Brain Tumor Segmentation

Project Documentation

Hewlett Packard Enterprise

- Team 6 Capstone Project

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Introduction

Last updated by | Jack Praveen Raj Ilango | Sep 18, 2021 at 1:47 AM GMT+5:30

Brain tumors are one of the most difficult and dangerous problems. If left untreated, any type of glioma may grow and press on other structures within the brain. Pressure on the brain can be harmful as it forces the brain against the skull, causing damage to the brain and hampering its ability to function properly. Thus, prompt diagnosis and treatment planning for brain tumors is of utmost importance.

Radiologists use MRI scans for detecting and segmenting the position of brain tumors. But the problem is, statistically, 65% of radiologists are overworked and under constant stress. This could lead to misdiagnosis of the cancer cells which could lead to fatal consequences like paralysis or even death.

Millions of deaths can be prevented through early detection of brain tumor. Early brain tumor detection using Magnetic Resonance Imaging (MRI) may increase a patient's survival rate. So automated identification and classification of tumors are important for diagnosis.

Brain tumor segmentation is the process of separating the tumor from normal brain tissues. In clinical routine, it provides useful information for diagnosis and treatment planning. However, it is still a challenging task due to the irregular form and confusing boundaries of tumors.

Segmentation of brain MRI scans can commonly be used for:

- Measuring and visualizing the anatomical structures of a brain.
- Delineating pathological regions
- Surgical planning, etc.

Acknowledgement

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We would like to extend our gratitude to the University of Pennsylvania, BraTS Challenge 2019, for providing us with a valuable dataset for our project.

We would also like to show our appreciation to the following sites for providing us with information for our project:

- Dataset Details: https://www.med.upenn.edu/cbica/brats-2019/
- UNet Model: https://towardsdatascience.com/medical-images-segmentation-using-keras-7dc3be5a8524
- ResUNet Model: https://github.com/DuFanXin/deep_residual_unet/blob/master/res_unet.py
- For Measurement Of IoU and Localization Error Metrics: https://github.com/quantumjot/unet_segmentation_metrics
- Azure Docker Containers: https://cloudskills.io/blog/azure-docker-containers
- Azure DevOps KanBan: https://docs.microsoft.com/en-us/azure/devops/boards/boards/kanban-basics?view=azure-devops

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These are the topics covered in the documentation:

Business Problem

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Business Statement:
A clinical solution of brain tumor segmentation for diagnosis and treatment planning.

Business Problem:
Diagnosis of a brain tumor is done by a neurologic exam, CT scan (computer tomography scan) and/or MRI scan, and other tests like an angiogram, spinal tap and biopsy.

Radiologists use MRI scans for detecting and segmenting the position of brain tumors manually. But the problem is, statistically, 65% of radiologists are overworked and under constant stress. A radiologist could improperly administer and interpret an MRI scan, which could result in a missed or delayed diagnosis of a brain tumor. This could cause a critical delay in a patient's diagnosis.

Segmentation of MRI scans to detect brain tumors significantly reduces the chances of missed diagnosis. It helps in an early detection of brain tumors, so that patients can have their treatment planned and initiated at a preliminary stage. This might reduce the risk and expand a patient's lifespan.

Functional Requirements

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These are the functional requirements used by our web application:

1) Input Dataset:

- The dataset contains images (in NIfTi format) of brain MRI scans that are 3-dimensional in nature.
- It also contains the masked image, i.e. the image with the position of the brain tumor marked.

2) Data Preprocessing:

- The masked images contain values ranging from 0 to 4, where 0 represents no tumor and 1, 2 and 4 indicates the presence of a tumor.
- Every value greater than 0 is converted to 1 so as to segment the masked images into two parts - tumor and non-tumor.
- Each 3-dimensional scan image is extracted and stored in a 3D array.
- Multiple 2D scan arrays are appended together to form a single 3D array.
- Datatype of the arrays are converted to 'float32' and normalised using mean and standard deviation.
- The above steps are performed for the respective segmentation masked images as well.

3) Deep Learning Model:

- UNet Model

4) Input Image:

- An MRI scan image of the brain.

5) Output Image:

- A masked image depicting the position of the tumor in the brain.

6) Web Application Development:

- Frontend - HTML, CSS and JavaScript
- Backend - Flask framework

7) Deployment:

- Docker Container
- Azure Container Registry
- Azure App Service

Non-Functional Requirements

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These are the non-functional requirements used by our web application:

- A powerful computer having GPUs is required to run the model for the web application.
- A fast internet connection is required.
- The users for the application need to be trained before availing the services.
- The application cannot display the output image instantly after uploading an MRI scan image. The model requires a bit of time to generate the output image.
- The web application has an easy to use User Interface that is intuitive and it does not require special training.
- The web application can only be used as a tool for prediction to assist doctors in detecting brain tumors. It cannot be used as a sole mean for detection. The doctors should use their skills and expertise to verify the output.

