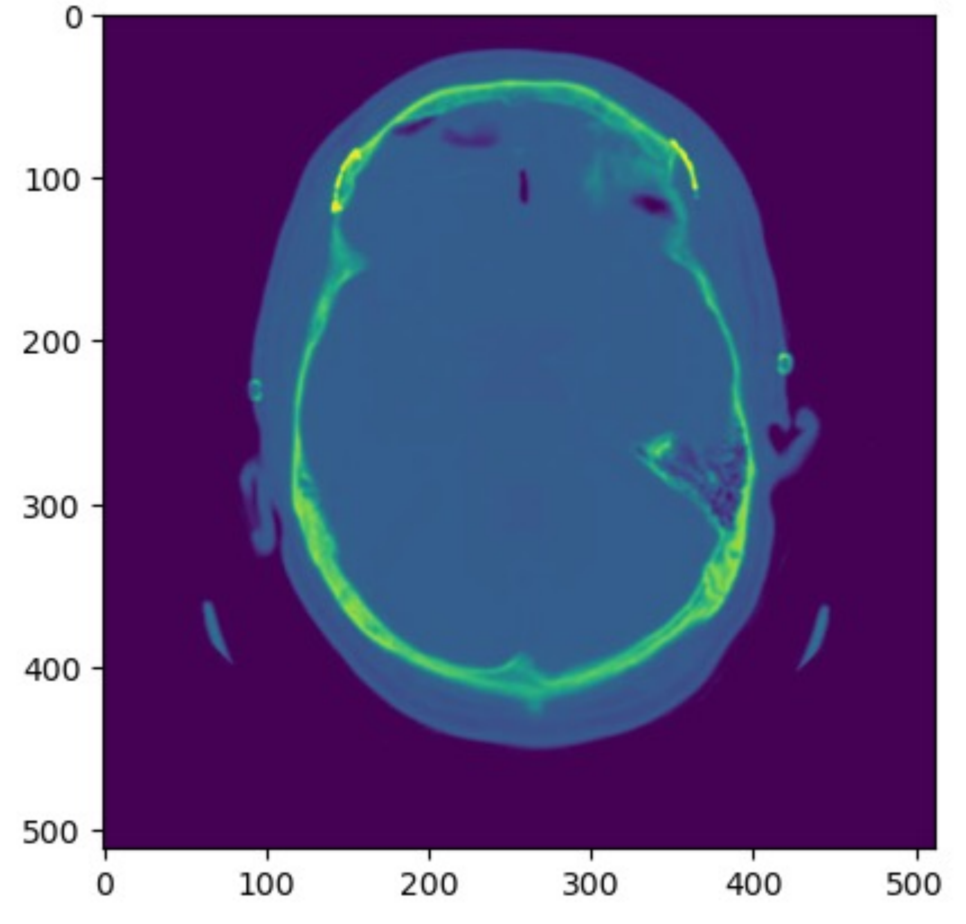
BRAIN HEMORRHAGE CLASSIFICATION WITH CT SCANS

David Pogrebitskiy, Scott Biggs,
Thomas Walewski, Jared Garfinkel,
Karenna Ng, and Sarah Baker

