Hemorrhage Detection

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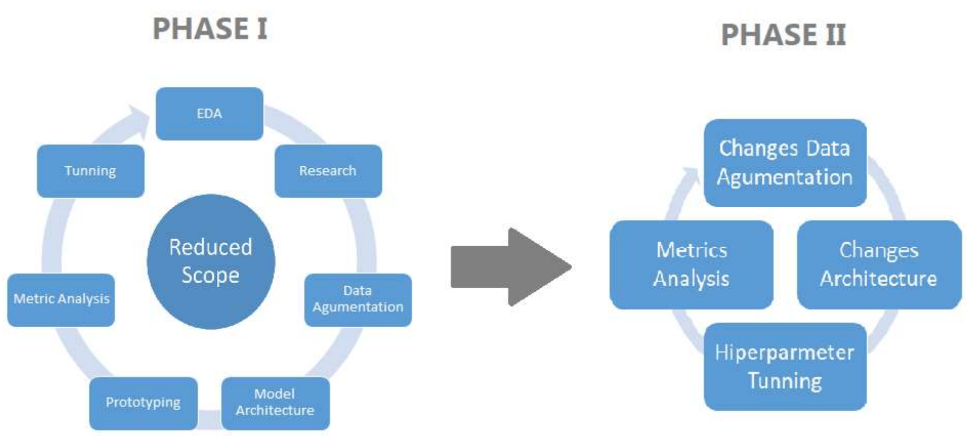
Introduction:

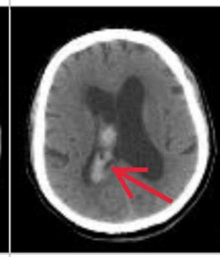
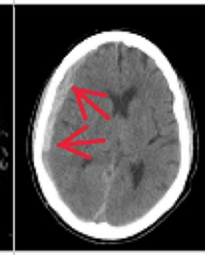
Most of the interpretations of medical data is usually done by highly skilled medical experts. The idea behind this project is to leverage the use of Machine Learning algorithms to make better decisions without the need of expert supervision. The results of this project can be used in Telehealth, which is the delivery of health care through technology such as mobile phones or computers. It can help reduce barriers to care for people who live far away from specialists or who have transportation or mobility issues.

This whole project is separated into two stages, where phase1 includes running a vgg16 model in the pre-trained network on a subset of the information, and the subsequent stage includes an inception_v3 model in the pre-trained network, which learns from the whole dataset.

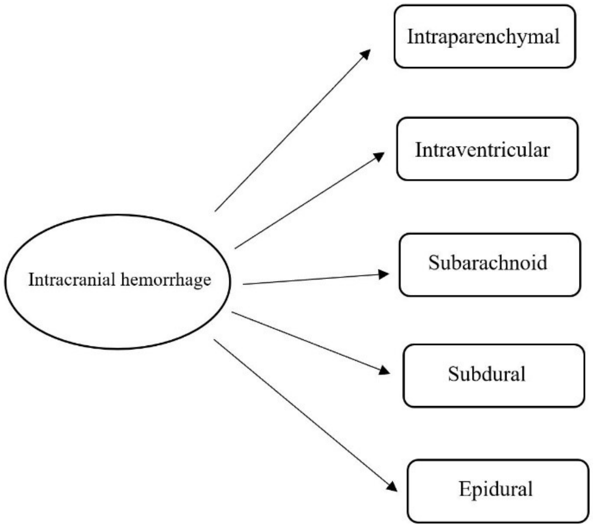


Description of the data set:

The dataset we intend use for this project can be obtained here. The training set consists of 750,000 DICOM images with the metadata, which is over 700 gigabytes. We have a dataset of 121,000 images which was be used to test the model, besides the 750,000 images already included in the training dataset.

	Intraparenchymal	**Intraventricular**	**Subarachnoid**	**Subdural**	**Epidural**
Location	Inside of the brain	Inside of the ventricle	Between the arachnoid and the pia mater	Between the Dura and the arachnoid	Between the dura and the skull
Imaging					
Mechanism	High blood pressure, trauma, arteriovenous malformation, tumor, etc	Can be associated with both intraparenchymal and subarachnoid hemorrhages	Rupture of aneurysms or arteriovenous malformations or trauma	Trauma	Trauma or after surgery
Source	Arterial or venous	Arterial or venous	Predominantly arterial	Venous (bridging veins)	Arterial
Shape	Typically rounded	Conforms to ventricular shape	Tracks along the sulci and fissures	Crescent	Lentiform
Presentation	Acute (sudden onset of headache, nausea, vomiting)	Acute (sudden onset of headache, nausea, vomiting)	Acute (worst headache of life)	May be insidious (worsening headache)	Acute (skull fracture and altered mental status)

