BraTS Tumour Segmentation using U-Net and CNN Modelling

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Overview

This research developed and evaluated Convolutional Neural Network (CNN) and U-Net models for segmenting tumour on MRIs of glioma patients.

The research consisted of three phases, each focusing on a different aspect of model building. Each phase was iteratively built upon the other.

Phase 1

Baseline CNN & Loss Functions

Categorical Cross-entropy

DICE Loss

Combined Loss

Dice Loss with Penalty

Phase 2

Architectures

Deeper Model

BatchNorm & Dropout

Depthwise Separable Convolutions

U-Net Model

Phase 3

Unsupervised Pretraining

Autoencoder

Pretraining without Warmup

Pretraining with Warmup

Finetuning

Architecture Finetuning

Training Parameter Finetuning

Evaluation

Evaluate on Test Set

Visualise Results

CNN Model Architecture

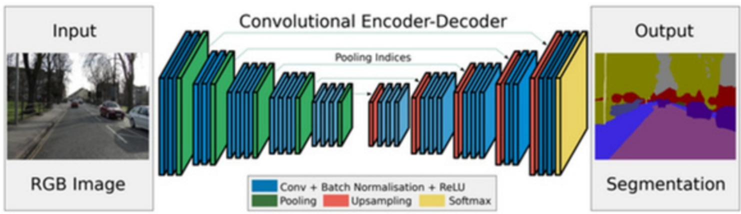
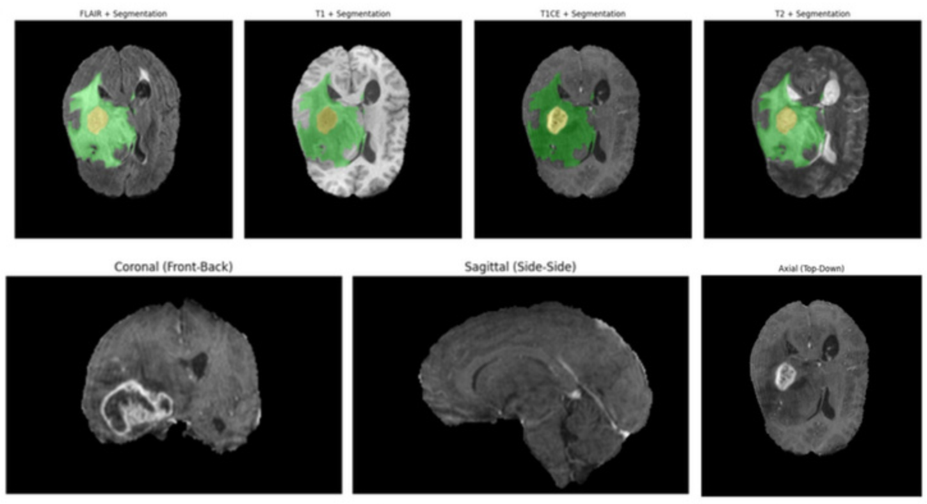
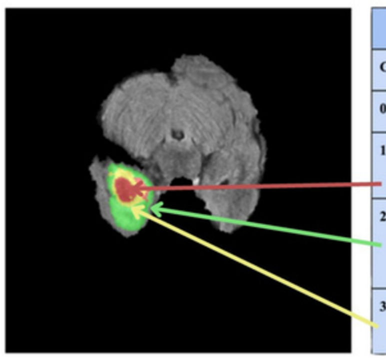


Image source: Wang et. al 2023 *Researches advanced in VSLAM for dynamic environment.*

Below are MRI images with the tumour segmentation masks overlaid. Additionally you can see the thre different perspectives of a 3D MRI.





Segmentation Mask Label Mapping		
Code	**Label**	**Description**
0	*Background*	• Non-tumor tissue, healthy brain regions, cerebrospinal fluid & skull.
1	*Necrotic and non-enhancing tumor core*	• **Necrotic areas:** dead tissue, potentially cystic • **Non-Enhancing Tumor:** solid tumor areas which show as a darker region.
2	*Peritumoral edema*	• Swelling or fluid accumulation in the brain tissue surrounding the tumor caused by blood-brain barrier breakdown • Edema appears brighter on T2-weighted and FLAIR images.
3	*Enhancing tumor*	• Aggressive, active tumour regions • This area brightens after receiving a contrasting agent.

Why Automate?

Giolmas are one of the most common forms of brain tumour but they are challenging to identify.

Manual segmentations of the same images by different experts can often be fairly different, particularly where intensity gradients are smooth or affected by artifacts.

