Developing a Live Surgical Aid for Brain Tumor Resection using Augmented Reality and Deep Learning

Problem

Craniotomy is the standard procedure for brain tumor resection, but in recent years, the development of minimally invasive surgery for this application has grown significantly. However, minimally invasive surgeries do have downsides - surgeons do not directly see the surgical site and are separated from preoperative scans in which the tumor location and other data is displayed, resulting in a loss of visual and haptic feedback.

Background Research

In 2020, an estimated 308,000 people worldwide were diagnosed with brain cancer and of those people, 251,000 died (Siegel et al., 2021). Brain cancer is the tenth deadliest cancer for both men and women and only 36% of patients survive the five years following their diagnoses.

The most common treatment for brain cancer is surgical removal of the tumors through a craniotomy, and this is the only available treatment (“Brain Tumor”, n.d.). Recent developments in surgical techniques have allowed for a minimally invasive approach to tumor resection as opposed to the standard craniotomy (“Surgery for Brain”, n.d.). When compared with the craniotomy, these surgeries are much safer as they reduce the risk of infection and damaging brain matter (“Minimally Invasive”, 2022). However, current systems for minimally invasive surgeries require surgeons to rely solely on two-dimensional (2D) external displays showing pre-operative scans, as well as a camera feed from the probe the surgeon uses to perform the surgery, as opposed to being able to directly see the patient’s anatomy (Meola et al., 2017). This results in a loss of haptic feedback, the ability to create and feel pressure, possibly creating a disconnect with the surgery from being unable to see the surgical site in real life and having to rely on deciphering the location of the tumor from separate 2D screens (Meola et al., 2017). With all these issues, only experienced neurosurgeons and facilities with advanced technologies can perform minimally invasive tumor resections, and even still, the risks of damaging vascular or nervous tissue are high due to the visual disadvantages, the small surgical field, and the cognitive overload of the procedure on the surgeon (Meola et al., 2017).

To avoid the burden of switching perspectives and translating information from separate 2D screens to the real-life surgical site, a comprehensive neuronavigational system is needed to visualize all of the data in one place. **Augmented reality (AR)**, a term used to describe the combination of real-life and computer-generated content, has been proposed and developed as a viable solution for certain minimally invasive operations that require precision with low visibility (Salehahmadi & Hajialiasgari, 2019). AR could be a beneficial utility to aid in brain tumor surgery by visualizing the tumor as well as nervous and vascular structures in one comprehensive 3D view.

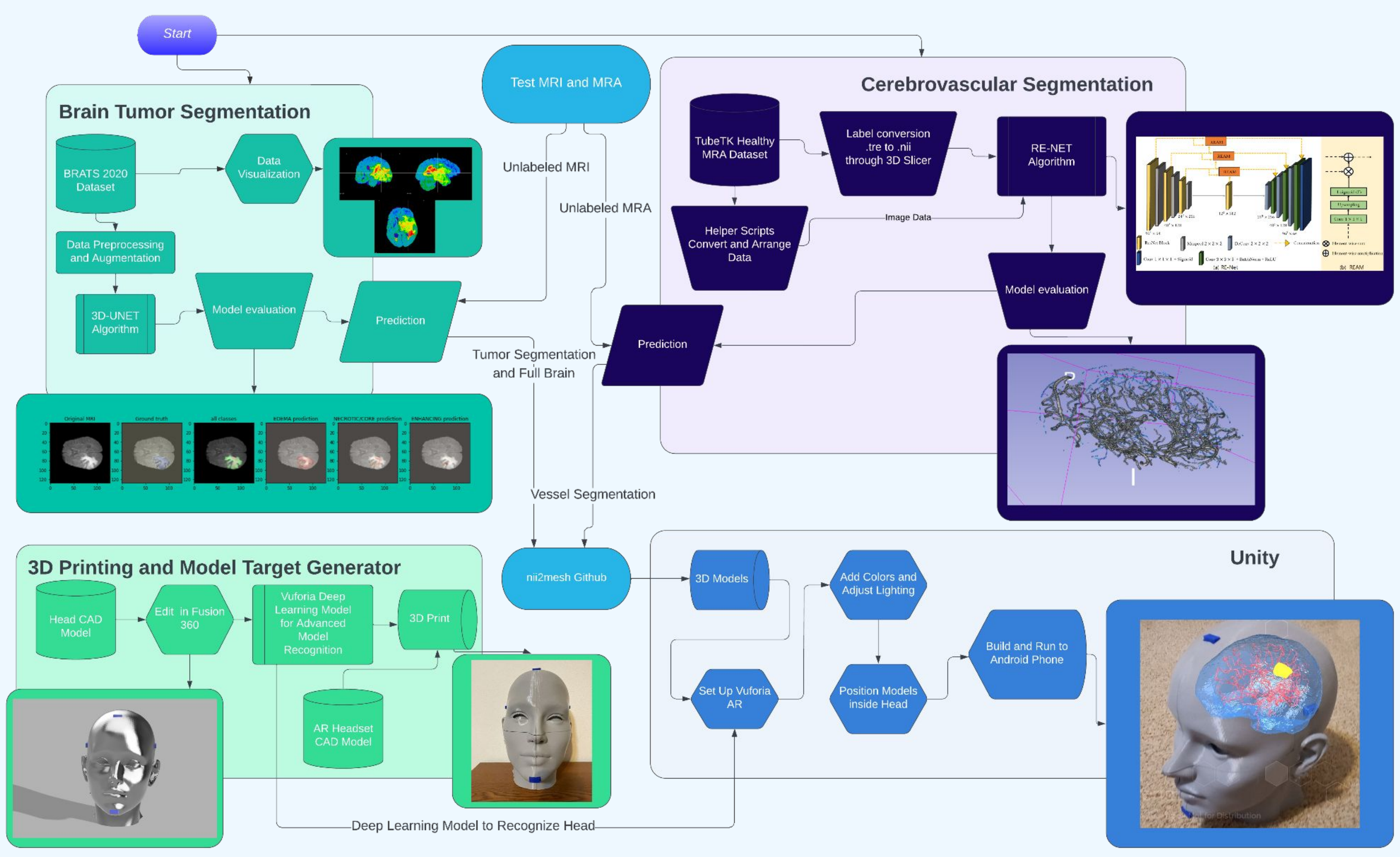
Augmented reality through the use of a head-mounted display has been applied to surgeries. A recent surgery done at Johns Hopkins utilized augmented reality for spinal fusion by displaying the exact positioning of the screws that were to be implanted into the spine on head-mounted AR goggles (“Johns Hopkins”, 2021).