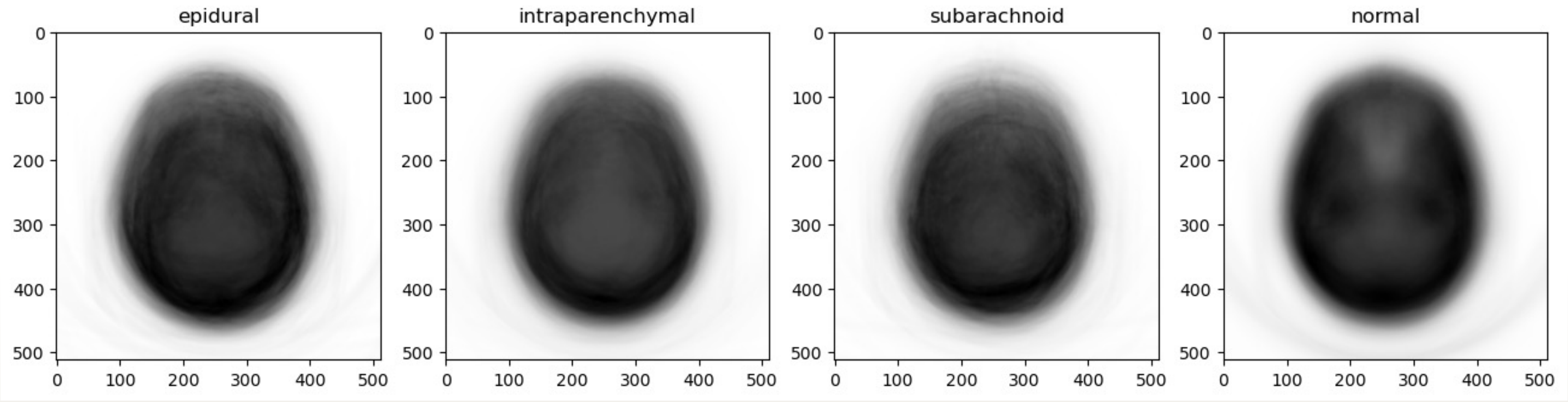
BACKGROUND

- Want to predict the occurrence and type of brain hemorrhages
- Model could be used to aid medical evaluation of CT scans
- Model predicts scan outcome and then human professional validates
- Using image data from CT scans (XN data source)
- Images taken from different sections of the head



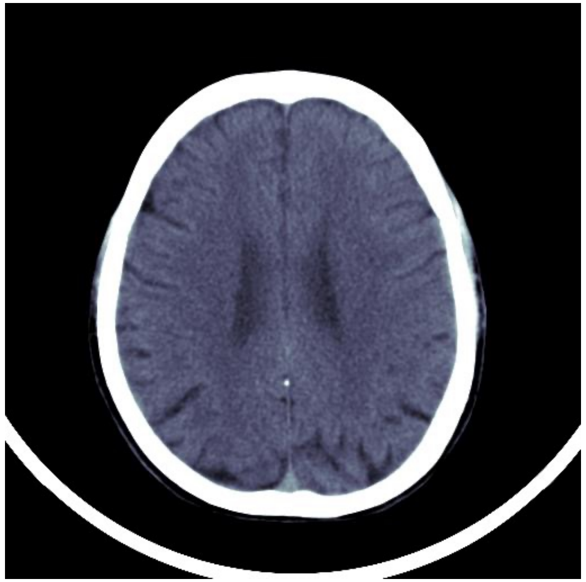
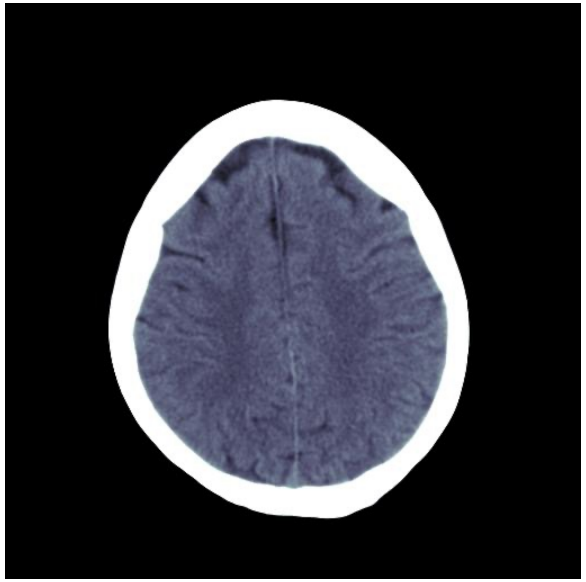
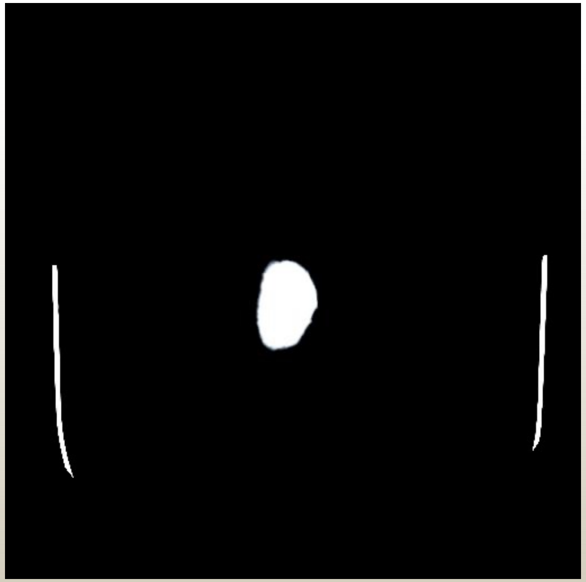
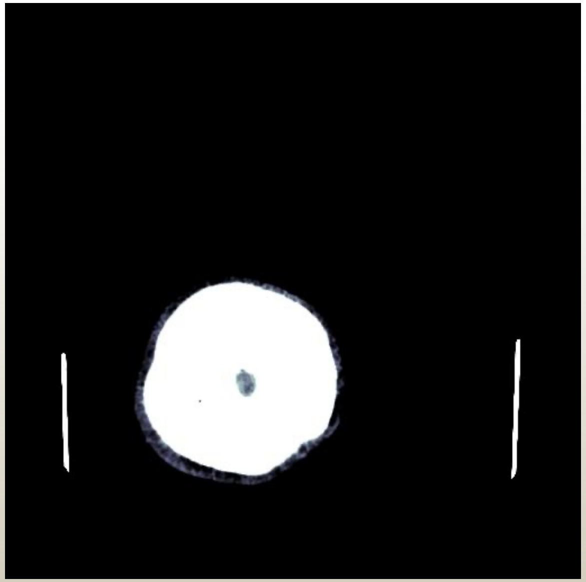
DESCRIBING THE DATA

