Intracranial Hemorrhage Classification using CNN

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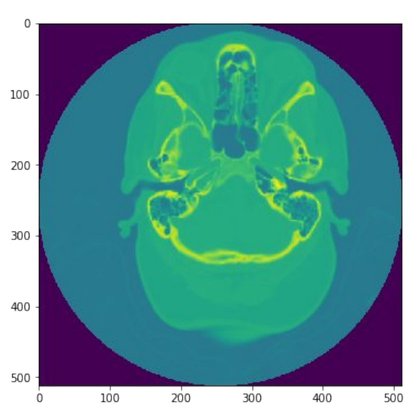
Overview

Intracranial hemorrhages have fatal consequences depending upon its subtype, location, and size. A fast and accurate classification using a machine learning algorithm well fitted to aid the current clinical workflow could provide critical assistance. In this project, I use a single slice of a CT scan in DICOM image format as input. Multi-class classification is conducted to diagnose intracranial hemorrhages and its five subtypes: intraparenchymal, intraventricular, subarachnoid, subdural, epidural. Transfer learning is applied based on ResNet-50 and linear windowing is compared with sigmoid windowing in its performance.

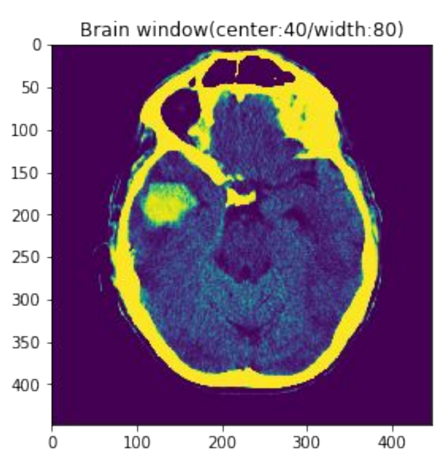
Data Preprocessing



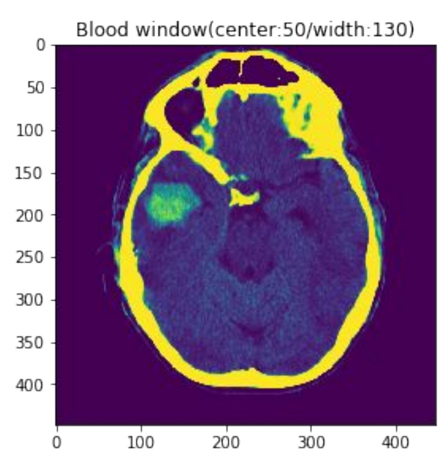
Original Image (512,512)

convert to HU

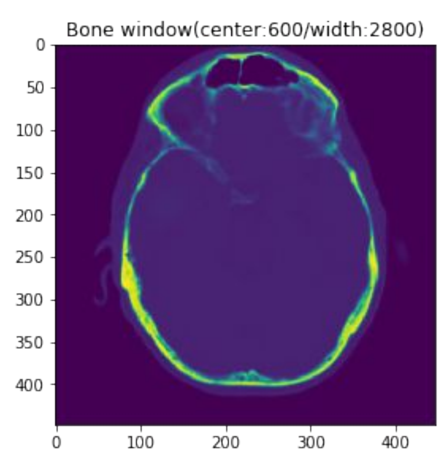
sigmoid windowing



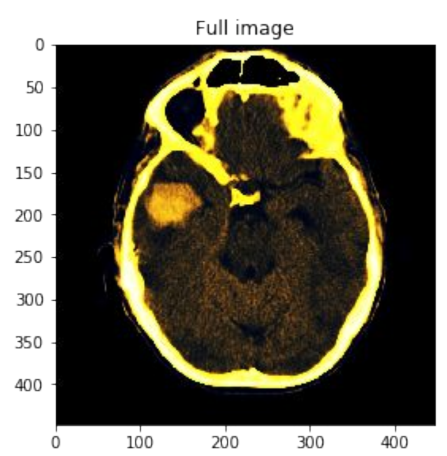
Brain window WW=80, WL=40



Blood window WW=130, WL=50



Bone Window WW=2800, WL=600



3 Windows Put Together

Model

Input Image (m, 224, 224, 3)

Dataset : undersampling to deal with data imbalance

ResNet-50:
pretrained imagenet
+ GlobalPooling2D
+ Fully connected(1024)
+ Fully connected(6)