Objectives

The objective of this project is to develop a **novel surgical live aid** using **AR** and **Deep Learning** to reduce the risk of brain tumor resections. This system will comprise of several sub-systems: the Segmentation, the Augmented Reality, and the Physical Markers. The Segmentation portion includes the deep learning models for **brain tumor segmentation** and **cerebrovascular segmentation** which generate the 3D models from unlabeled medical scans. The Augmented Reality portion consists of rendering and displaying in Unity. The Physical Markers consist of the object upon which the 3D models will be superimposed.

Materials

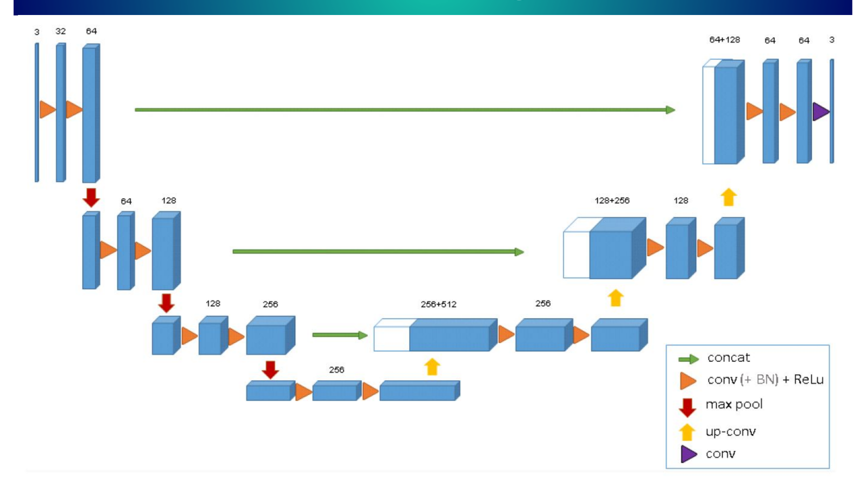
Computer	Android Phone	3D Printer	BraTS 2020 Dataset	TubeTK Healthy MRA
MATLAB	Google Colab	Unity Game Engine	Vuforia	Slicer