- Six Categories:
  - Epidural
  - Intraparenchymal
  - Multiple
  - Normal
  - Subarachnoid
  - Subdural
- 750,000+ total images



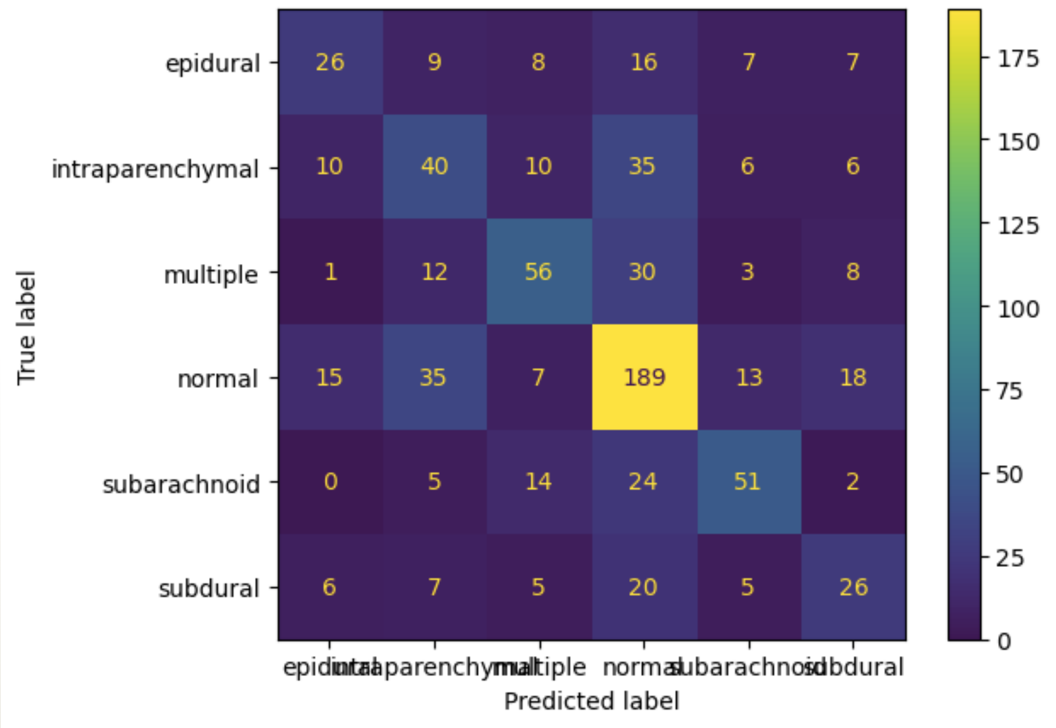
CLEANING THE DATA

- Used the brain bone window, which performed best on a test algorithm
- CT scans taken from different points in the head
- Want to select images that have clear hemorrhages
- Use brightness levels to parse CT scans to find quality images
- Around 8,000 entries used for data analysis
- Needed to make labels match for images selected for the models

