BRAIN TUMOUR PREDICTION & MODEL COMPARISION

STANLEY PRAKASH J (23200443), NIRMAL KUMAR (23202314) | DATA & COMPUTATIONAL SCIENCE, UCD

INTRODUCTION

BACKGROUND

Brain tumours are among the most serious and life-threatening conditions, with an estimated **241,037 new cases** and **189,382 deaths** globally projected for **2024**.

Despite significant advances in medical imaging and treatment options, the prognosis for brain tumour patients remains poor.

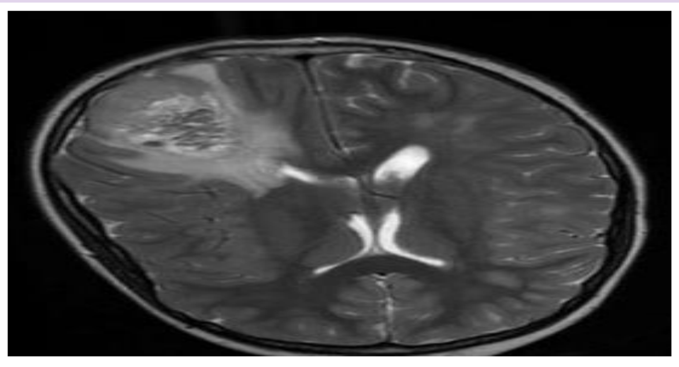
OVERVIEW

This is largely due to the challenges in early detection and the complexity of the brain, which often leads to delayed diagnosis when the tumour has already reached an advanced stage.

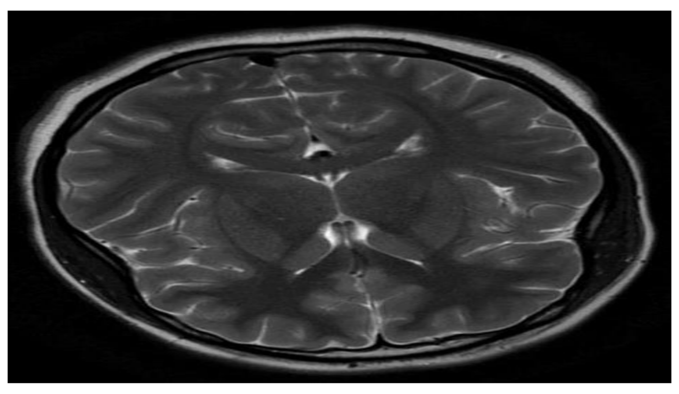
The primary objective of this project is to develop an efficient and accurate detection model for brain tumours using convolutional neural networks (CNNs) implemented in TensorFlow & Keras. This model aims to classify MRI images of the brain into two categories: tumorous and non-tumorous

DATASET

MRI-SCANS



MRI Image Showing Presence of Brain Tumour



MRI Image Indicating Absence of Brain Tumour

The dataset contains over 40 brain MRI images from patients in various stages of diagnosis, organized into "tumorous" and "non-tumorous" categories. Due to the limited dataset size, data augmentation techniques were employed to enhance the training data for building and comparing predictive models. Each MRI image represents a 3D scan of the brain, with multiple axial slices showing cross-sectional views. The number of 2D slices per image can vary depending on the MRI machine used and the specific protocol followed during the scan.

MRI Image Showing Presence of Brain Tumour:
This MRI scan reveals the presence of a brain tumour, which appears as an abnormal mass or lesion within the brain tissue. The tumour may vary in size, shape, and location, often showing up as a distinct region of different intensity compared to the surrounding healthy brain tissue. The presence of the tumour can cause displacement or compression of adjacent brain structures, which is visible in the image. This image is crucial for the early detection and diagnosis of brain tumours, allowing for timely medical intervention.

MRI Image Indicating Absence of Brain Tumour:
This MRI scan depicts a healthy brain with no visible signs of a tumour. The brain tissue appears uniform and consistent, with no abnormal masses or lesions. All brain structures are intact and appropriately positioned, without any displacement or compression. This image serves as a baseline reference for what a normal, tumour-free brain should look like on an MRI scan, helping to differentiate between healthy and tumorous conditions in clinical practice.

Glioblastoma Multiforme (GBM):
Glioblastoma multiforme is the most aggressive and common type of primary brain tumour. It arises from astrocytes, which are star-shaped glial cells in the brain. GBM tumours are characterized by their rapid growth and tendency to invade nearby brain tissue, making them challenging to treat effectively.

Ependymoma:
Ependymomas arise from ependymal cells, which line the ventricles of the brain and the central canal of the spinal cord. They can occur in both children and adults but are more common in children.

DATA AUGMENTATION

WHY DID I USE DATA AUGMENTATION?

Since this is a small dataset, There wasn't enough examples to train the neural network. Also, data augmentation was useful in tackling the data imbalance issue in the data.

Before data augmentation, the dataset consisted of:
20 positive and 20 negative examples, resulting in 40 images.
After data augmentation, now the dataset consists of:
1814 images.