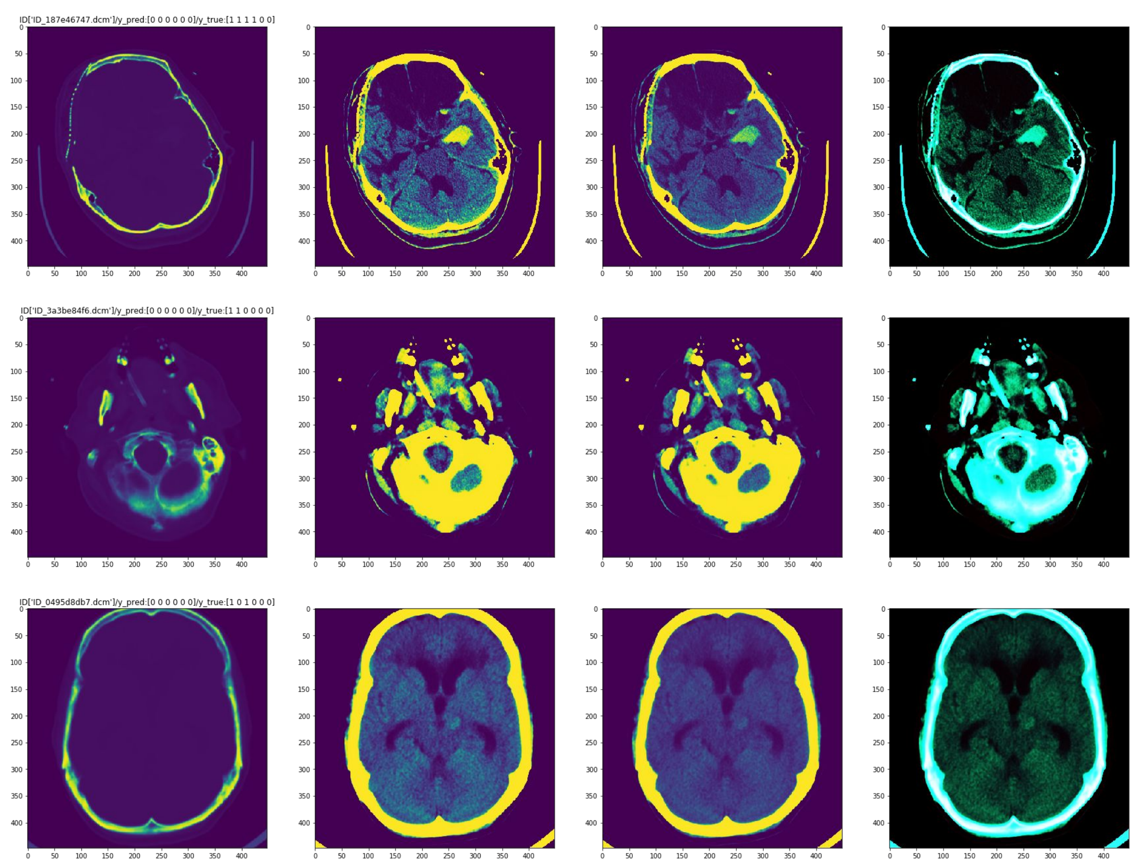
Label (m, 6):
any
epidural
intraparenchymal
intraventricular
subarachnoid
subdural