Procedure

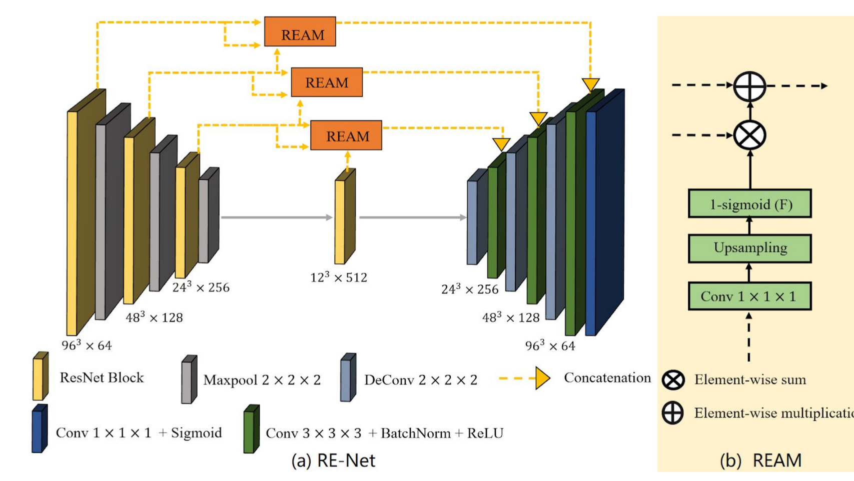
1. Install the BraTS and TubeTK Healthy MRA datasets, import them into MATLAB, and use MATLAB’s Nifti file functionality in conjunction with volshow() to visualize the data in 3D, as well as in slices.
2. To start **brain tumor segmentation**, open a Google Colab notebook, import the necessary libraries, and load in the dataset BraTS 2020 Dataset. Visualize the data and load it into Keras Data Generators.
3. Write metric calculation functions for the DiCE Coefficient, precision, sensitivity, specificity, and IOU to use during training and evaluation
4. Program the 3D U-Net and train the model on the train and validation sets; whilst training use metric calculation functions such as IOU and DiCE coefficient
5. Evaluate the model, upload a test file for prediction, and export as a .nii file. Visualize the predictions and generate confusion matrices and ROC curves to find the optimal threshold.
6. For **cerebrovascular segmentation**, convert the binary labelmaps in .tre file to .nii file through Slicer. Prepare the datasets and load them in Data Generators. Implement the RE-Net algorithm and train the model, again utilizing metric functions plotted through the Visdom framework.
7. Evaluate the model, upload a test file for prediction, and again utilize the ROC curve to find the optimal threshold.
8. Convert both test files to a .obj file using the nii2mesh Github repository.
9. Import the .obj files into Unity and add materials to them.
10. Design a 3D head CAD model and 3D print it. Additionally, export it to Model Target Generator, create an advanced model target, and export it as a .unitypackage
11. Import the Unity Package into Unity, and position the 3D models correctly within the head.
12. Install Vuforia, add an AR Camera, and build the project to an Android phone. The 3D models should be superimposed on the 3D printed head CAD model

Photos/Diagrams



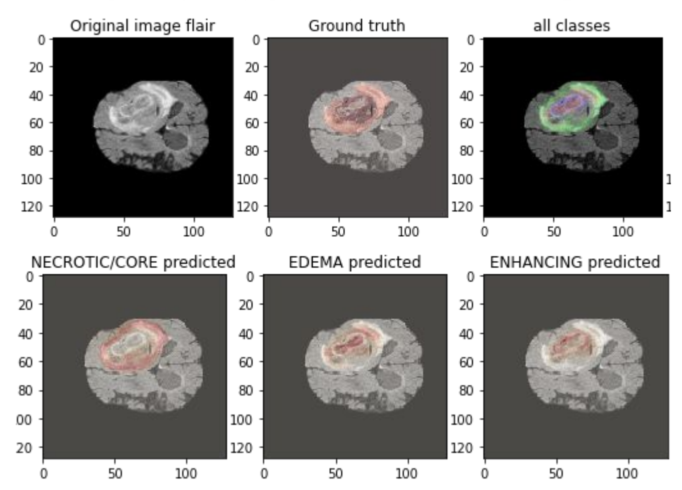
3D U-NET

Image from: Review: 3D U-Net — Volumetric Segmentation (Medical Image Segmentation)

