NCCT Segmentation for Brain Haemorrhage Detection

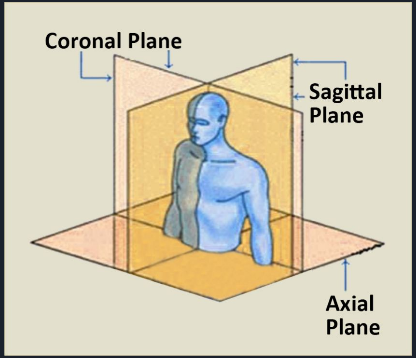
Ashwin Rao - 2019101049

Harshwardhan Prasad - 2019102021

Shaurya Dewan - 2019101017

NCCT Brain Imaging: An Introduction

- NCCT imaging is a type of X-Ray imaging used to obtain cross sectional images of the body or organs like the brain.
- NCCT scans give us three views or slices of the brain: coronal, sagittal and axial. These are cross sections along the XY, YZ and XZ planes respectively.
- NCCT scans are useful to detect tumors, haemorrhages and other abnormalities in brain tissue.

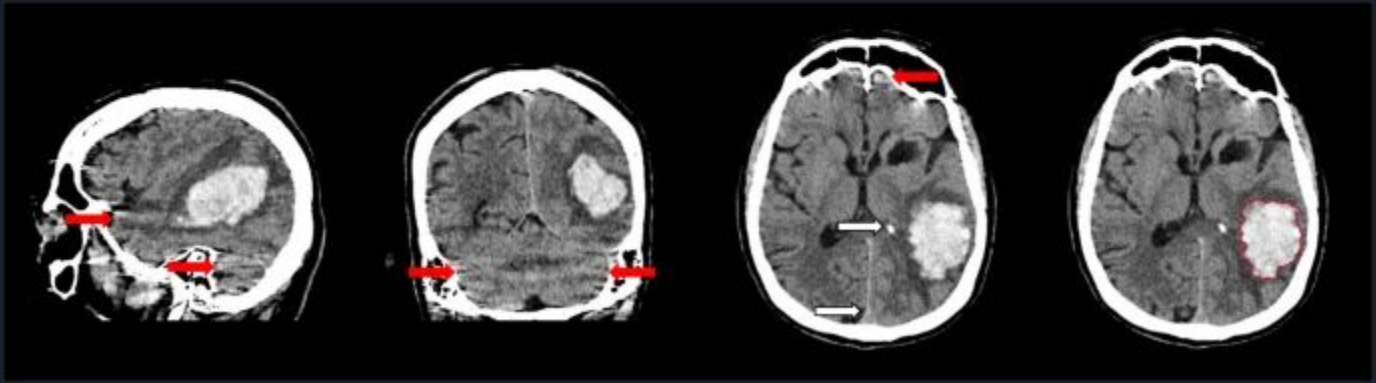


A Segmentation Problem

- We pose the detection of brain haemorrhage as an **image segmentation problem**. We attempt to segment NCCT scans by color.
- The difference in color is due to a difference in the density of blood. Regions of the brain affected by a haemorrhage have a much higher density of blood than the rest of the brain, giving it a distinct appearance compared to its surroundings.
- We take a **deep learning approach** to image segmentation, using the **UNet architecture** for the neural network.
- This is a **supervised learning problem**. Hence, annotation of the training set is required. This must be done by professionals in the field. Luckily, we had access to existing datasets to train our model.

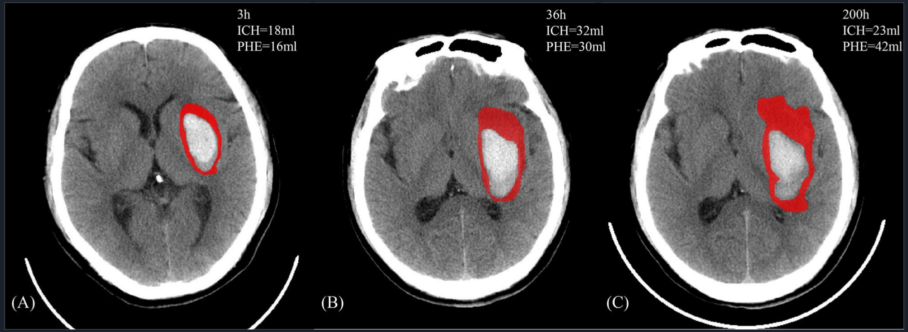
A Segmentation Problem: Challenges

- The main challenge is that the model must distinguish between affected regions from unwanted noise and other artifacts in NCCT images.
- In the image below, the red arrows point to lighter areas in the brain scan which are not blood clots, which, however, look similar in appearance to the large haemorrhage, outlined in red.