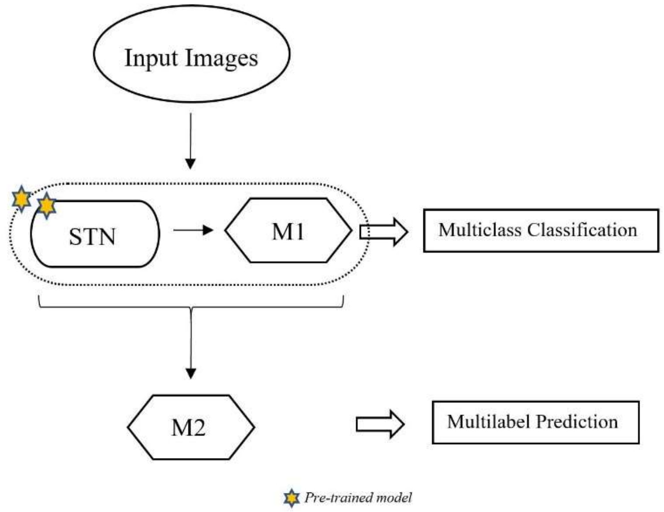
Intracranial hemorrhage (ICH) refers to acute bleeding inside the brain and is a life-threatening emergency that needs immediate medical attention. It is classified into 5 types as follows and each type of hemorrhage occurs at a specific location due to several reasons inside the brain.



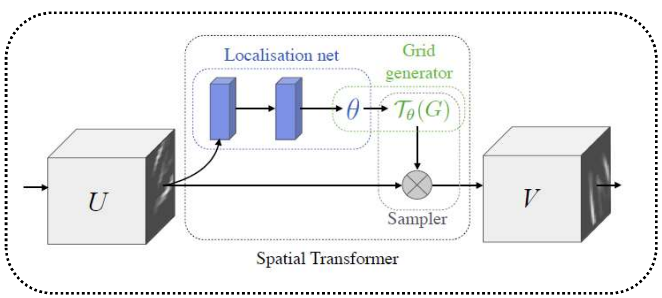
Epidural	Subdural	Intracerebral
It occurs when blood accumulates between the skull and the outermost covering of your brain.	A subdural hematoma is a collection of blood on the surface of your brain.	Intracerebral hemorrhage is when there's bleeding inside of the brain.
It usually occurs after a head injury, and usually with a skull fracture.	It is typically the result of moving the head rapidly forward and stopping, such as in a car accident.	It is not usually the result of injury.

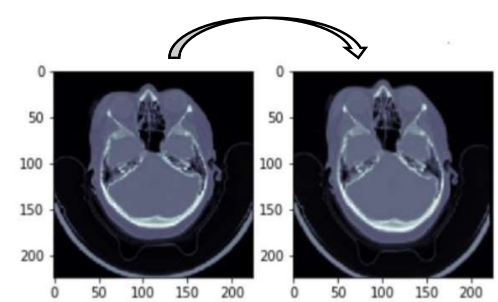
Network Architecture:

The image below is a brief outline about the network architecture. The idea is to build a multi-class classification model first and then proceed to build a multilabel classification model. The MRI scans are sent into a Spatial Transformer Network, which spatially aligns our images. These images are then sent into our first model, which results in a multi-class classification. A combination of this STN and first model is used as a pre-trained network for our second model, which results in Multi-label prediction for the scans.

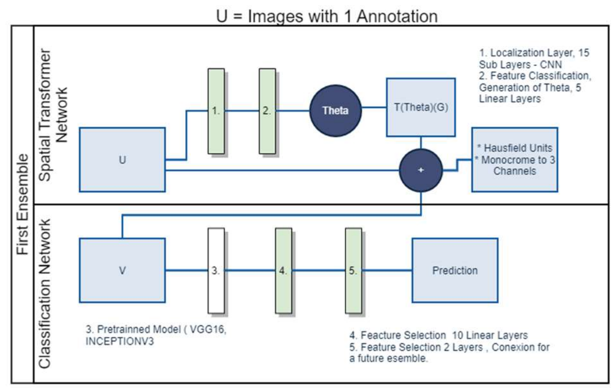


- *Spatial Transformer Network*: The STN has 2 layers of different sizes. The first layer is the localization net, which generates theta matrix, which spatially aligns our images. The idea behind using this algorithm is that, in our project, we are dealing with the brain, which has a spatial alignment. Tumor has a spatial position within the brain. So, moving the brain around to do data augmentation did not seem like a good idea.

