Intracranial Hemorrhage Classification using CNN
Hyun Joo Lee hjlee22@stanford.edu

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)
- **Input Image** (m, 224, 224, 3)
- **Dataset**: undersampling to deal with data imbalance
- **Model**
  - **Label** (m, 6): any epidural intraparenchymal intraventricular subarachnoid subdural
  - **Parameters tuned**
    - batch size
    - windows used
    - balance of training set data
    - sigmoid windowing vs linear windowing
- **Loss**: binary cross entropy

Results
<table>
<thead>
<tr>
<th>Window (WL, WW)</th>
<th>Any P R F1</th>
<th>Epidural P R F1</th>
<th>Intraparenchymal P R F1</th>
<th>Intraventricular P R F1</th>
<th>Subarachnoid P R F1</th>
<th>Subdural P R F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear (40,80)</td>
<td>0.1 0.3 0.2</td>
<td>0 0 0 19 0.1 0 0 198 0.1 0.1 0.1 150 0 0 0 203 0 0 0 242</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear (50,130)</td>
<td>0.2 0.4 0.2 0.2</td>
<td>0 0 0 16 0.1 0.2 0.1 190 0.1 0.2 0.1 158 0 0 0 212 0 0 0 281</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear (100,220)</td>
<td>0.2 0.4 0.2 0.2</td>
<td>0 0 0 21 0.1 0.1 0.1 193 0 0 0 130 0.1 0.1 0.1 185 0 0 0 268</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(40,80),(50,130),(800,2800)</td>
<td>0.8 1 0.9 0.8</td>
<td>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</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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
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.