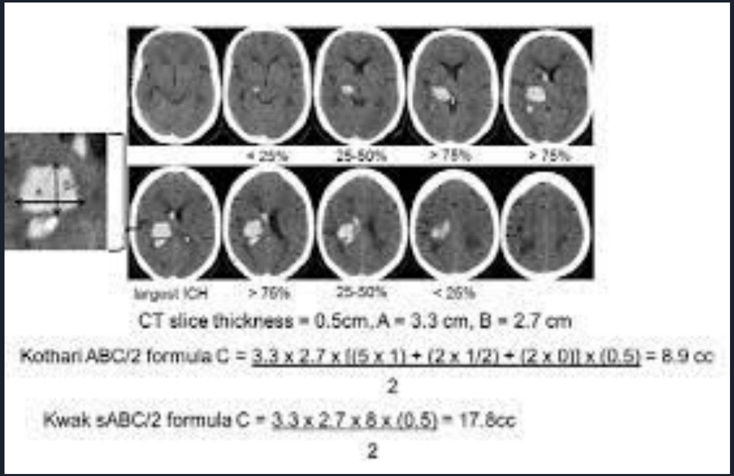
A Segmentation Problem: Challenges

- Irregularity of the haematoma and different stages of clot formation may further contribute to obscure haemorrhage boundaries and internal heterogeneity of the clot.
- The diagram shows how the boundary and appearance of a haemorrhage changes with time.



Existing Methods

- The prevailing method is the ABC/2 method
- A = greatest hemorrhage diameter by CT, B = diameter 90° to A, C = approximate number of CT slices with hemorrhage multiplied by the slice thickness
- Significant volume estimation error due to irregular shapes
- Time-consuming as requires doctors to manually annotate/estimate the required parameters/variables for the above formula



A Segmentation Problem: Improvements

Use of domain knowledge

- Posing the problem as a vanilla image segmentation task requires no domain knowledge.
- The specificity of the model to the task at hand can be improved by incorporating heuristics or ideas of professionals in the segmentation process.
- **The use of domain knowledge** has the potential to greatly improve the performance of the network, particularly in hard-to-detect images where the network may need some extra help to accurately predict boundaries of the haemorrhage.