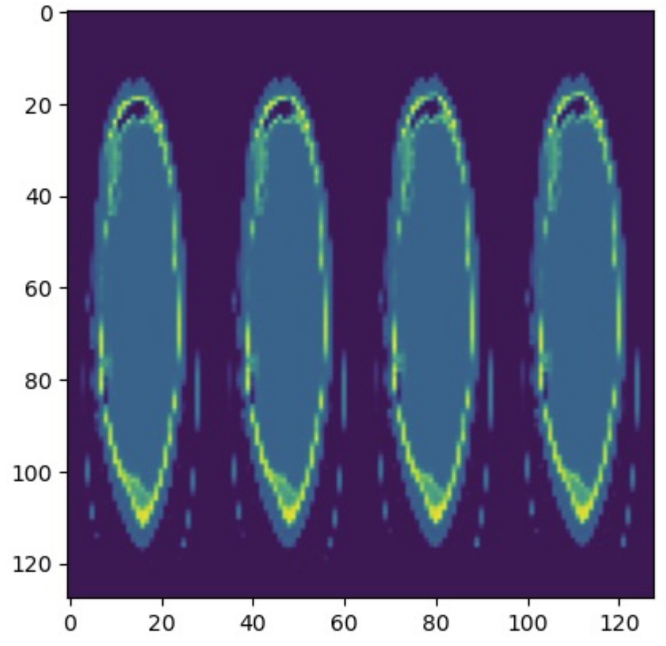
MODEL 1: LOGISTIC REGRESSION

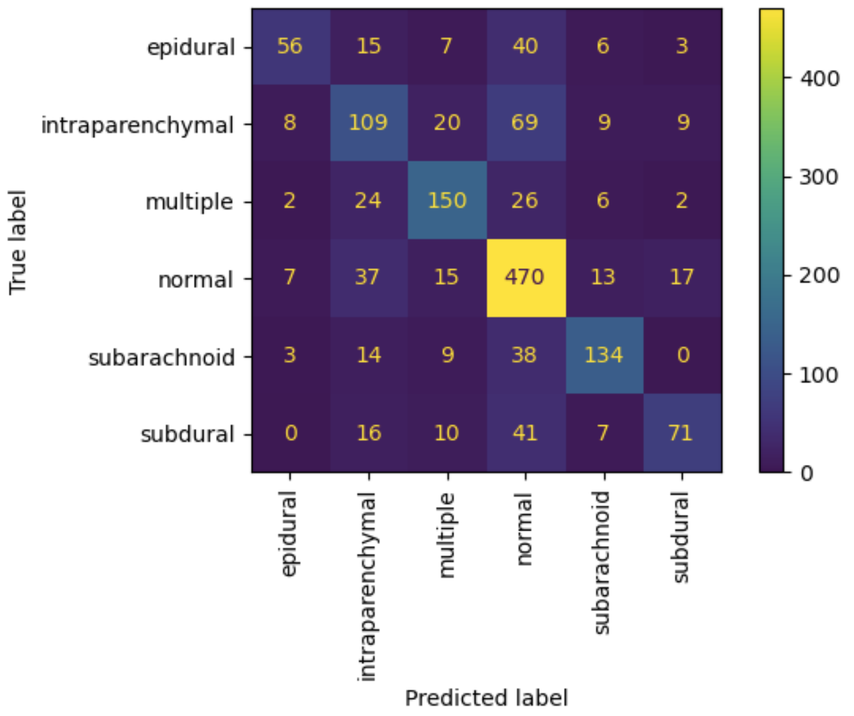
- SoftMax Logistic Regression
- No Down Sampling
- 80/20 Split in Training/Testing
- 732 entries in the test data
- 53% model accuracy
- Brought up by ability to predict "normal" cases
- Other classes range for 36% to 53% accuracy