U-Net Model with Skip Connections

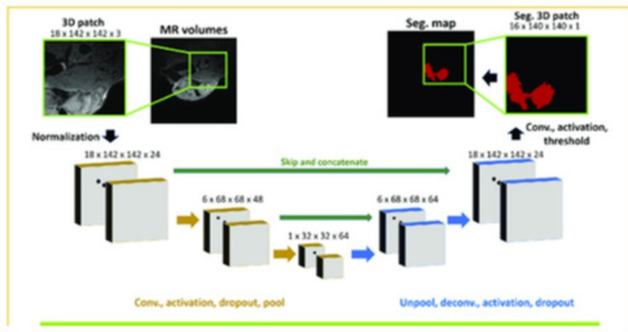


Image source: Holbrook et. al 2020 *MRI-Based Deep Learning Segmentation and Radiomics of Sarcoma in Mice.*

CNNs and U-Net Models

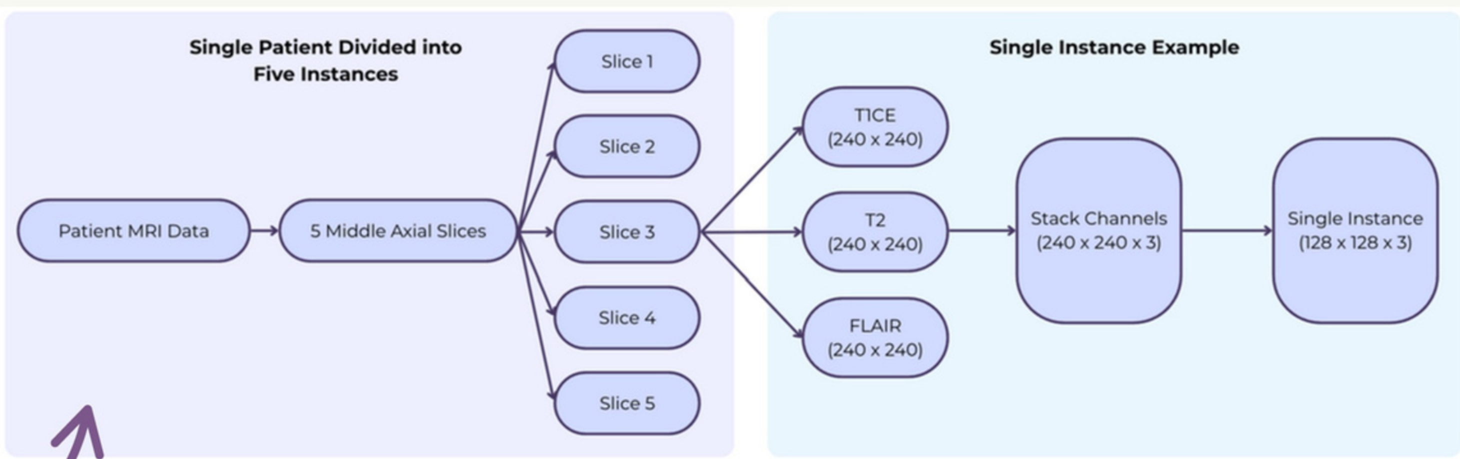
Convolutional Neural Networks (CNNs) and U-Net Models are deep learning models designed for image and spatial data. They use convolutional layers to learn local patterns, such as edges or textures, through filters. A U-Net model is a CNN which contains skip connections, allowing information to pass directly from the lower to higher layers in the network.

BraTS Challenge

The dataset was sourced from the 2020 BraTS challenge.

The Brain Tumor Segmentation (BraTS) Challenge is an annual challenge aimed at providing a dataset and framework for benchmarking brain segmentation algorithms which was established in 2012

This dataset consisted of 3D scans which were reduced to 2D images following this framework.

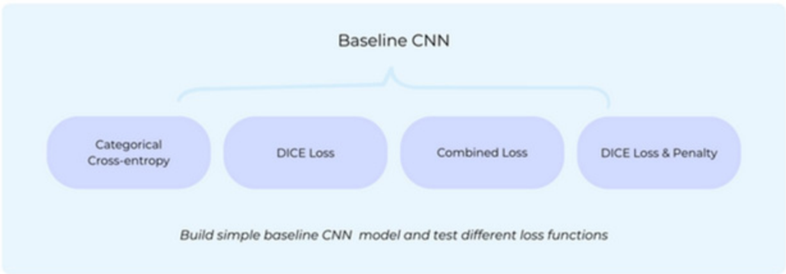


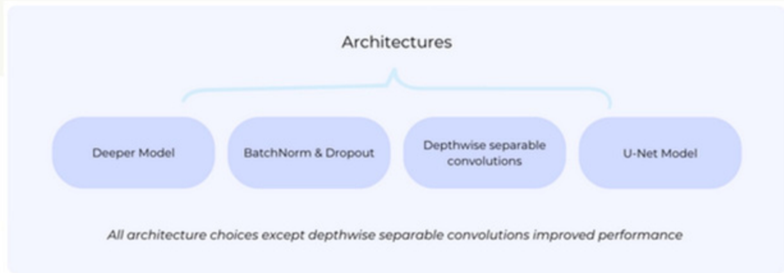
Phase 1: Loss Function

Phase 1 found that the DICE Loss with a penalty term performed best as the loss function.