Note: these 1814 examples contains also the 40 original images.

DATA PRE-PROCESSING

The images in the dataset are initially captured in various dimensions and resolutions, with each image potentially varying in size and aspect ratio. To ensure consistency and compatibility with neural network architectures, preprocessing steps are applied. First, the relevant portion of each image containing only the brain is cropped, focusing on the most critical region for analysis. Each image is then resized to a uniform shape of (240, 240, 3), where 240x240 represents the width and height, and 3 denotes the color channels. This resizing is essential as it standardizes the input dimensions, making it feasible for neural network processing. Next, normalization is performed to scale the pixel values to a range between 0 and 1, which aids in stabilizing the training process. For data management, the dataset is divided into three subsets: 70% is allocated for training, 15% for validation, and the remaining 15% for testing. This systematic approach ensures that the images are uniformly prepared and distributed for effective model training and evaluation.

3D Grayscale Slices Dataset for Neural Network Training

MODEL IMPLEMENTATION

MODEL EVALUATION PROCESS

The dataset is first divided into training, validation, and test sets using the split data function. This function takes the input data X and labels y, and splits them into three subsets: training (75%), validation (15%), and test (15%). Specifically, the function first separates the data into training and a combined test-validation set, then further splits the test-validation set into equal parts for validation and testing.

After the split, the training set consists of 1,269 examples, the validation set has 273 examples, and the test set includes 272 examples, each with a shape of (240, 240, 3) for the images and (1) for the labels. Additionally, a helper function hms_string is defined to format the time elapsed during model training into a more readable hours, minutes, and seconds format.

Finally, the compute_f1_score function is implemented to evaluate the model's performance. This function converts predicted probabilities into binary class predictions using a threshold of 0.5 and then calculates the F1 score, a metric that balances precision and recall, making it ideal for assessing the model's performance, especially in cases with imbalanced data.

ACCURACY ON THE TESTING DATA

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Test Loss = 0.5735647678375244
Test Accuracy = 0.7647058963775635
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F1 SCORE ON THE TESTING DATA

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F1 score: 0.8511627906976744
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F1 SCORE ON VALIDATION DATA

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F1 score: 0.8697674418604652
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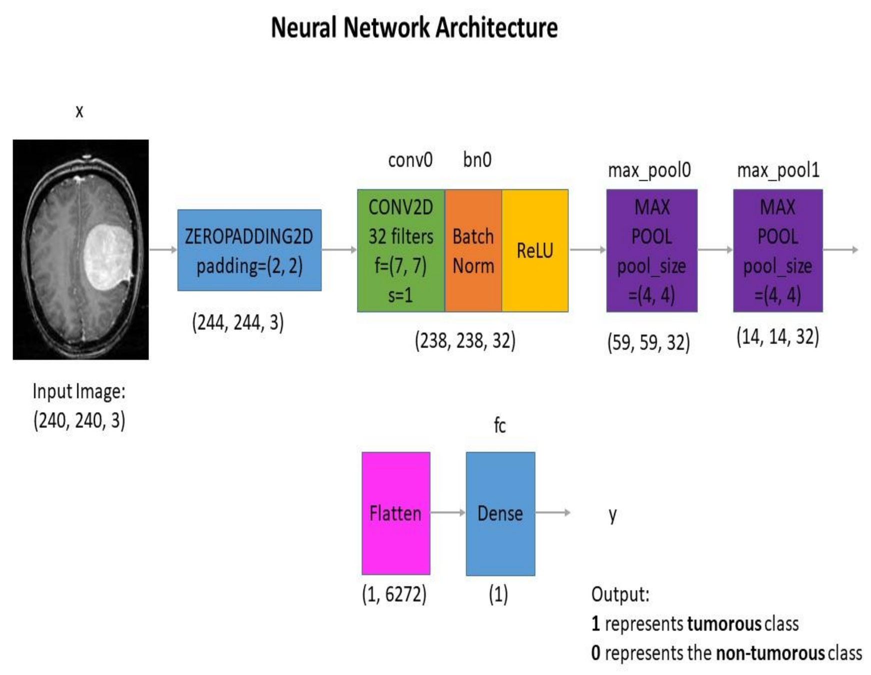
CNN