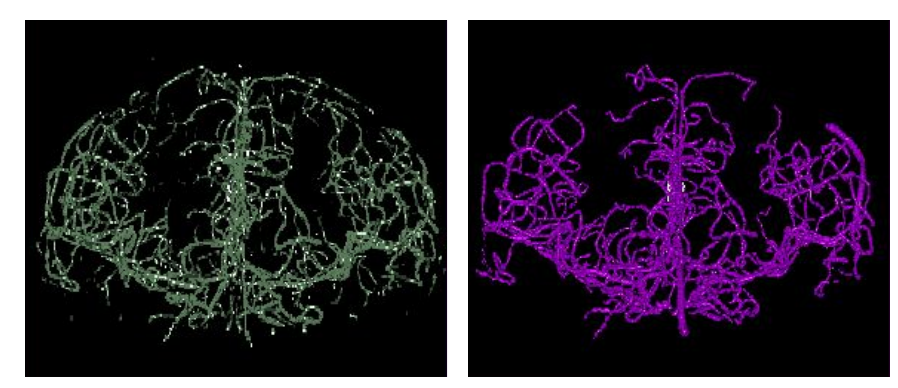


RE NET

Image from: https://link.springer.com/chapter/10.1007/978-3-030-59725-2_7

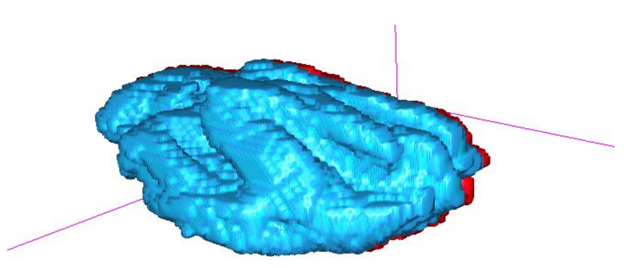


Brain Tumor Segmentation Predictions

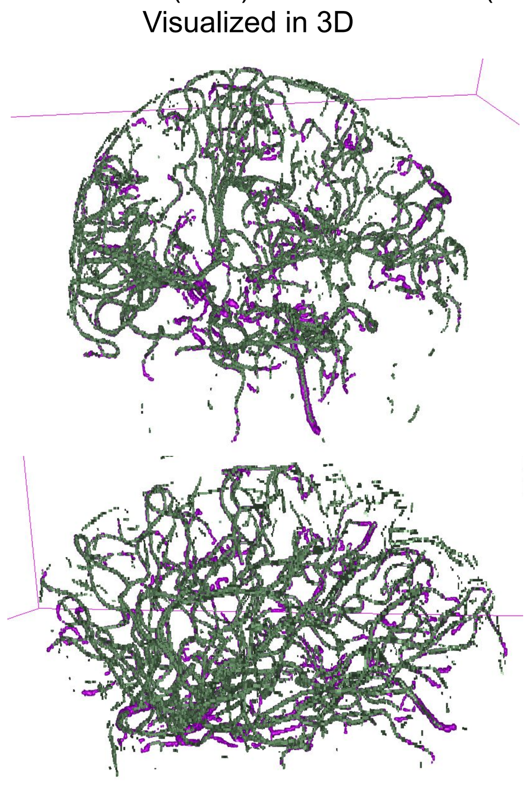


Cerebrovascular Segmentation Coronal View - Prediction (Green) and Truth (Purple)