Solution Statement

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The project attempts at building a web application for the diagnosis of brain tumors using brain MRI scans. It highlights the tumor position using UNet deep learning model.

Often radiologists fail to detect a brain tumor from MRI scans. Hence, brain tumors can go relatively unnoticed for a great period of time. If the treatment is not started at the right time, it can cost a human life.

With the help of this web application, radiologists can double-check an MRI scan to verify the presence of a brain tumor. Users can upload a brain MRI scan image to the application and get a masked image of the brain, emphasizing the position of the brain tumor.

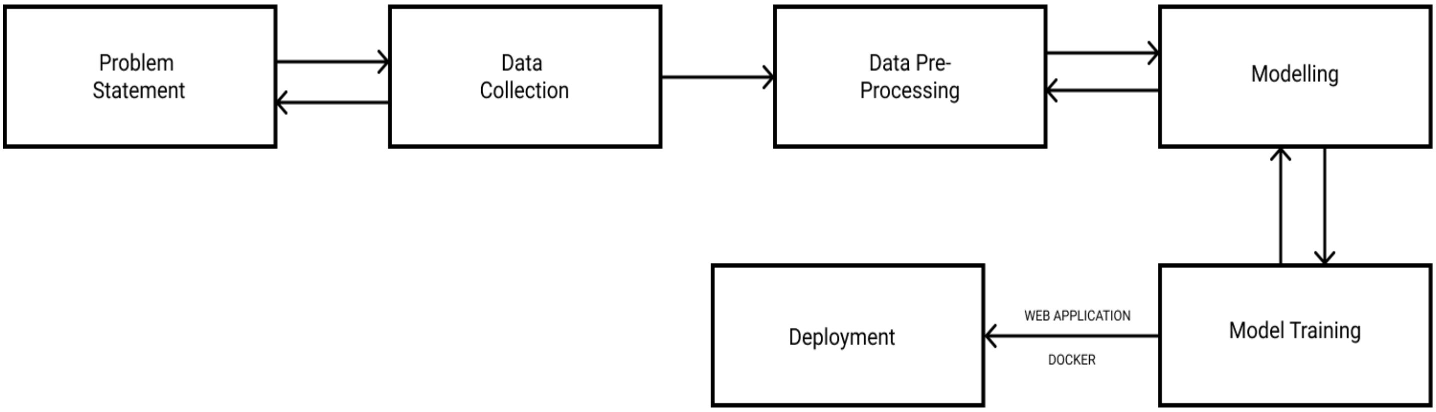
The web application aims at contributing to the healthcare sector, especially to radiologists by providing useful information for diagnosis and treatment planning.

Flowcharts

Last updated by | Jack Praveen Raj Ilango | Sep 19, 2021 at 4:13 PM GMT+5:30

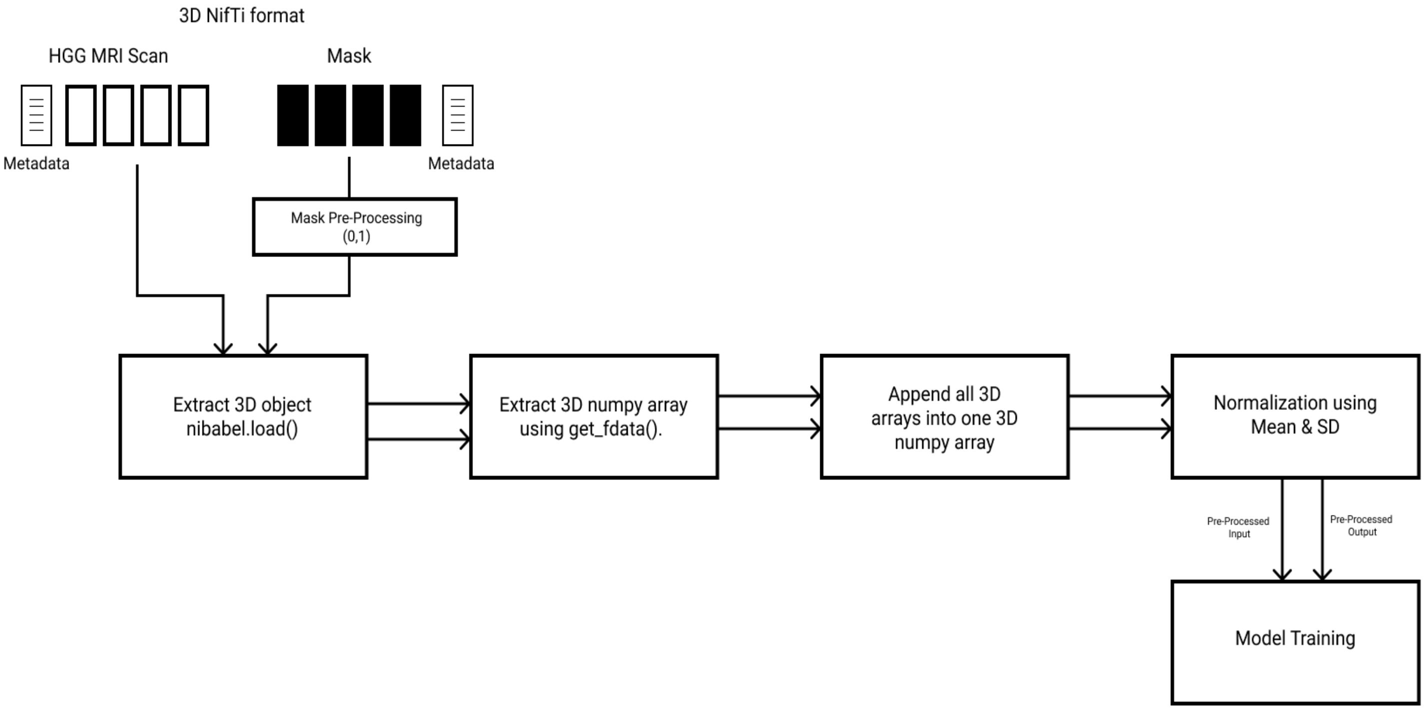
System Design:

This diagram showcases the architecture of our project. We used this as a reference to plan the implementation of our project in a systematic and methodological manner.



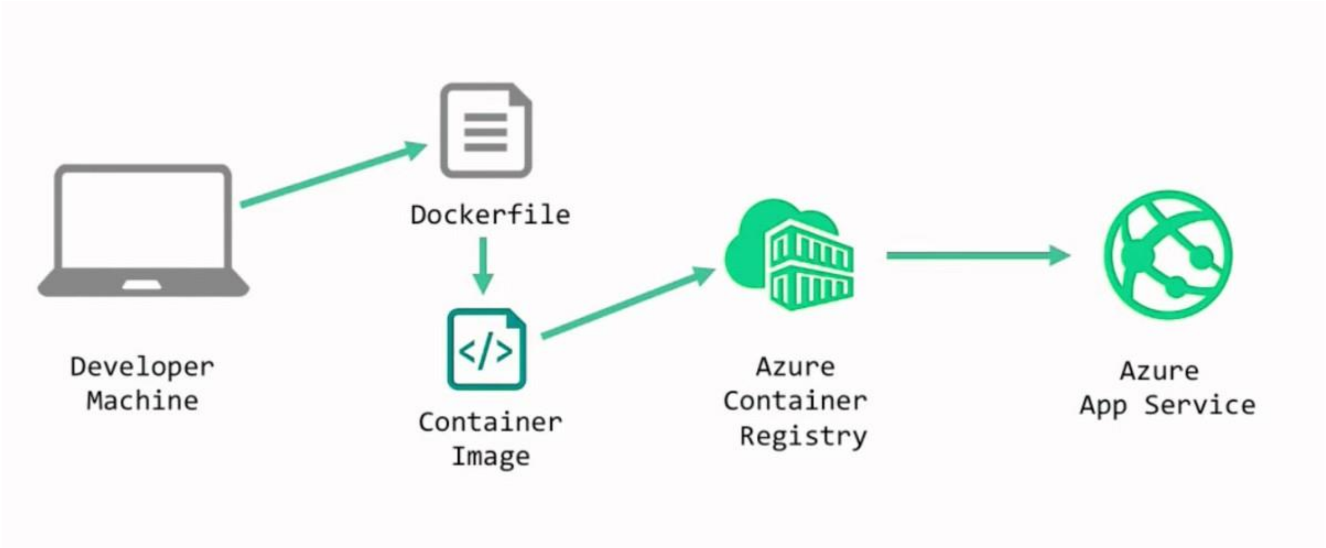
Training Architecture:

The following diagram showcases the training architecture of our project. This was used in the data pre-processing and training for both the UNet and ResUnet models.



Deployment Architecture:

This diagram showcases the deployment architecture of our project. This was used to finalize our deployment strategy and it clearly explains how the web application was deployed.