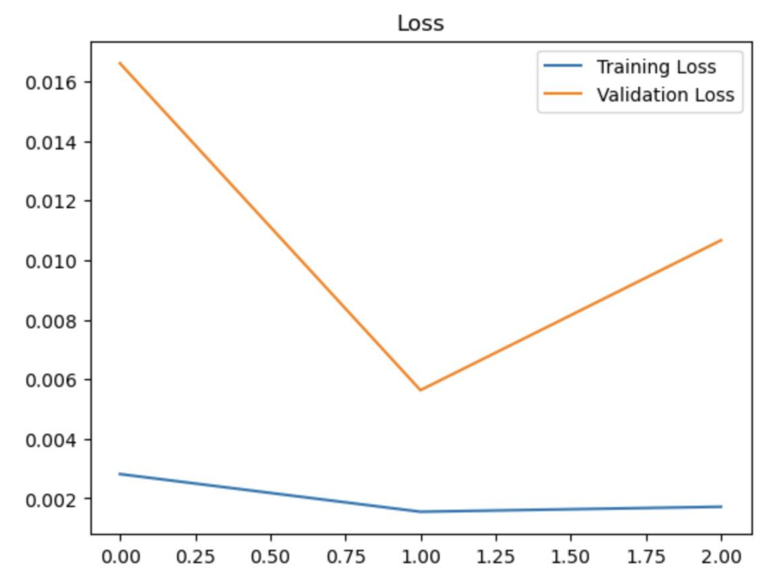
A Convolutional Neural Network (CNN) is a specialized deep learning model designed for processing grid-like data, particularly images and videos. In this case, the model was trained on 240x240 pixel images, using a custom architecture optimized for computational efficiency. The network begins with a zero-padding layer followed by a convolutional layer with 32 filters, each with a (7, 7) kernel size and a stride of 1. This is followed by batch normalization and ReLU activation to enhance training speed and introduce non-linearity. The model then includes two consecutive max-pooling layers, both with a filter and stride size of (4, 4). Finally, the output of these layers is flattened into a 1D vector and passed through a dense layer with a sigmoid activation function for binary classification. This architecture was chosen to balance performance and computational efficiency, particularly due to hardware limitations, while still effectively processing the input images.

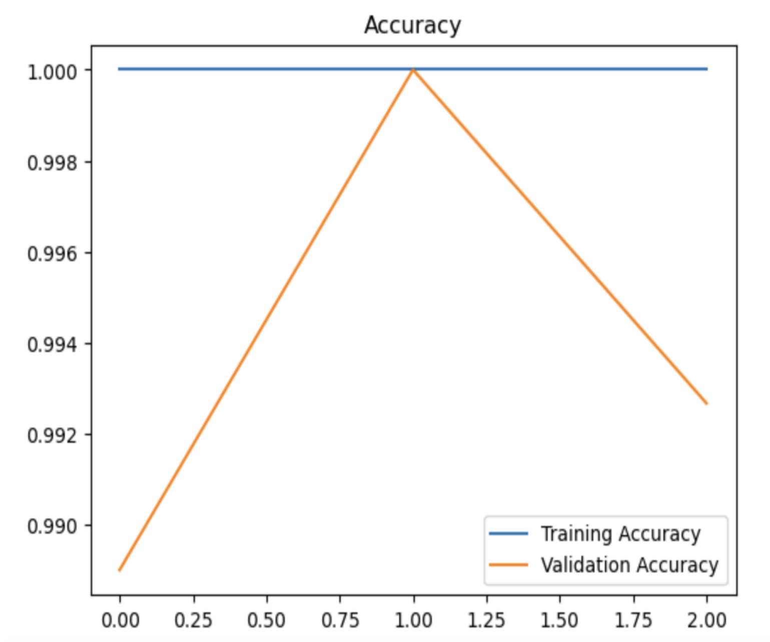
2D CNN ARCHITECTURE



Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 240, 240, 3)	0
zero_padding2d_1 (ZeroPadding2D)	(None, 244, 244, 3)	0
conv0 (Conv2D)	(None, 238, 238, 32)	4,736
bn0 (BatchNormalization)	(None, 238, 238, 32)	128
activation_2 (Activation)	(None, 238, 238, 32)	0
max_pool0 (MaxPooling2D)	(None, 59, 59, 32)	0
conv1 (Conv2D)	(None, 57, 57, 64)	18,496
bn1 (BatchNormalization)	(None, 57, 57, 64)	256
activation_3 (Activation)	(None, 57, 57, 64)	0
max_pool1 (MaxPooling2D)	(None, 14, 14, 64)	0
flatten_1 (Flatten)	(None, 12544)	0
fc1 (Dense)	(None, 128)	1,605,760
fc2 (Dense)	(None, 1)	129

Total params: 1,629,505 (6.22 MB)





RESULTS

The model successfully detects brain tumours with an accuracy of 81% on the test set and an F1 score of 0.85. These results are impressive, especially given that the dataset is balanced.

CONCLUSION

In this project, we developed a Convolutional Neural Network (CNN) to detect brain tumours from medical images. Given the small and imbalanced dataset, I employed data augmentation to enhance the diversity of the training data, which expanded the dataset significantly. The custom CNN architecture was carefully designed to balance computational efficiency with performance, considering hardware limitations. After training and evaluation, the model achieved an accuracy of 81% and an F1 score of 0.85 on the test set, demonstrating its effectiveness in detecting brain tumours. This project showcases the power of deep learning in medical image analysis, even with limited resources.

REFERENCES

1- Integrated Genomic Analysis of LGGs.
REF_1

2- The Role of FLAIR in Brain Tumour Imaging.
REF_2

3- Deep Learning for Brain Tumour Segmentation.
REF_3