MIE429 Capstone Proposal - Andromeda Medical Imaging

Background:

Strokes: Strokes are a leading cause of disability and the 3rd most common cause of death amongst developed countries [1]. During a stroke, a blood vessel that delivers oxygen and nutrients to the brain is blocked by a blood clot, causing parts of the patient's brain to be damaged or die. This results in a loss of motor and neural function, along with premature aging.

Importance of Imaging: Neurologists rely on medical imaging to find tissues affected by stroke. During diagnosis, these tissues are categorized as either **penumbral** (affected but not yet dead tissue) or **core** (tissue that is already dead). The more penumbral (saveable) tissue there is, the more likely it is that a surgical procedure would be worth performing at the risk of surrounding living tissue.

Existing Solutions: There are four common medical imaging techniques [1]. (1) Manual Diagnosis from CT imaging, while standard, is challenging for general physicians to interpret. (2) Contrast enhanced single phase CTA (sCTA) can show vessel blockages, but it cannot determine if the brain tissue supplied by that vessel is still alive and functioning (if it is viable) or if it has already been damaged due to a lack of blood supply. (3) Multiphase CT angiography (mCTA) lacks tissue viability and is hard to interpret. (4) CT perfusion (CTP) assesses tissue viability, but is time-consuming, resource-intensive, and costly.

Motivation: Large medical centers can use expert stroke neurologists and advanced imaging like CTP. We aim to identify penumbral tissue volumes using a fast, automated method that is more accessible to rural areas, which may lack advanced equipment and sufficient expertise.

Problem Statement: Our client, Andromeda Medical Imaging (AMI) Inc, has taken their first step towards addressing this issue with the Simple Perfusion Reconstruction Algorithm (SPIRAL) [1]. This provides perfusion imaging from a mCTA scan, highlighting affected tissue areas (see Figure 1). However, the resulting image is still too coarse-grained for precise clot detection. We propose **AMI-Net**, *a Deep Learning (DL) model to automate precise detection of the blood clot from the raw mCTA scan or generated SPIRAL image.*

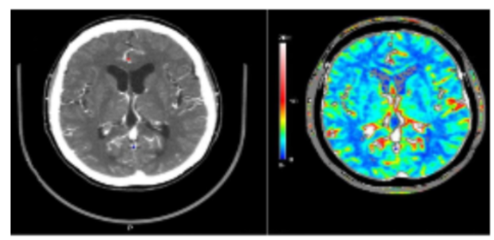

Figure 1: A raw CT scan (left) and an example Perfusion scan (right) [2]

Functional Requirements	(1) Must accept input data in the form of raw mCTA scans or generated SPIRAL images (2) Must determine a categorical site of the occlusion/clot (AMI-Net v1). (3) Must output a segmentation of the clot location (AMI-Net v2).
Objectives	(1) Should precisely identify the stroke site in a focused segment of a cranial blood vessel. (2) Should identify the stroke site in a short amount of time. (3) Should have a low memory footprint.
Constraints	(1) Must run in under 5 minutes for a single patient. (2) Must be able to run on a single CPU (8-16 GB)

Table 1: Our solution must meet the following requirements, informed by our client meeting.

Data:

How it is obtained: The data is available in a University of Calgary OneDrive link. It is obtained by first retrieving CT scans and mCTA angiograms of patients' brains. These CT scans consist of stacks of 2D images of the brain at different depths. Each angiogram is passed through AMI's existing in-house machine learning model (SPIRAL) which outputs the probabilities of penumbral tissue being present in different regions of the brain. These are called **augmented perfusion maps** and are visualized as a color map shown in **Figure 1.**

<u>Key Features:</u> The angiograms are in .NII format, are 512 by 512 pixels in dimension, and vary in depth (as low as 16 slices thick, usually ~200). Also, each angiogram is 50-70 MB, and there are 3 angiograms per patient. Notably, our dataset is imbalanced, with 90% of the CT scans belonging to patients with an actual stroke. Hence, 10% of the data comes from patients without a stroke, this is known as "mimic" data. We will be provided with 100 sets of angiograms to start (from 100 patients). By the end of November, we expect to have 1000-1500 sets of angiograms. We will also be provided with a map of the cerebral arteries. For each angiogram, we are provided with labels that outline the categorical location of the blood clot in terms of cranial artery location.