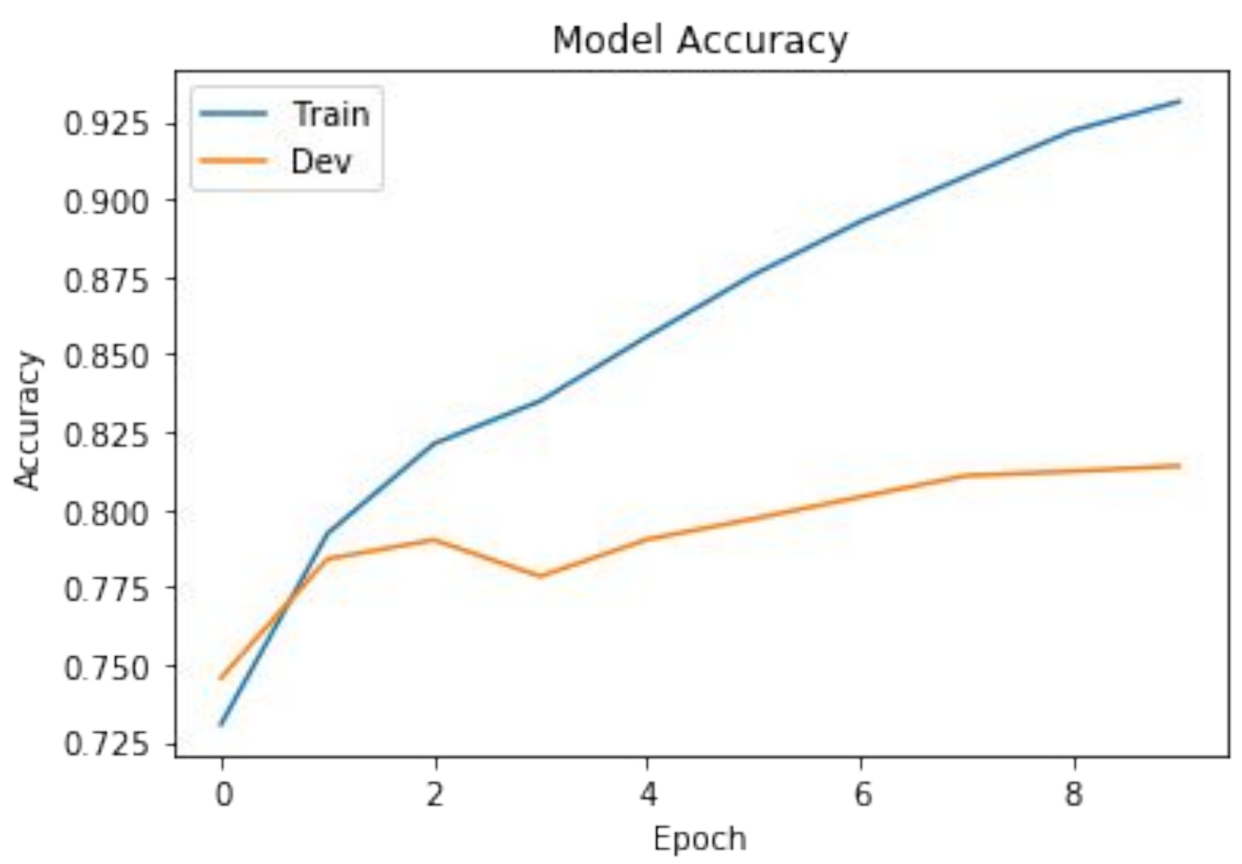
Loss:
binary cross entropy

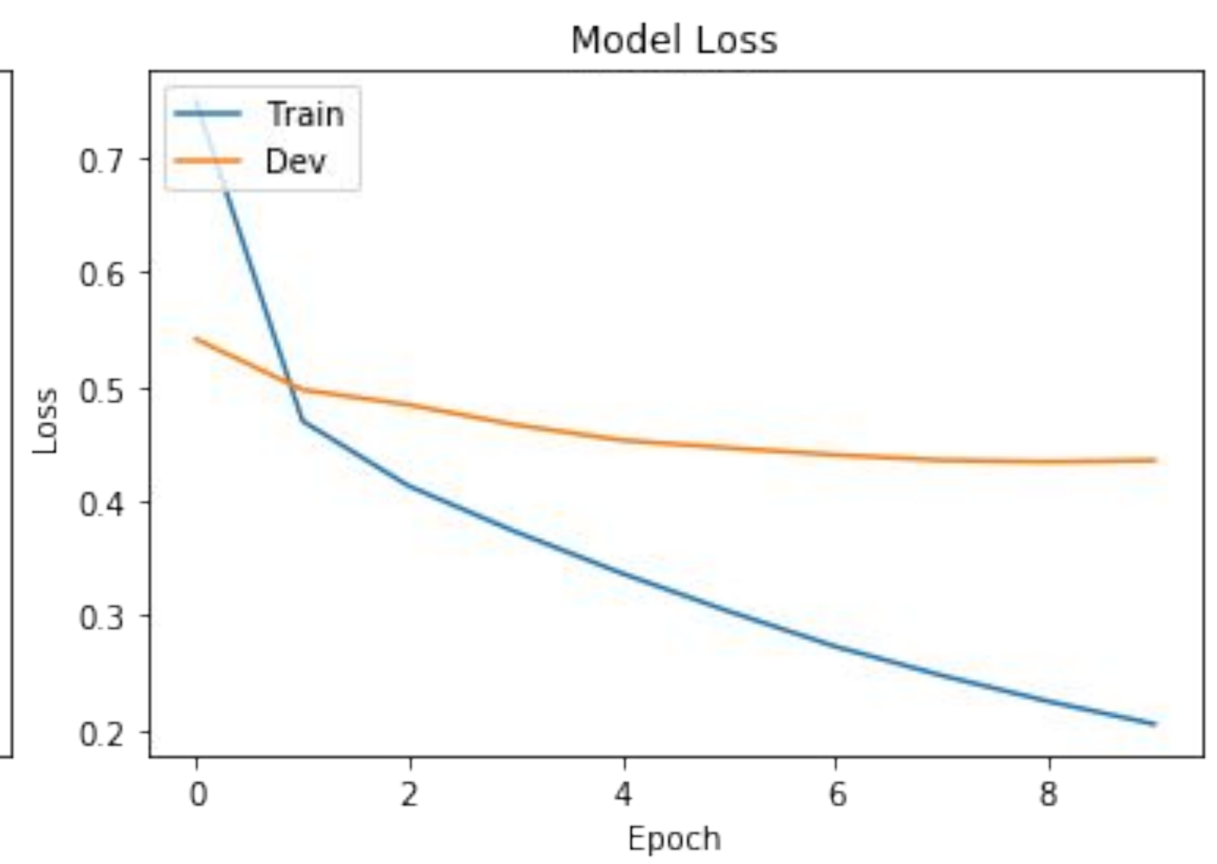
Parameters tuned
- batch size
- windows used
- balance of training set data
- sigmoid windowing vs linear windowing

