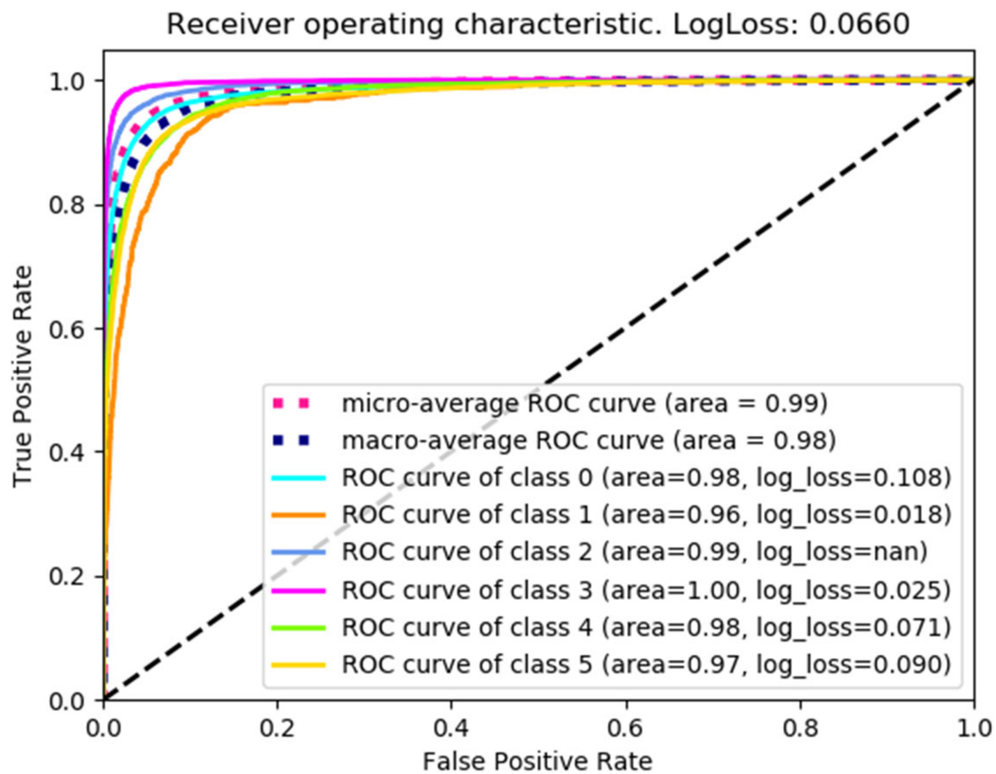
Neural Network:

- Input features: 54 = 9 models x 6 classes -> reshape (9,6,1)
- Using CNN:
    - kernel (NUM_MODELS,1) to learn the correlation between 9 models
    - kernel (1, NUM_CLASSES) to learn the correlation between 6 classes
- Mix-up augmentation works pretty well

Light gradient boosting machine (LightGBM):

- We build 6 seperate models for 6 classes

ROC AUC Performance



Results from validation of fold 1 from the EfficientNet-B5 model

Classes:

0. Any
1. Epidural
2. Intraparenchymal
3. Intraventricular
4. Subarachnoid
5. Subdural

Similar study achieved average ROC-AUC scores in the region of 0.93. See figure 3d of: *Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network, Hai et al. April 2019*

Important and Interesting Findings

- Overfitting was a commonly reported issue:
  - Most models only needed approx. 5-7 epochs to reach the best validation score
  - Early stopping was essential
- Both pre-processing methods have strengths & weaknesses:
  - Method #1 benefitted most from the post-processing
  - Method #2 already captured some of the spatial detail but could only utilize one CT window
  - Ideal for model ensembling
- Treating this as a 3D problem gives the best results:
  - Using the metadata effectively was key
  - Worth bearing in mind when labelling future radiological datasets

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