MODEL 2: CONVOLUTION NEURAL NETWORK

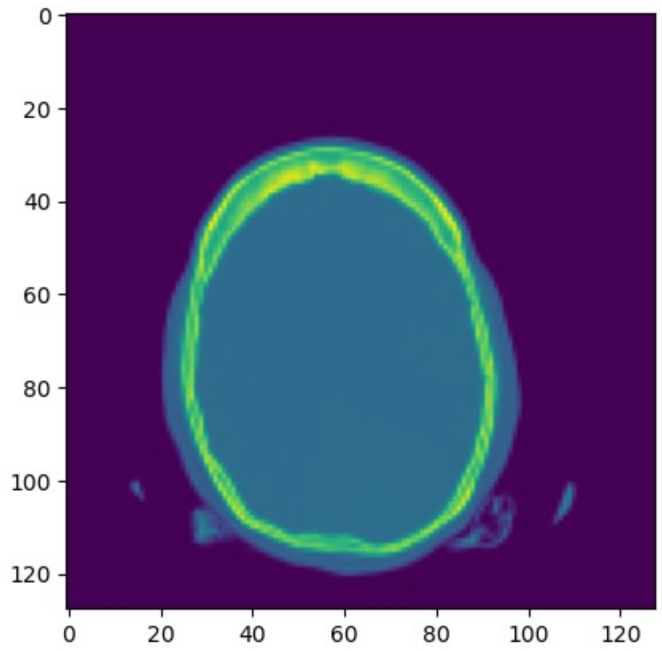
- Larger sample size, around 8000
- Down sampling in one axis
- 67% testing accuracy
- 84% accuracy on "normal" category
- Other categories range in accuracy from 47% to 71%

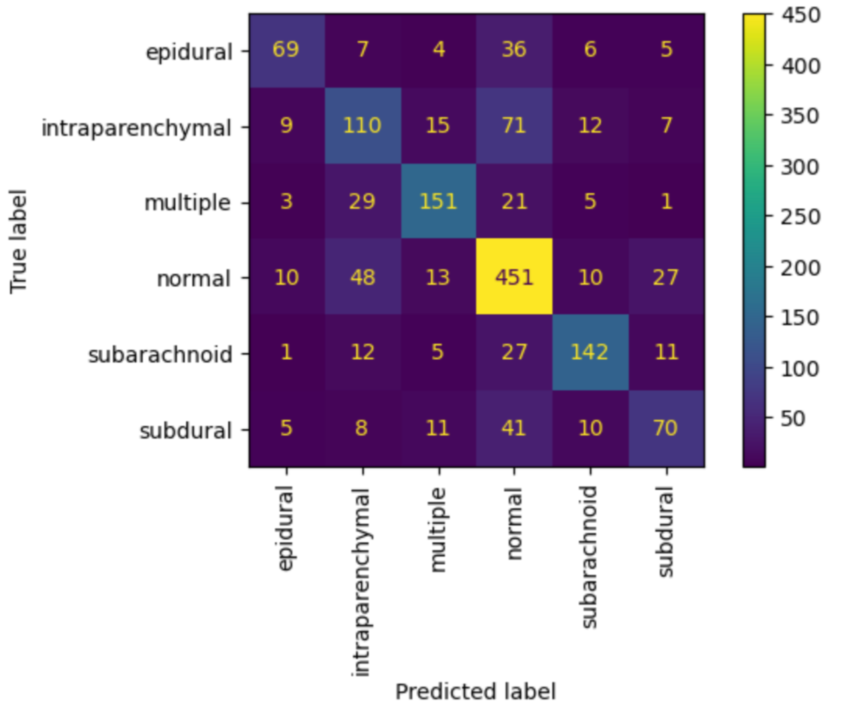




MODEL 3: CONVOLUTION NEURAL NETWORK 2

- Cleaner down sampling (on both axes)
- Sample size around 8000
- 69% testing accuracy
- Only a slight improvement