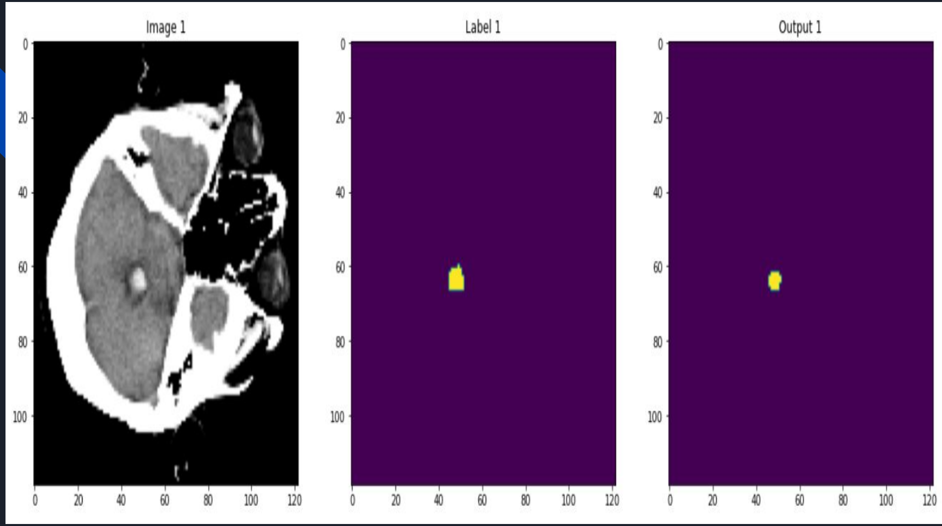


Image 1
Label 1
Output 1

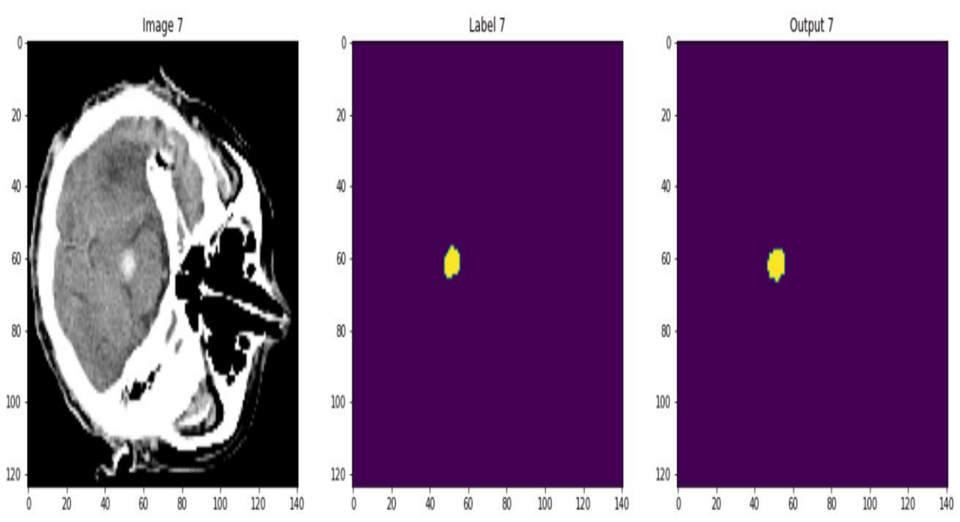



Image 7
Label 7
Output 7

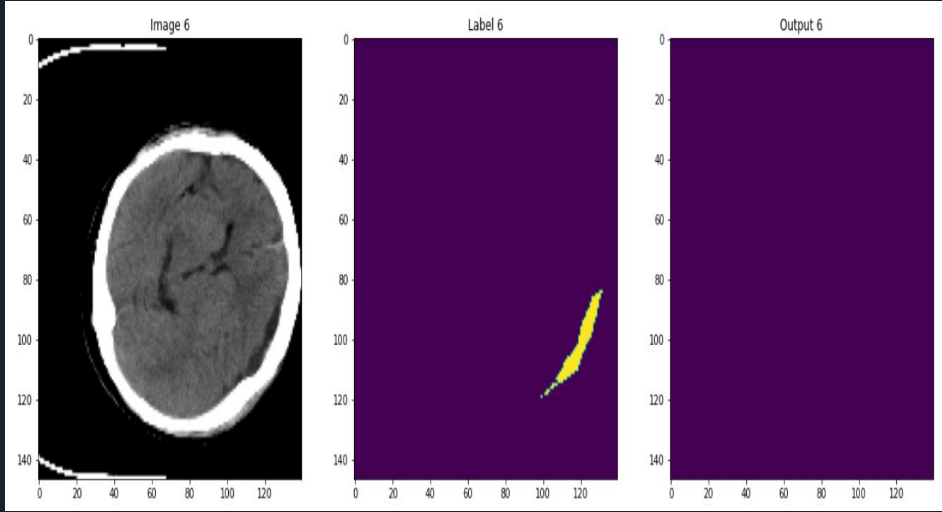



Image 6
Label 6
Output 6

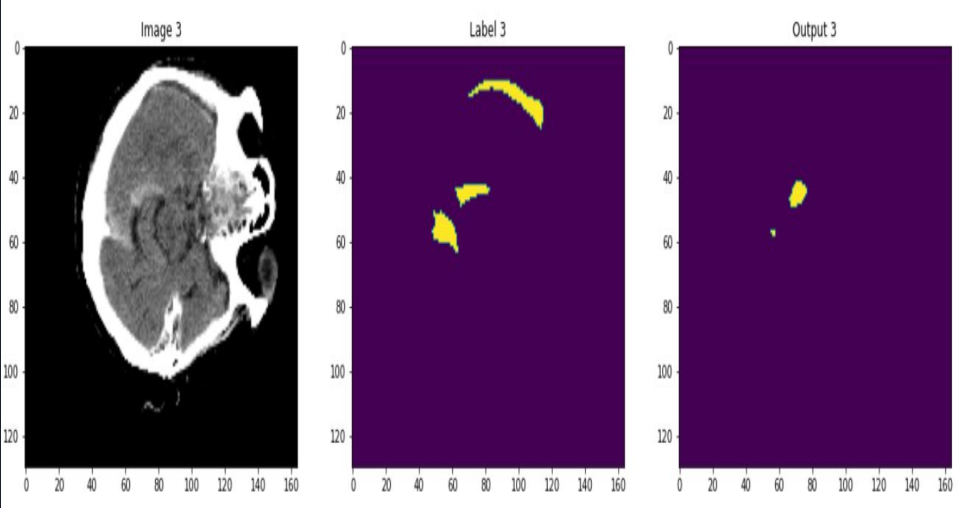
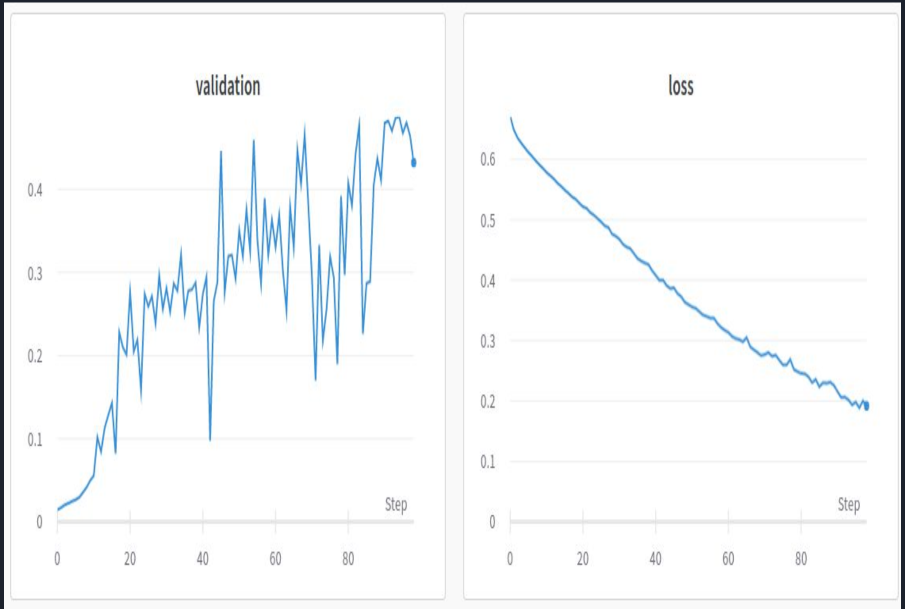