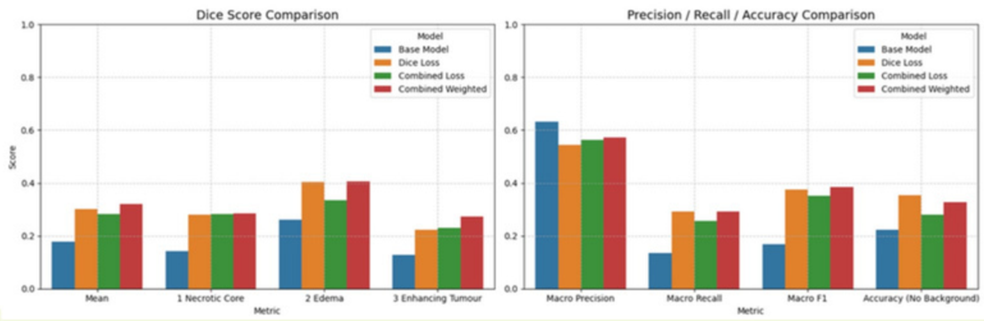
Phase 2: Architecture

In Phase 2 we iteratively increased the model's architectural complexity. All the architecture adjustments, except for depthwise separable convolutions, improved the model's performance

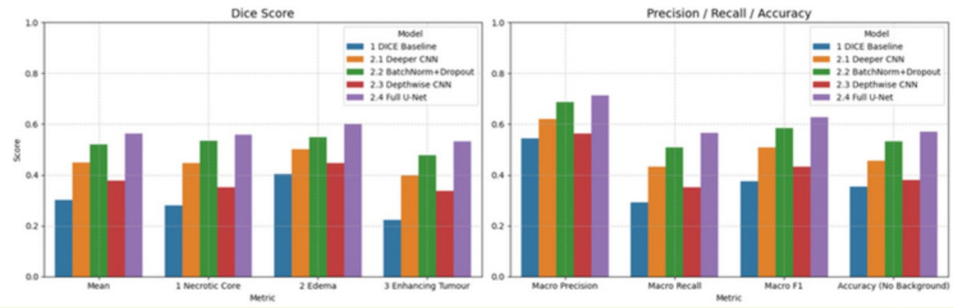




Plot of the results of each round from Phase 1



Plot of the results of each round from Phase 2

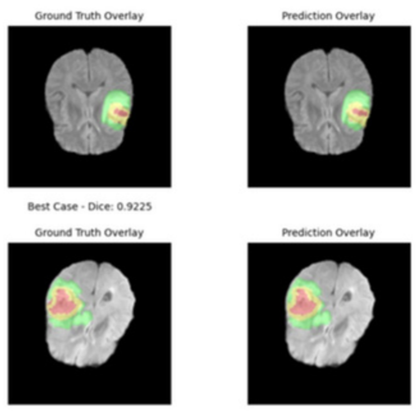


Phase 3: Unsupervised Pretraining, Fine Tuning & Test Set Evaluation

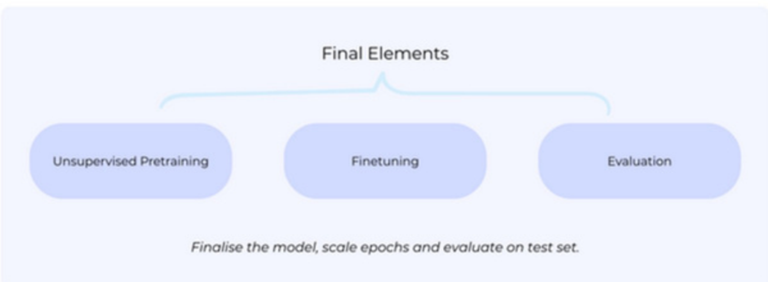
The unsupervised pretraining section included building an autoencoder which trained to a near perfect reconstruction. Pretrained weights were tested using unfrozen and warmup strategies. Two Keras Tuner rounds were run: the first tuned model architecture and the second tuned training parameters.