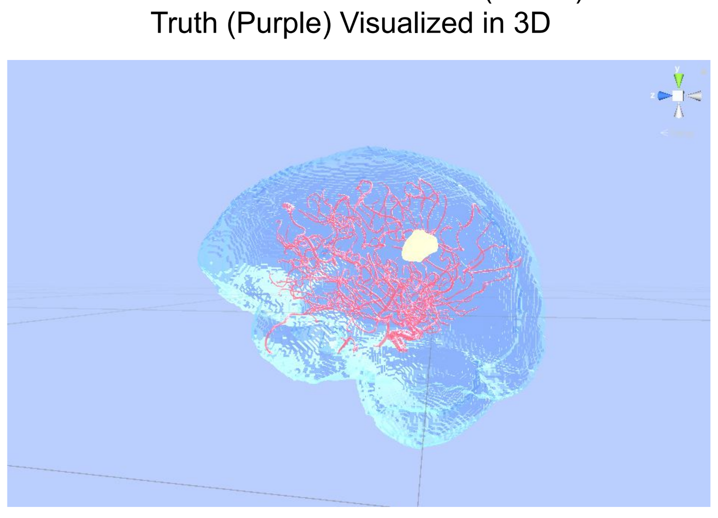
Photos/Diagrams



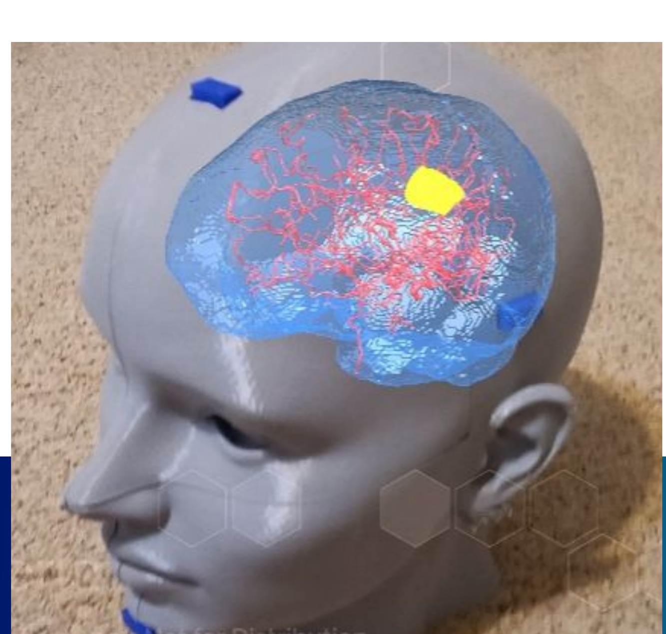
Tumor Prediction (Blue) and Tumor Truth (Red) Visualized in 3D



Cerebral Vasculature Prediction (Green) and Truth (Purple) Visualized in 3D



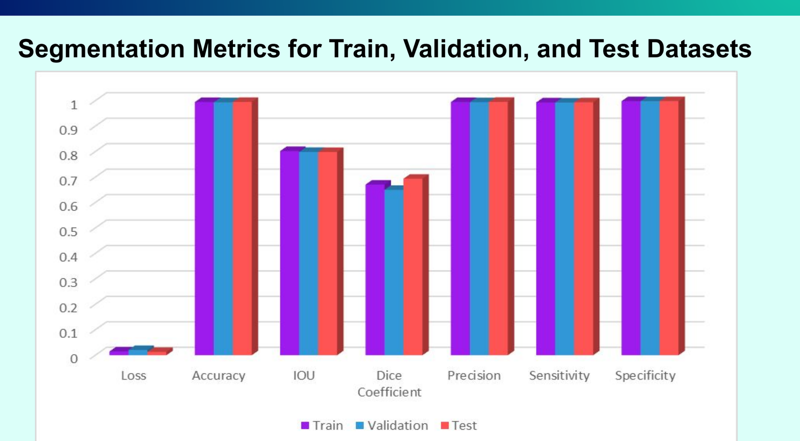
3D Comprehensive Visualization Rendered in Unity

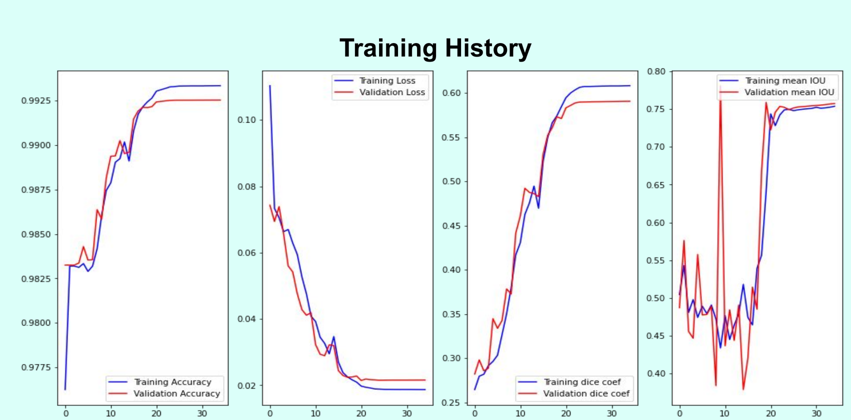


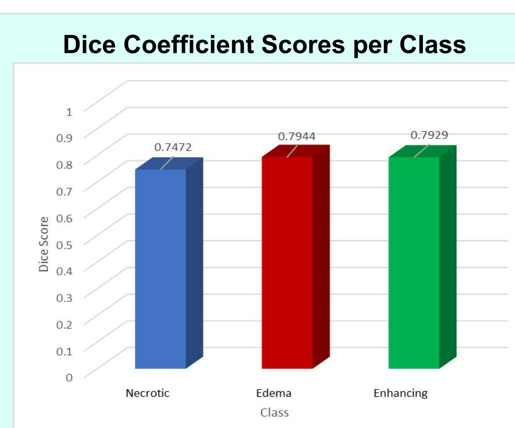
3D Comprehensive Visualization Superimposed on 3D-Printed Head