Image 3
Label 3
Output 3

Results

- Fairly good results given the simplicity of the UNet model
- Training error reduced from 67% to 20% within 100 epochs and still converging
- Maximum validation mean dice accuracy/metric of 48.75% achieved
- Highly fluctuating validation metric but general upward trend observed
- Does well for regular shaped cases like circular/spherical haemorrhages
- Conservative for bigger and more irregular shaped cases
- Minimal false positives observed



Analysis

- Basic UNet model with roughly 4-5 layers provides a good starting point/baseline giving minimal false positives (which can be excessively harmful) and performing well for regular shapes
- Experimented with few different number of channels per layer, found minimal effect but increasing channels provides some improvement
- Increase in the number of layers also provides some small enhancement
- To significantly improve results, need to incorporate domain specific knowledge such as expected/probable location of haemorrhages, more data with irregular shapes, maximum possible size/volume, etc.

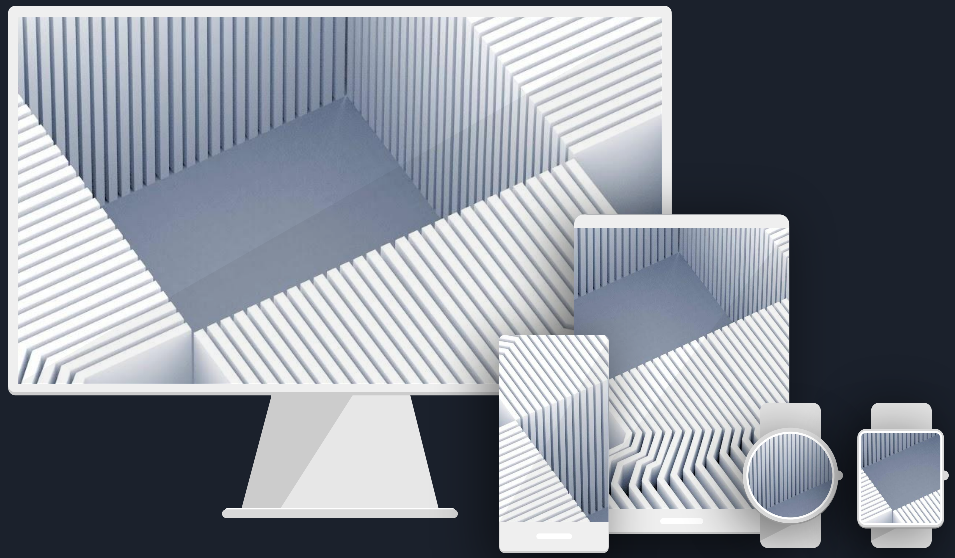
Individual Contributions

All team members contributed equally to all parts of the project. The main split up of tasks included:

- Using the PyTorch data loader to process NCCT Images (these are much different than normal RGB Images).
- Understanding the UNet architecture and creating the model.
- Analyzing outputs of the model and compiling results.

Overall, this project gave us an introductory exposure to the vast world of medical image processing.

Thank you!



Ashwin Rao
Harshwardhan Prasad
Shaurya Dewan