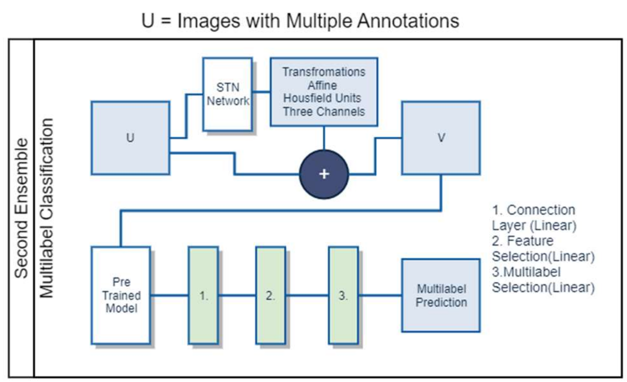




- *Model_1*: This model, with one annotation, was built based on the results of this publication. In this model, we introduced spatial transformation network, we have training layers 1,2,4, &5, and a pre-trained network *(layer3)*. The Spatial Transformer Network will generate a matrix of transformation, theta, which will be applied to the MRI images. The images will then be transformed and fit into the pre-trained network *(VGG16 in phase1 and inception_v3 in phase2)*, to which we added two additional layers for the model to make a multiclass classification.



- *Model_2*: The pretrained model for the second model is Model_1. We added three more layers for our pre-trained model to make a multilabel prediction. The results from Model_2 can tell us if any brain has more than one type of hemorrhage.



Experimental setup:

The model was built in Pytorch, along with AWS. Most of the models that were publicly available were created using PyTorch, and we decided to proceed due to the abundance in the availability of information. We created a DataLoader, as it is not convenient to load all the images individually into memory. We created batches. We used Shiny for presenting our findings. Pycharm is used as the Python editor. We used two pre-trained models, vGG16 and inception_v3 for transfer learning, as good number of papers claimed an improvement in performance after the use of inception_v3. After running the model several times, a batch of size 15 and 10 gave better results, so we decided to use 10 (Lilian please correct this). Based on the performance of our prototype model, we could see that there was a significant improvement in class prediction after the second model, we decided to use two models. We implemented a GridSearchCV to determine the best tuning parameters (Lilian please check). We used a receiver operating characteristic curve to determine how well our model is performing in classifying each of the classes. This performance was significantly enhanced after running the second model. The use of function loss in validation phase is not a good option, instead accuracy and other metrics were used.

Results:

Describe the results of your experiments, using figures and tables wherever possible. Include all results (including all figures and tables) in the main body of the report, not in appendices. Provide an explanation of each figure and table that you include. Your discussions in this section will be the most important part of the report.

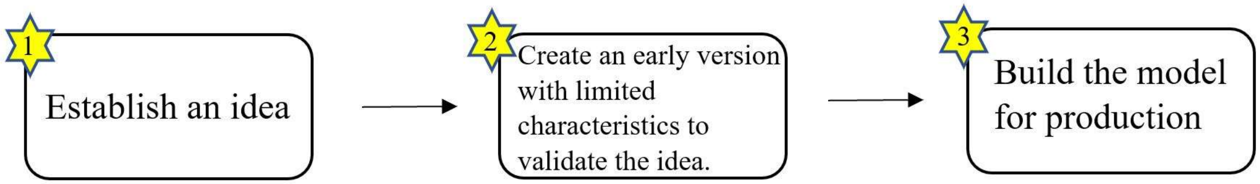
Summary and conclusions:

Running the prototype model on a subset of the data was crucial for us to ensure we were in the right path. Modelling on the entire dataset took a lot of time, and the workaround would have been laborious. Instead, we decided to approach the prototype first, and made sure we were able to interpret the results, based on which we built our final model using inception_v3. Proper research was of immense help in laying the footage for this project. A lot of impressive work was done on this project, and we were able to leverage those findings to build upon our own models.

For our future work, we would like to:

- Implement other algorithms with more complex pre-trained networks.

- See if a similar model can be used to detect other MRI images such as Lungs, etc.



(Lilian, please add rough bullet points, and I will elaborate)

7. References. In addition to references used for background information or for the written portion, you should provide the links to the websites or github repos you borrowed code from. We investigated various resources such as Kaggle Discussion Blogs, Published Article[1], Published Article[2], Deep Learning for Medical Image Analysis and Online courses to make sure we attain sufficient background in regards to Biomedical image analysis.

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8. A separate appendix should contain documented computer listings (code).

- I think code for DataLoader, STN, Model 1 and Model 2 will do. Or is that too much?