Results

Window (WL, WW)		Any P	Any R	Any F1	Any #	Epidural P	Epidural R	Epidural F1	Epidural #	Intraparenchymal P	Intraparenchymal R	Intraparenchymal F1	Intraparenchymal #	Intraventricular P	Intraventricular R	Intraventricular F1	Intraventricular #	Subarachnoid P	Subarachnoid R	Subarachnoid F1	Subarachnoid #	Subdural P	Subdural R	Subdural F1	Subdural #
Linear	(40,80)	0.1	0.3	0.2	587	0	0	0	19	0.1	0	0	198	0.1	0.1	0.1	150	0	0	0	203	0	0	0	242
Linear	(50,130)	0.2	0.4	0.2	616	0	0	0	16	0.1	0.2	0.1	200	0.1	0.2	0.1	158	0.1	0	0.1	212	0.1	0	0	281
Linear	(100,220)	0.2	0.4	0.2	585	0	0	0	21	0.1	0.1	0.1	193	0	0.2	0.1	130	0.1	0.1	0.1	185	0.1	0	0	268
(40,80),(50,130),(600,2800)		0.8	1	0.9	80	0.5	0.5	0.5	19	0.5	0.7	0.6	31	0.8	0.2	0.3	29	0.6	0.4	0.5	32	0.7	0.3	0.4	35







Conclusion & Future

The highest performing algorithm was chosen that had the lowest validation loss, which was the one using sigmoid windowing with 3 different windows.

Since using different windowing techniques resulted in significantly different results, the next step would be to find the best window setting values for sigmoid windowing[1]. Then, test the most successful models with the different window settings. In addition, I would make the classification into a 2 step process to first detect intracranial hemorrhages and then to classify the subtypes.

Reference

[1] Hyunkwang Lee, Myeongchan Kim, and Synho Do. Practical window setting optimization for medical image deep learning. arXiv preprint arXiv:1812.00572, 2018.
[2] A. Kumar, J. Kim, D. Lyndon, M. Fulham, and D. Feng. An ensemble of fine-tuned convolutional neural networks for medical image classification. IEEE Journal of Biomedical and Health Informatics, 21(1):31–40, Jan 2017.
[3] Hai Ye, Feng Gao, Youbing Yin, Danfeng Guo, Pengfei Zhao, Yi Lu, Xin Wang, Junjie Bai, Kunlin Cao, Qi Song, Heye Zhang,Wei Chen, Xuejun Guo, and Jun Xia. Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network. European Radiology, 29(11):6191–6201, Nov 2019.
[4] Mohammad Arbabshirani, Brandon Fornwalt, Gino Mongelluzzo, Jonathan Suever, Brandon Geise, Aalpen Patel, and Gregory Moore. Advanced machine learning in action: identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration. npj Digital Medicine, 1, 12 2018.

I used brain CT scan images of size (512, 512) as input to determine whether
which was and used ResNet-50 to classify each image
scale image to Hounsfield Units(HU) and select three different contrasts to highlight the window of interest. Next, I use the pretrained weights from imagenet for
ResNet-50 a 5 classes each representing subtype: intraparenchymal, intraventricular, subarachnoid, subdural, epidural.