Brain Tumour Classification with Explainable AI-XAI

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Μάθημα: Εφαρμογές Τεχνητής Νοημοσύνης

Contents

Introduction

- With the advancements in AI, there has been a growing interest in utilising ML and DL techniques in the Medical field, to automate many tasks like Brain tumour Detection and classification.

- However, the lack of interpretability in traditional AI models hinders their adoption in clinical practice. In this project, we created two DL models for Brain Tumour recognition using explainable AI-XAI.

Data

As we mentioned above the goal of this project is to create and compare two DL models and the use of XAI.

The dataset in this case is MRI-Magnetic Resonance Imaging set, which can be found in the Kaggle website below:

[Brain Tumour Data-set]

Data

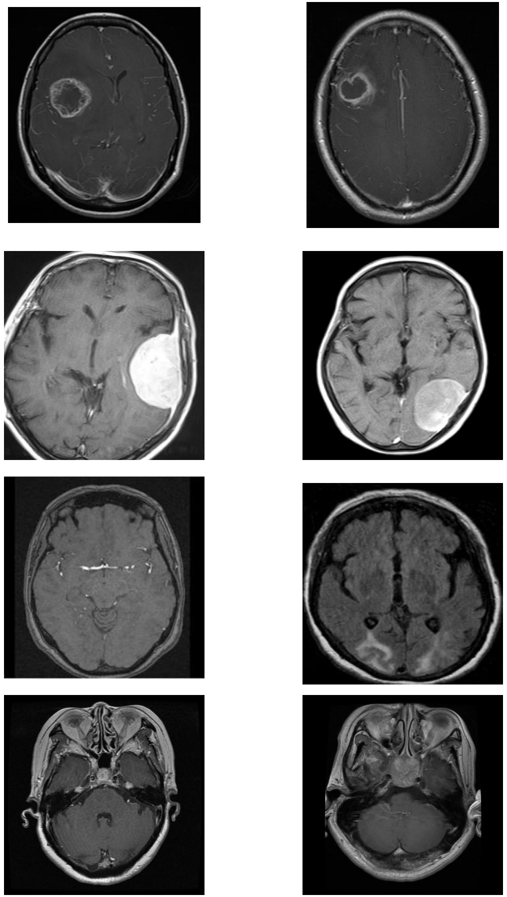
This dataset consists of four major categories

1. Gliomas: are tumors that develop from glial cells, which are supportive cells in the brain. They are the most common type of primary brain tumour.

2. Meningioma: Meningiomas are tumours that arise from the meninges, which are the protective membranes surrounding the brain and spinal cord. They are usually benign and grow slowly.

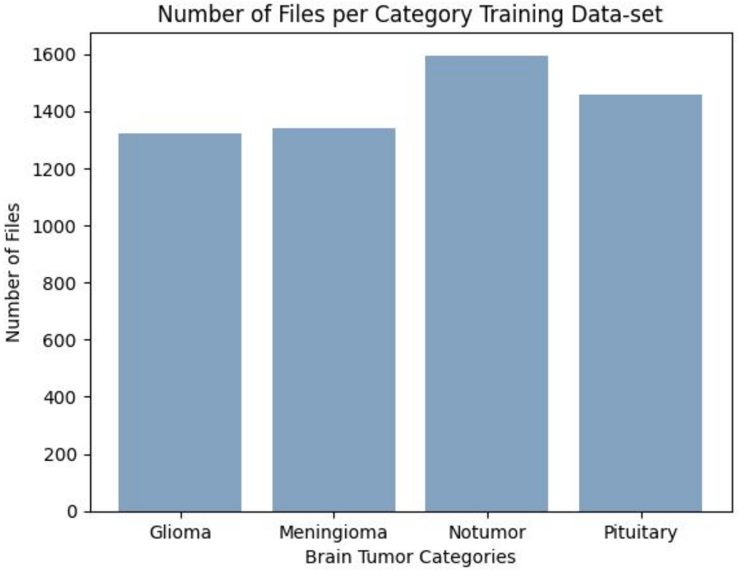
3. No tumour: In this case we get MRI’s that have no tumour, which means that the brain of the patient is healthy.