DICE & Macro Metrics

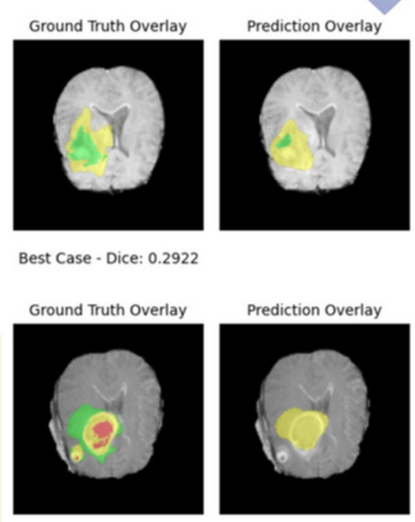
The plots for each round show the DICE scores and macro accuracy metrics for each round. DICE scores capture the overlap between the predicted and human-annotated masks. The macro metrics are the individual metrics calculated for each class which are then averaged over each class.

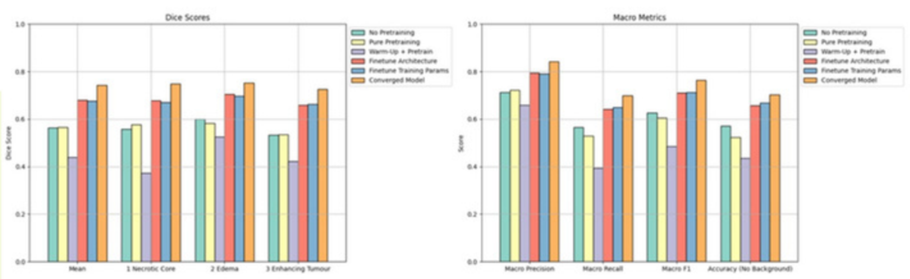


Predictions from Final Model



Predictions from Baseline Model

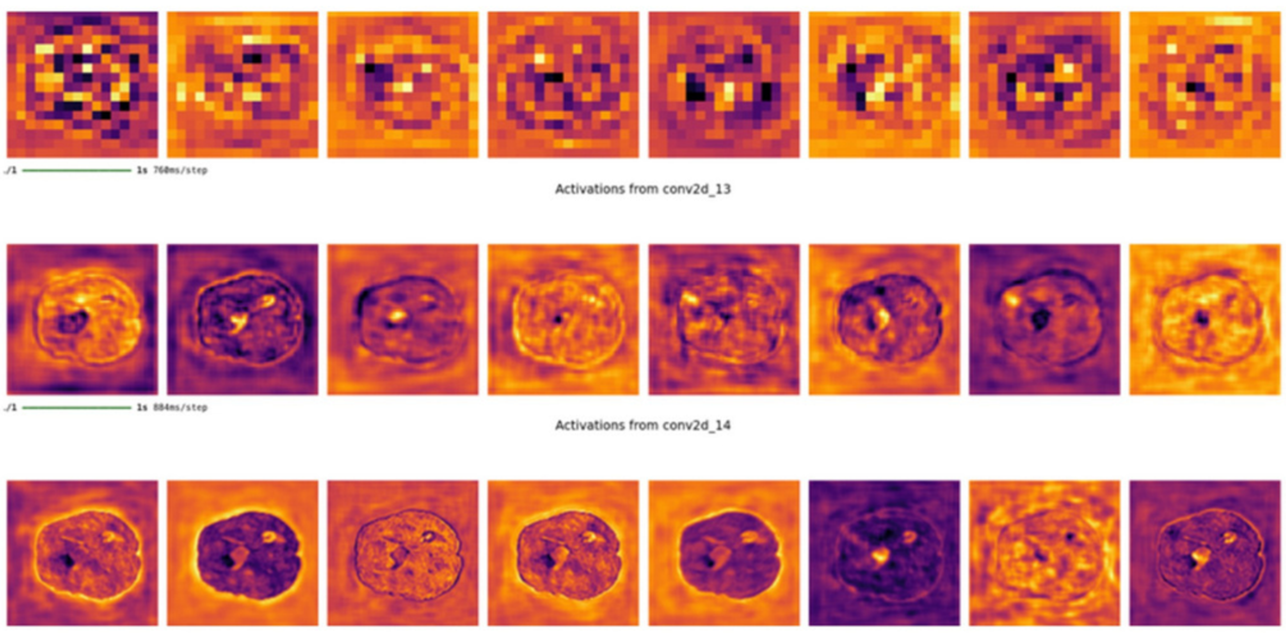




Simple Baseline vs Final Model

The baseline model could identify the tumour boundary but could not discriminate between different tumour subregions.

However, the final model can identify the subregions of the affected sites.



Visualising what the Model Learns

We can visualise the feature maps of the convolutional layers of the model. This allows us to see how the model learnt features from the data.

As we can see, the model is able to identify tumour regions fairly well within the first layer. We can also see the compression and upsampling process which happens in a CNN designed for segmentation tasks. As we travel through the layers, the resolution of the feature maps diminishes, becoming highly pixellated, before the upsampling process reintroduces granular detail.