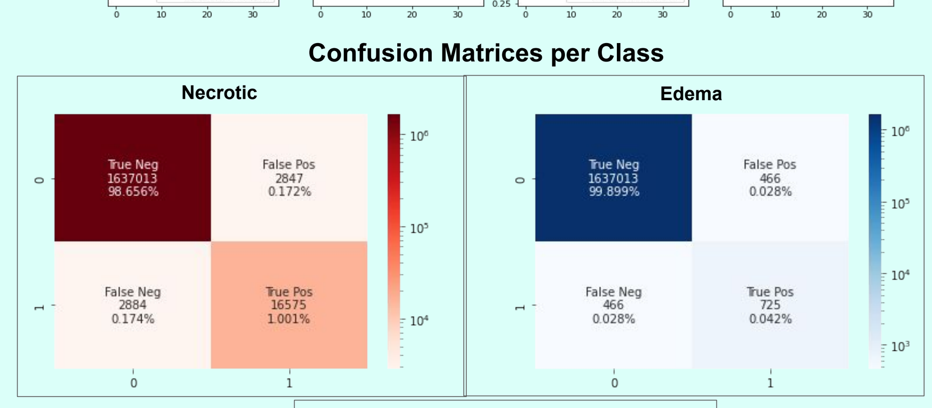
Data/Observations

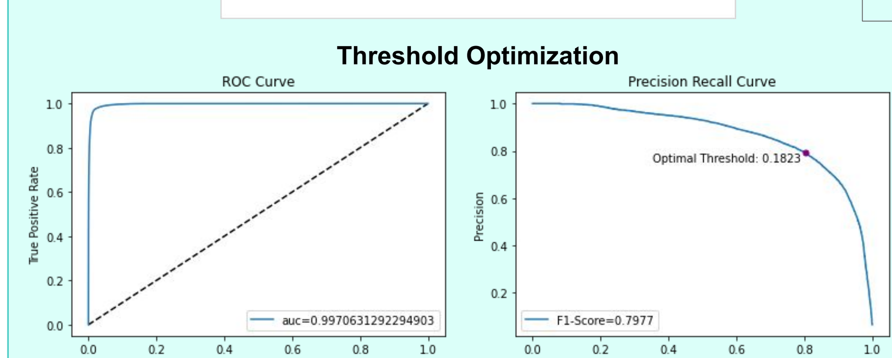
Brain Tumor Segmentation

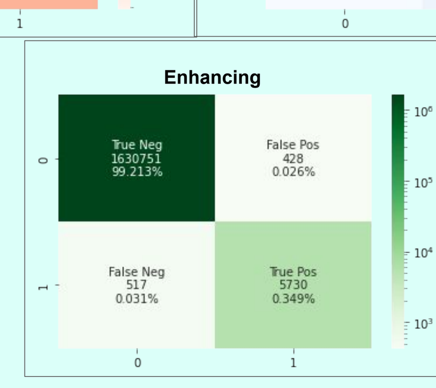




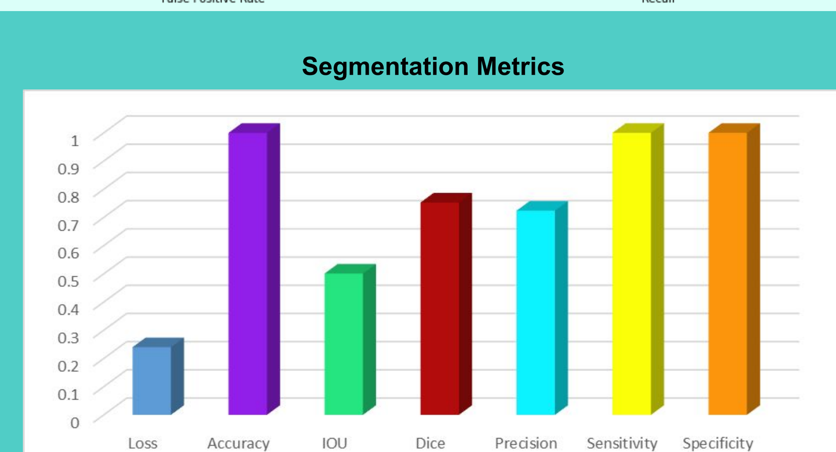


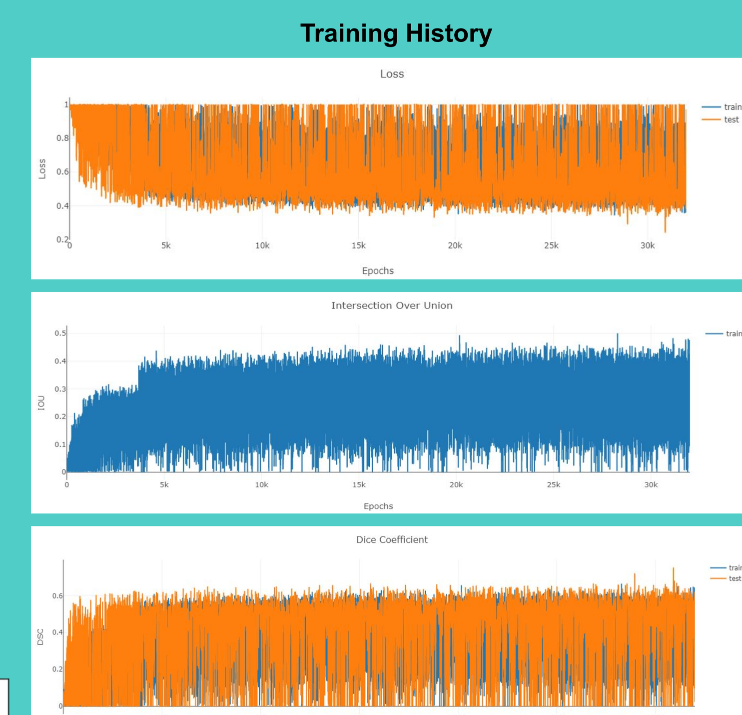


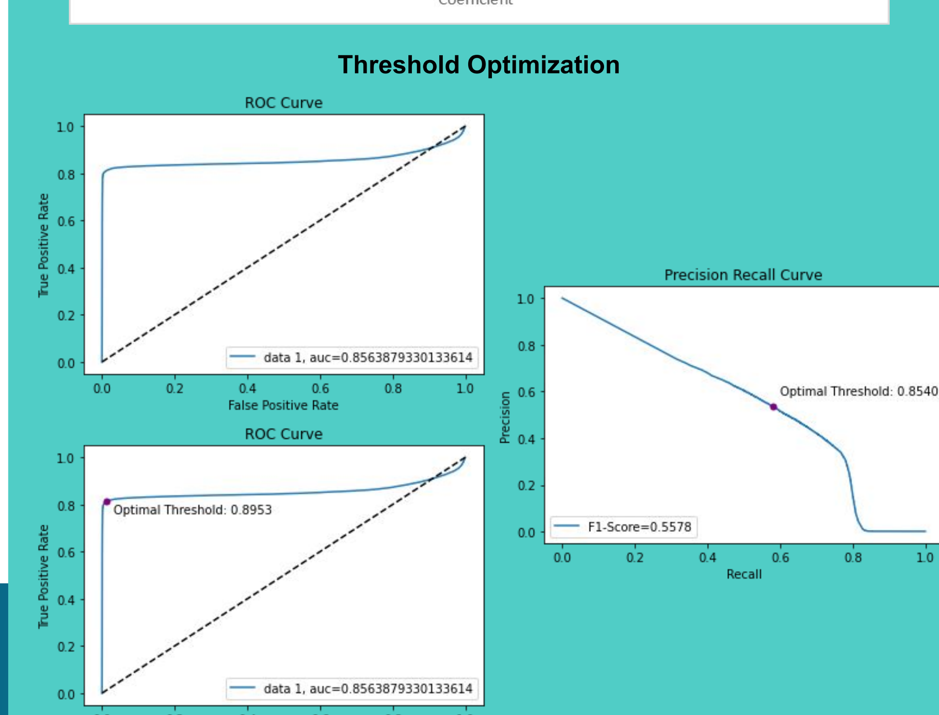


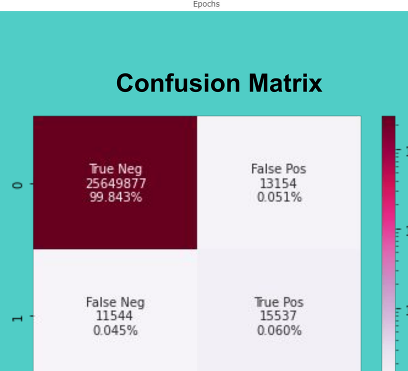


Cerebrovascular Segmentation









Results

Data was collected based on the evaluation of two deep learning models: brain tumor and cerebrovascular segmentation.

The brain tumor segmentation model output similar results in terms of metrics for the train, validation, and test datasets. The dice coefficient score was 0.69 for the brain tumor segmentation model, which implies the model is exceptionally accurate, however, some incorrect predictions are present. Taking into consideration the size of the tumor as well as the application of this project, certain slight inaccuracies, for example, pixels between the class boundaries which is where the model made most of the incorrect predictions, are negligible.

Of the three classes, necrotic, edema, and enhancing, the edema class was segmented the most accurately with a dice score of 0.7944; the enhancing class also had a close dice score of 0.7929. The necrotic class had a slightly lower dice score of 0.7472 most likely due to unclear boundaries on the MRI between the edema and tumor core. The tumor is the core on the inside, the edema, which is a buildup of fluid, surrounds the tumor, and enhancing refers to the section surrounding the edema that is easily visible in a contrast-enhanced MRI due to the concentration of blood vessels. Slight gradient differences between these classes can lead to some model inaccuracies, but these are usually negligible for the purpose of this project..