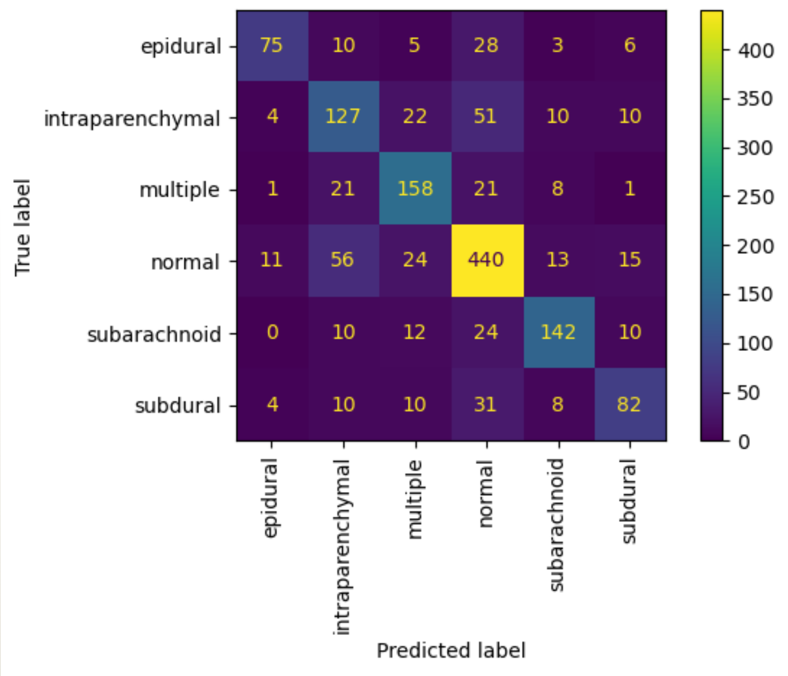




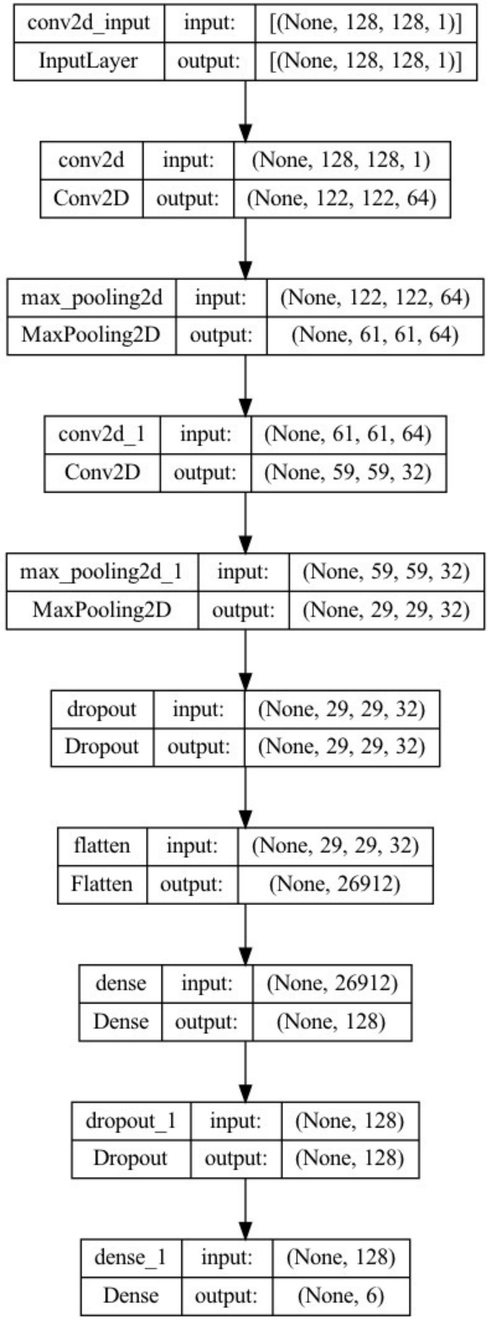
MODEL 4: FINAL CNN WITH ACCURATE DS

True Label Down	epidural	intraparench	multiple	normal	subarachnoi	subdural	Accuracy Rate		Total Accuracy Rate
epidural	75	10	5	28	3	6	59.06%		69.99%
intraparenchymal	4	127	22	51	10	10	56.70%		Accuracy W/o Normal
multiple	1	21	158	21	8	1	75.24%		63.85%
normal	11	56	24	440	13	15	78.71%		Total Entries
subarachnoid	0	10	12	24	142	10	71.72%		1463
subdural	4	10	10	31	8	82	56.55%		

- Better Down Sampling
- Lowered Accuracy with "normal" categorization
- Increased accuracy with other categories
- Small increase in total model accuracy offset by performance shifts
- Better model due to interest case in non-"normal" hemorrhages



FINAL MODEL IMPLEMENTATION



FUTURE IMPROVEMENTS

- We could not process multiple CT images at a time as an input. In a real situation, there would be several scans from multiple levels on the same patient. We were unable to implement it here, but we believe this would significantly improve results.
- We would use even more data, especially data for the labels that have fewer entries in the data we used. This would help more evenly train the model and improve its accuracy.
- We would increase our GPU, as long training times prevented us from using full resolution data or adding many more convolutional layers, which likely would have improved performance.

THANKS & RESOURCES

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Papers Referenced:

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