Neural Network Design

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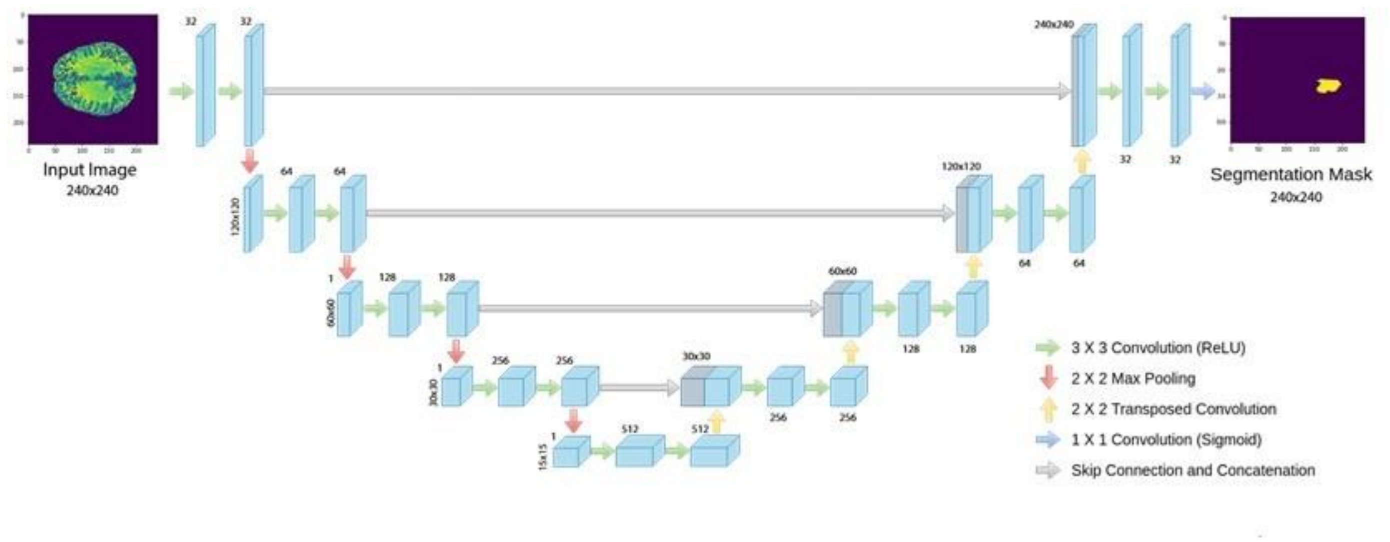
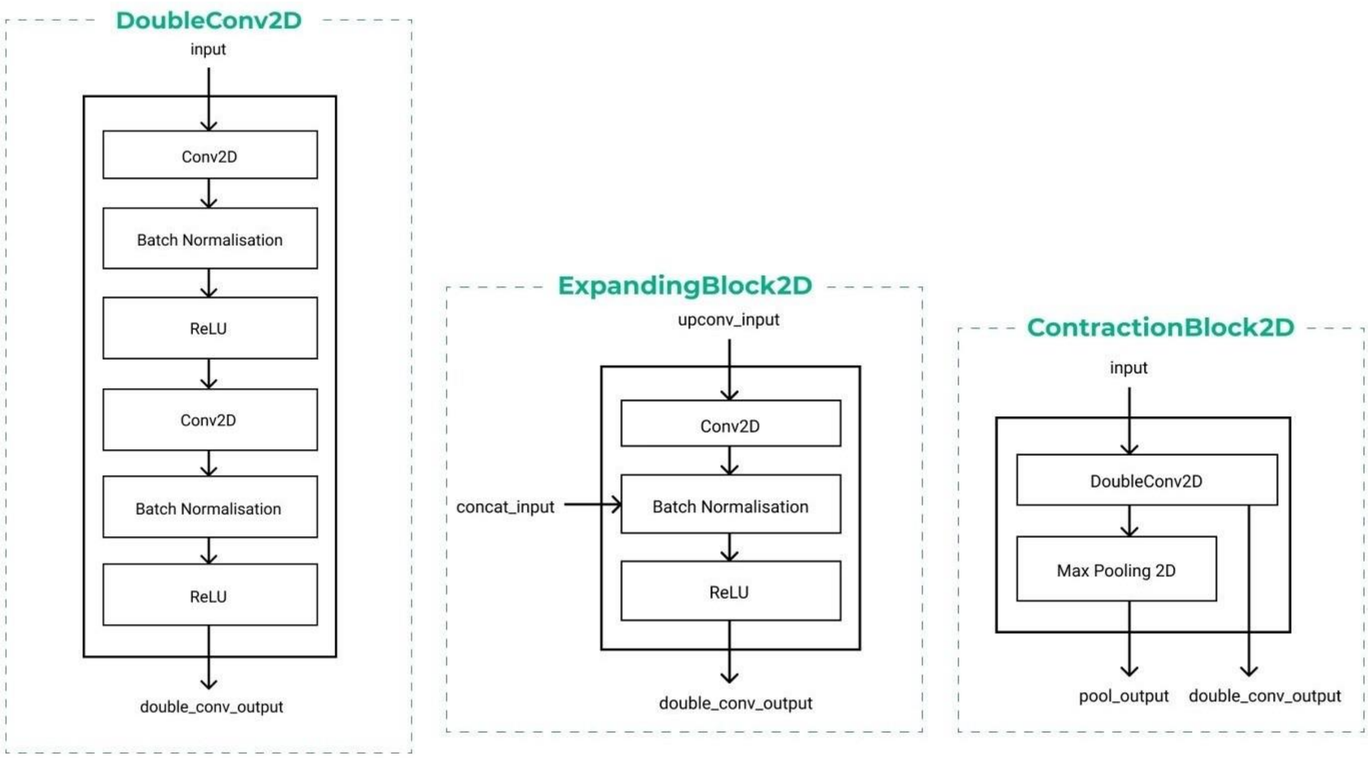
The following diagram shows the Neural Network Design for UNet:

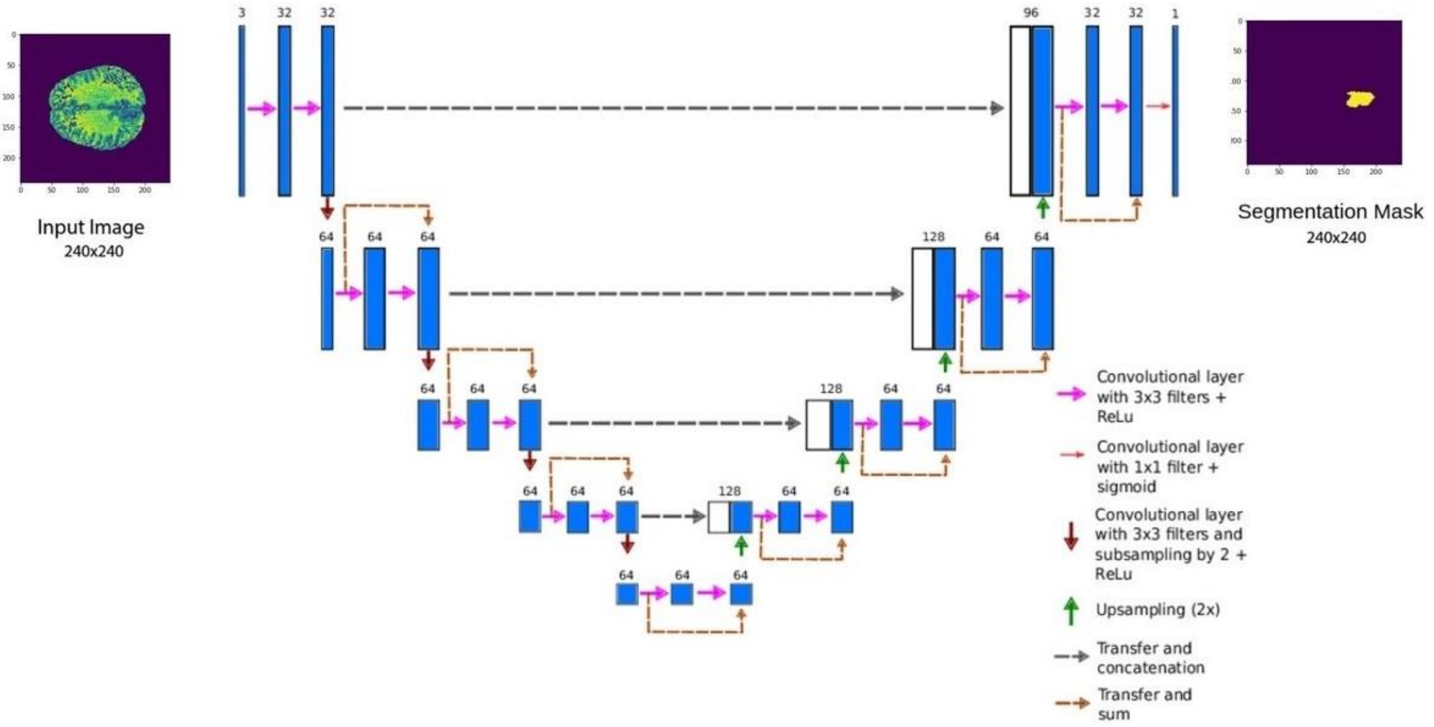


Block-wise Diagram for UNet Architecture:

The UNet architecture can be divided into the following blocks:

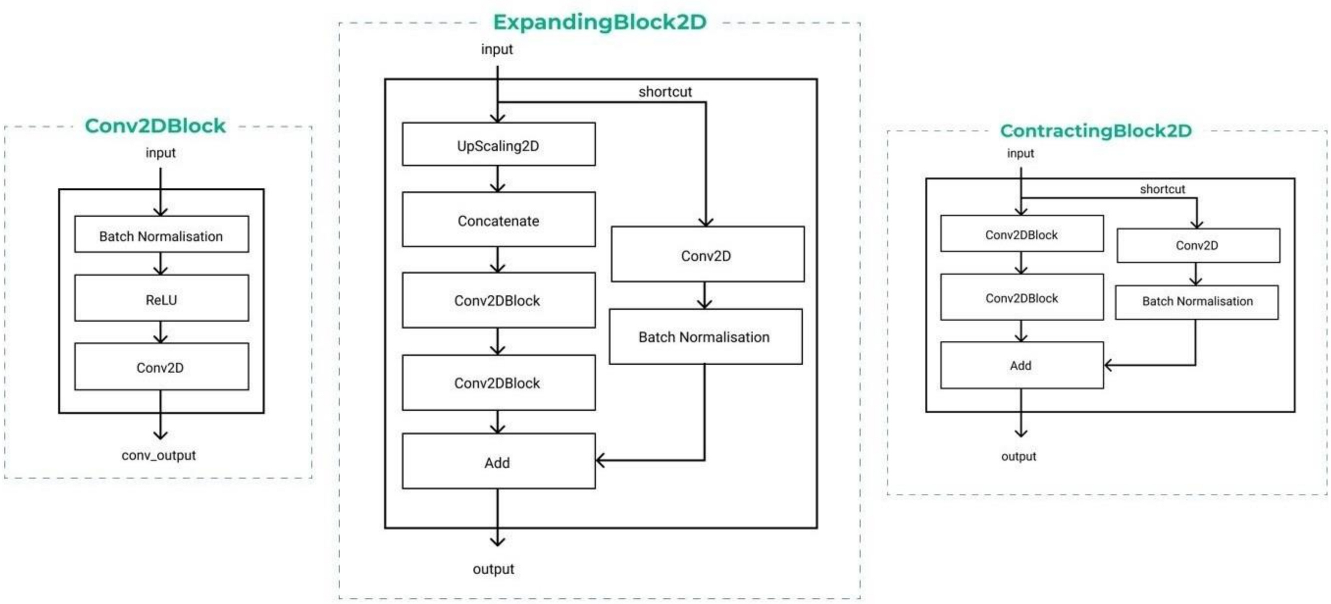


The following diagram shows the Neural Network Design for ResUNet:



Block-wise Diagram for ResUNet Architecture:

The ResUNet architecture can be divided into the following blocks:



Model Comparison with Metrics

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The following two models are tried for training the dataset:

- UNet
- ResUNet

Initially, the two models were run on the whole dataset for 2 epochs and the metrics obtained were:

Model Name	Train Dice Coefficient	Validation Dice Coefficient
UNet	19.30	5.85
ResUNet	56.77	3.30

From the above table, it is clear that the ResUnet model suffers from overfitting. Hence, the UNet model is selected and is used for brain tumor segmentation of MRI scans.

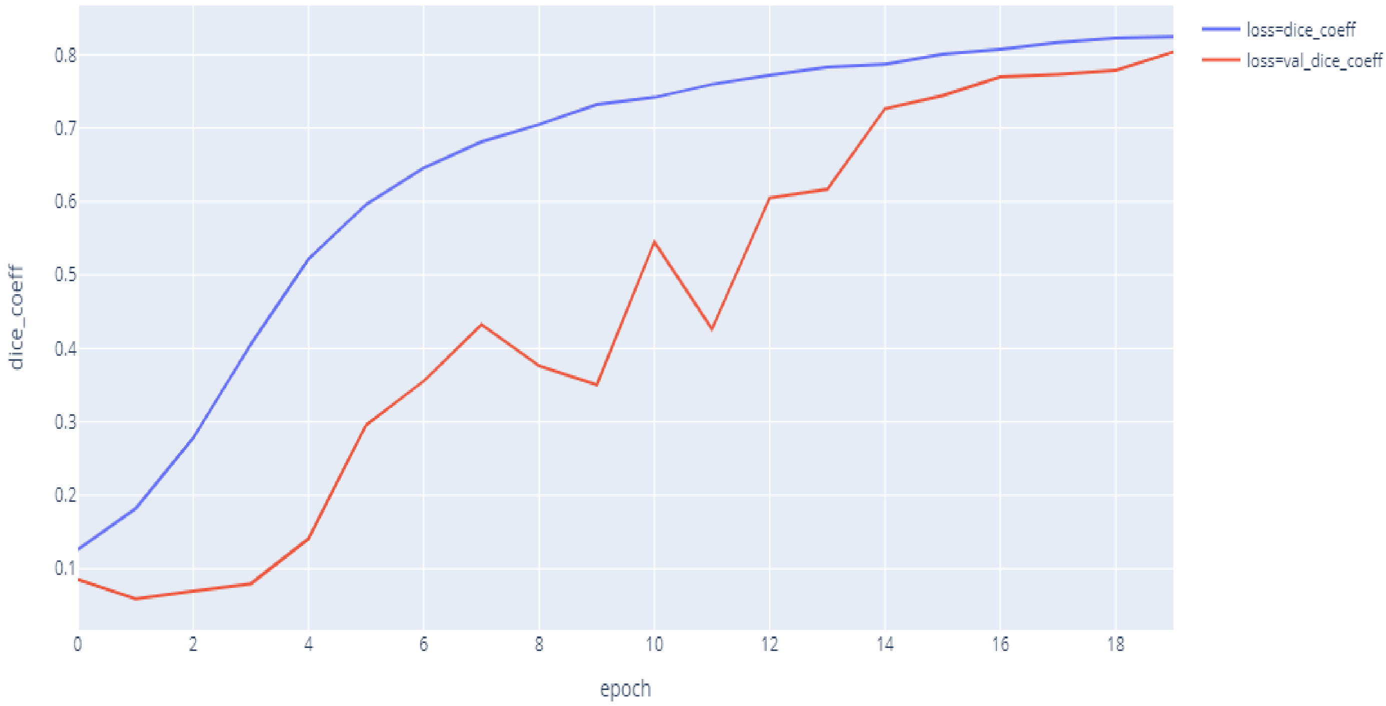
The metrics obtained from UNet are as follows:

Model Name	Dice Coefficient	IoU	Localization Error
UNet	72.777	0.670	12.032

Graphs and Charts

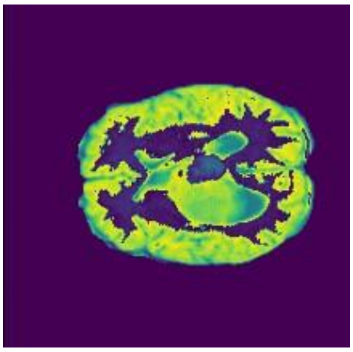
Last updated by | Jack Praveen Raj Ilango | Sep 19, 2021 at 2:25 PM GMT+5:30

The following chart compares the DICE Coefficient for testing and validation sets:



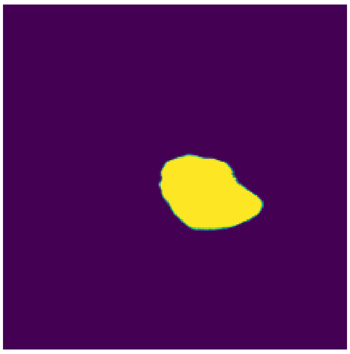
The input and the output images are shown below:

Source Image:



Ground Truth:

Predicted Image:



Deployment

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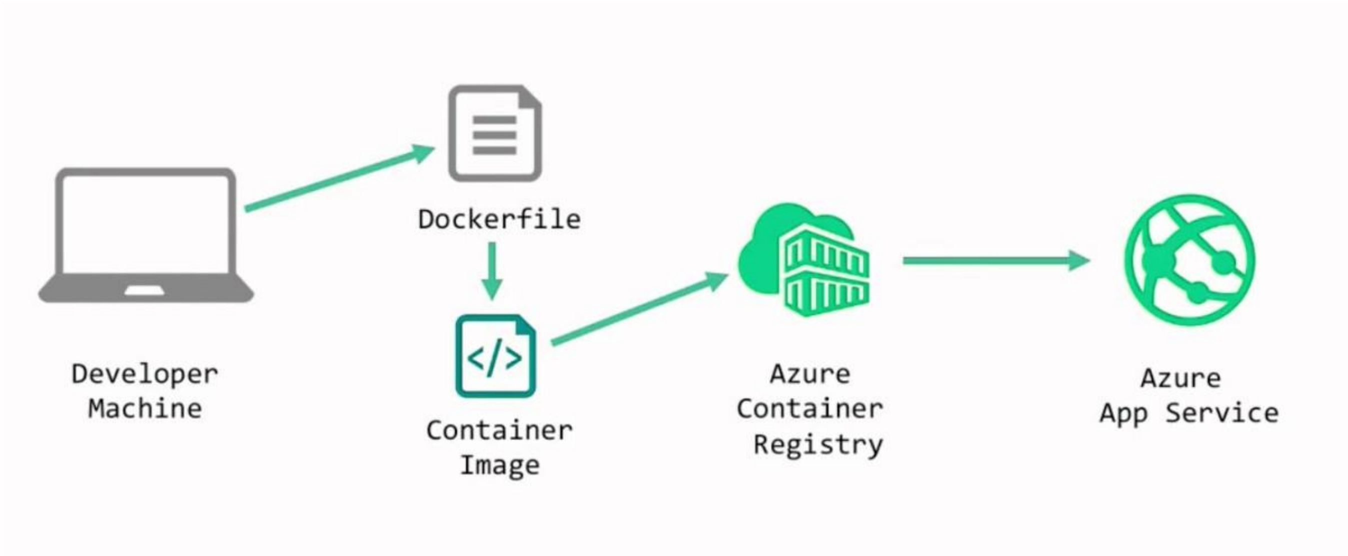
To make the model usable by the healthcare professionals, a user-friendly web application is built using the following resources:

Cloud Resources:

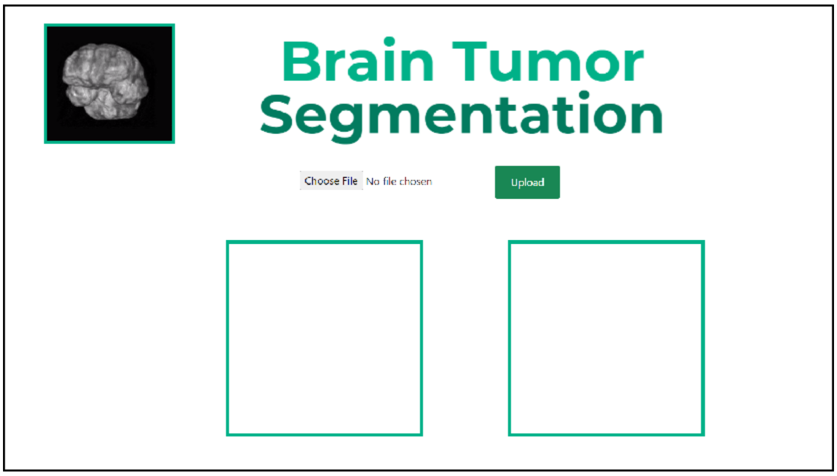
- Data Preprocessing and Modelling - Azure Notebook
- Model Training - Azure Compute Instances
- Deployment and Docker - Azure Container Registry, Azure Container Instances and Azure App Service

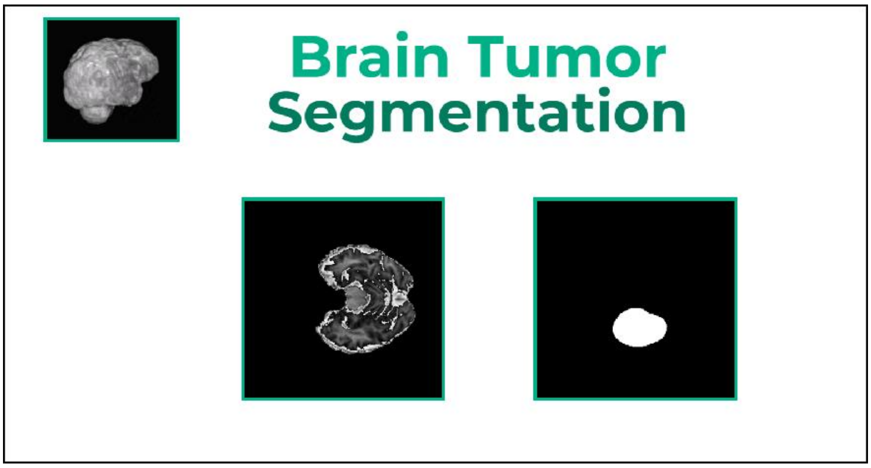
Deployment:



- The web application is built in our local machine using HTML, CSS and Flask framework.
- Docker extension is used to make the Docker file, which in turn is used to make the Docker image. (If we do not want to deploy it on Azure, We can use this image to build a local container in order to containerise the web application.)
- A new container registry is made in the Azure portal.
- We can use the existing image or create another Docker image to use with the container registry.
- A Docker container is built and is linked with the web application using their respective port numbers.
- We login using the username and password that is generated while creating the container registry and push the Docker image to the container registry.
- The Docker image is now visible in the Azure portal.
- The web application is built using the Azure App Service by filling in the required details like registry name, image name and registry source.

User Interface Demo:





User Interaction and Usability

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End-users can use the model for the segmentation of brain MRI scans to detect brain tumors with the help of a web application.

- User needs to upload an MRI scan of the brain to the web application.
- The UNet model would start working on it and generate a masked image, accentuating the position of the tumor.
- This masked image is then displayed to the user on the web application.

Future Enhancements

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These are some of the future enhancements that can be done to our web application:

- The model can be modified and enhanced to detect the position of tumors in any organ of the body using MRI scan images, and not restricted to brain tumors only.
- Develop a new 3D model to process 3D Nifti file input directly, without converting it into 2D slices.
- 3D visualization of the output can be provided ie, the brain and the segmented position of the tumor.
- The web application can be modified to incorporate a functional dashboard comprising patient details.