Three confusion matrices were generated, one for each class, and voxels in the true negative category compromise an overwhelming percentage because the tumor is relatively small compared to the entire scale of the MRI. With the heatmap on a logarithmic scale, larger percentages are colored darker, and it can be concluded that both the true negative and positive values are much greater than the false negative and positive values. The brain tumor segmentation model has a near-perfect ROC curve shown in the Threshold Optimization section, as it maximizes the area under the curve (AUC) signifying an extremely accurate model. The Precision-Recall Curve was used to plot and calculate an optimal threshold using the F1 Score. This method returned a threshold of 0.1823, meaning the model is very confident when predicting true negatives.

The same metrics were used to evaluate the cerebrovascular segmentation model. The dice coefficient score, calculated from predictions on the validation dataset, was 0.75 signifying a high degree of accuracy in prediction. An ROC Curve shown in the Threshold Optimization section was also plotted for the cerebrovascular segmentation model and the AUC was calculated to be 0.856, meaning the prediction correlates well with the ground truth at a certain threshold. Analyzing the shape of the ROC curve, the threshold of 0.5 currently set to produce the binary mask from the prediction is likely to not be the most effective threshold. To find the optimal threshold, the G-mean and Precision Recall Curve were utilized. The G-mean is the square root of recall times precision, and is plotted on the ROC Curve. The Precision-Recall curve is separate graph plotted with recall/sensitivity on the x-axis and precision on the y-axis. The F or F1-score is then calculated and plotted against the curve to find the optimum threshold. Calculating the G-mean returned an optimal threshold of 0.8953, while the F-Score returned an optimal threshold of 0.5578. Both thresholds were able to significantly reduce the amount of false positives, thus increasing the overall accuracy of the prediction.

Conclusions and Next Steps

With the development of minimally invasive surgeries as a method for brain tumor resection as opposed to the standard craniotomy, the risk of infection and recovery time has greatly decreased. However, minimally invasive surgeries do possess several disadvantages, such as the fact that the surgeon is separated from the surgical site, resulting in a loss of visual and haptic feedback. Additionally, the surgeon is separated from preoperative scans from which they get the position of the tumor and other data, in both minimally invasive surgeries and craniotomies. These disadvantages only allow for exceptionally skilled neurosurgeons to perform minimally invasive operations, and even still, they pose significant risks to the patient.

To aid this issue and significantly increase the safety of brain tumor resections, a **novel live surgical aid** was constructed utilizing both deep learning and augmented reality. A deep learning model, using a 3D U-NET, was programmed and trained on the BraTS 2020 dataset to automatically segment brain tumors in 3D from MRIs. A second deep learning model utilizing the RE-NET algorithm was constructed and trained on the TubeTK Healthy MRA Database to segment cerebral vasculature from a Magnetic Resonance Angiography (MRA). A third deep learning model was then trained to recognize a physical target in real life, a 3D-printed head that would serve as the demonstration target for augmented reality. The 3D models were then implemented and rendered in Unity and uploaded to an Android-based augmented reality headset.

The evaluation of this system was based on the segmentation accuracy of the brain tumor and cerebral vasculature, in which their models returned DiCE scores of 0.69 and 0.75, respectively, signifying exceptional accuracy. The thresholds that were used to produce each binary mask were then optimized using an ROC curve and a Precision-Recall Curve, producing significantly more accurate predictions.

This project will be continued to further optimize the AR end of the system; implementing locational trackers and devices that will greatly enhance the positioning and orientation of the superimposition. Rather than placing the burden solely on the prediction of the AI, actual locational arguments from the camera using angular velocity sensors and several nearby markers will be used to create a 3D rendering of the scene, and from there the exact position and orientation of the models can be determined.

This project has extensive applications, the main purpose being intended for the live and **intraoperative use in craniotomies and minimally invasive resections.** Surgeons can wear the augmented reality headsets to be able to clearly see an adjustable and **comprehensive visualization of the position of the tumor, blood vessels, and other data.** This removes the need for the surgeon to constantly switch perspectives, between the surgical site/endoscope feed and the separate 2D screens. This novel AR surgical aid can also be used for **preoperative planning**, as rendering the tumor, vasculature, etc. in 3D will allow for more effective planning and collaboration. A third important application of this surgical aid and AR in general is its use in **medical training**, so medical students can visualize how the surgery occurs through a more interactive experience.

All photos, images, and graphics were done by the researcher unless otherwise stated.