Proposed Methodology:

<u>AMI-Net V1:</u> We intend to explore multiclass image classification techniques because they can output a category corresponding to the general region of the clot. Our proposed solution involves training and evaluating such techniques; namely, convolutional neural networks (CNNs) based on the MobileNetV2 architecture [3] and vision transformer models based on the EfficientFormer architecture [4]. With 3.4M and 3.5M parameters respectively, the MobileNetV2 and EfficientFormer models are both suited for inference on low RAM devices. While the EfficientFormer has been demonstrated to have better performance on image classification benchmarks, its disadvantage is that the transformer architecture requires more data in order to overcome the lack of induction biases. Using the pre-trained model weights from ImageNet will help us mitigate the effects of limited training data. Additionally, we intend to experiment with a significantly lower-parameter CNN-XGBoost architecture proposed in [5]. Having been proven to work in a similar medical setting (Covid-19 prediction from CT scans), this method is a good candidate. Each model will be trained to take as input CT angiogram images/perfusion color maps and output its categorical prediction of which artery in the brain the clot is located in.

<u>AMI-Net V2:</u> The next step is to prepare a segmentation of the clot. Our first model of choice is the U-Net architecture which is a state-of-the-art deep-learning semantic segmentation model that uses convolution and residual connections [6]. Our second choice is to experiment with the Mask-RCNN model which works by first using a region proposal network to detect regions of interest and then predicting a segmentation mask for each region of interest [7]. Since a Mask-RCNN only processes areas of interest, it would be more computationally efficient. At the same time, it may consequently miss out on relevant global information which a U-Net would have captured. Each model takes the same input as before and produces a precise segmentation of the clot location.

<u>Evaluation Method:</u> We intend to run nested cross validation. For AMI-Net V1, we choose the model with the highest accuracy. For AMI-Net V2, we choose the model with highest dice coefficient, as it is usually used for medical image segmentation tasks [8].

Deliverables and Outcomes:

The client has specified two models, to be completed in order.

<u>AMI-Net V1:</u> A model that, given input mCTA images, can detect blood clots and their region in the brain (i.e. which hemisphere of the brain, artery, and segment of the artery it occurs in).

<u>AMI-Net V2:</u> A model to output a precise segmentation map of the clot location (not just the region).

Our projected next steps are as follows:

1. Once we obtain the raw data, we will expand the dataset by using non-stroke regions as data for the "normal" class. We will also explore different preprocessing and augmentation pipelines.
2. Training and evaluating the CNN-XGBoost, MobileNetV2 and EfficientFormer architectures once we obtain the 100 patients' data consisting of mCTA angiograms and SPIRAL perfusion maps.

3. We intend to experiment with the U-Net and Mask-RCNN models using the full dataset of mCTA scans and SPIRAL maps from 300-1000 patients.

References

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[7] Kaiming, H. et al. "Mask RCNN". Facebook AI Research (FAIR). 24 Jan 2018

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Attribution Table

Member Name	Contribution	Future Work
Alaap Grandhi	Contributed to "Data" and "Proposed Methodology" sections	Model training and hyperparameter tuning
Haani Ahmed	Contributed to "Data" and "Proposed Methodology" sections	Model training and hyperparameter tuning
Hshmat Sahak	Wrote up background/problem statement sections, editing proposal	Data processing and augmentation
Nabil Mohamed	Contributed to background/problem statement section, editing proposal	Model training and hyperparameter tuning

Yawar Ashraf	Wrote the outcomes/deliverables section	Model evaluation
Equal Contribution	Development of functional requirements, objectives, constraints	Report writing