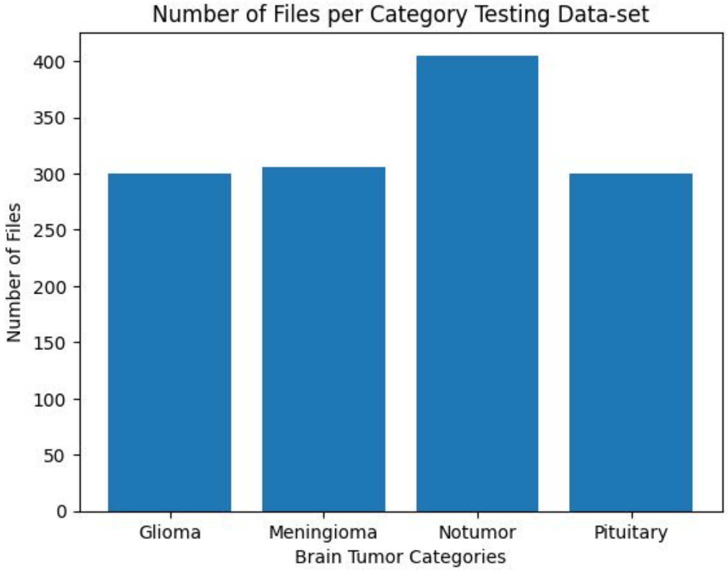
4. Pituitary: Pituitary tumours develop in the pituitary gland, which is a small gland lo- cated at the base of the brain.



Data

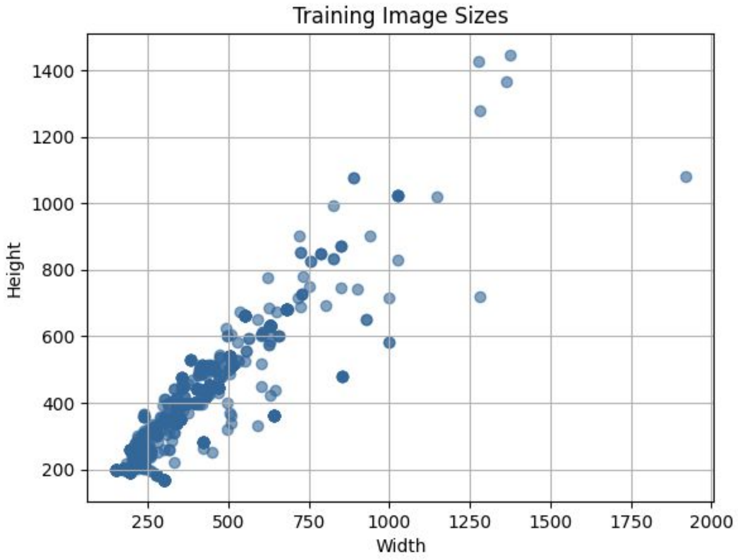
A important step when working with ML or DL is to ensure about the data distribution in order to avoid the use of an imbalanced dataset. In this case the training and test set had the following distributions:

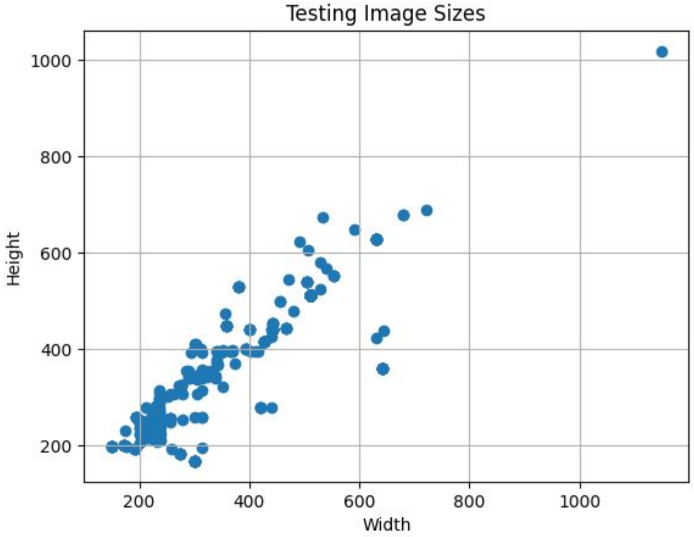




Data

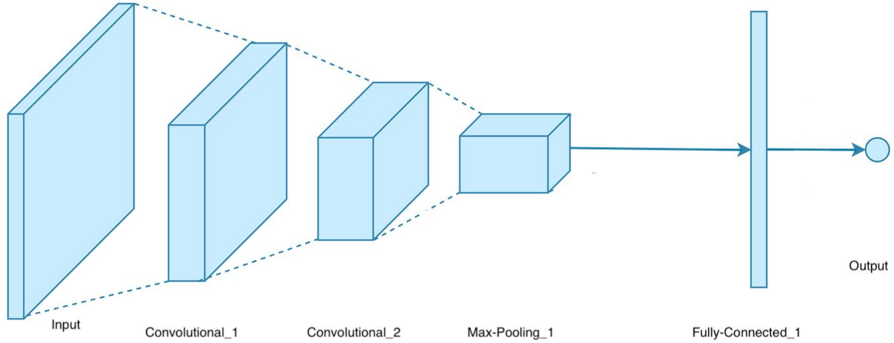
The next step in data preprocessing when working with image data is to check for the image sizes, since both DL models use a certain image size:





Convolutional Neural Network

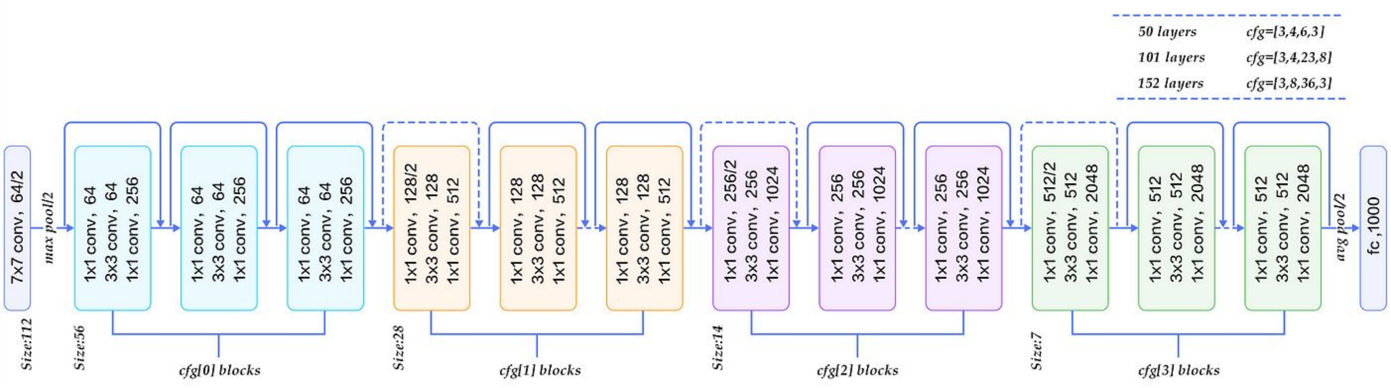
In this project we used a simple Convolutional Neural Network (CNN) architecture to tackle the challenging task of brain tumor classification.



By utilizing XAI methods such as Grad-CAM (Gradient-weighted Class Activation Mapping) we gained valuable insights into the CNN's decision boundaries and identified the key regions of the brain scans that contributed most to the classification results.

Resnet-50 Model

In this project we also used a Resnet-50 pre-trained model to compare the performance of our model to this state-of-the-art model for the challenging task of brain tumor classification.



In the same way we used XAI methods such as Grad-CAM in order to find the Resnet-50 decision boundaries.

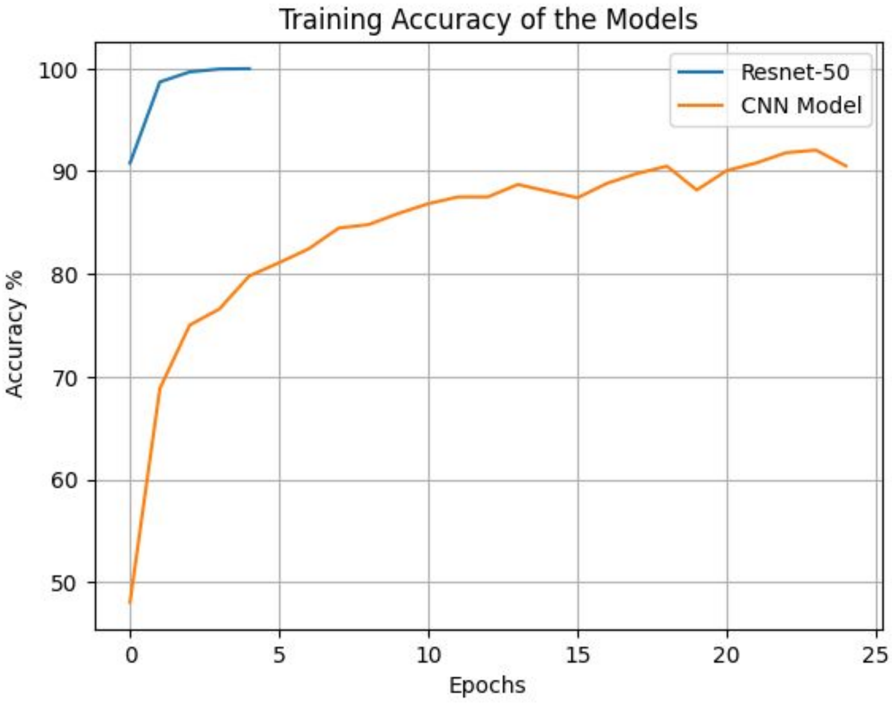
Accuracy Metrics (1/2)

Hyper-parameters of the CNN model are the following:

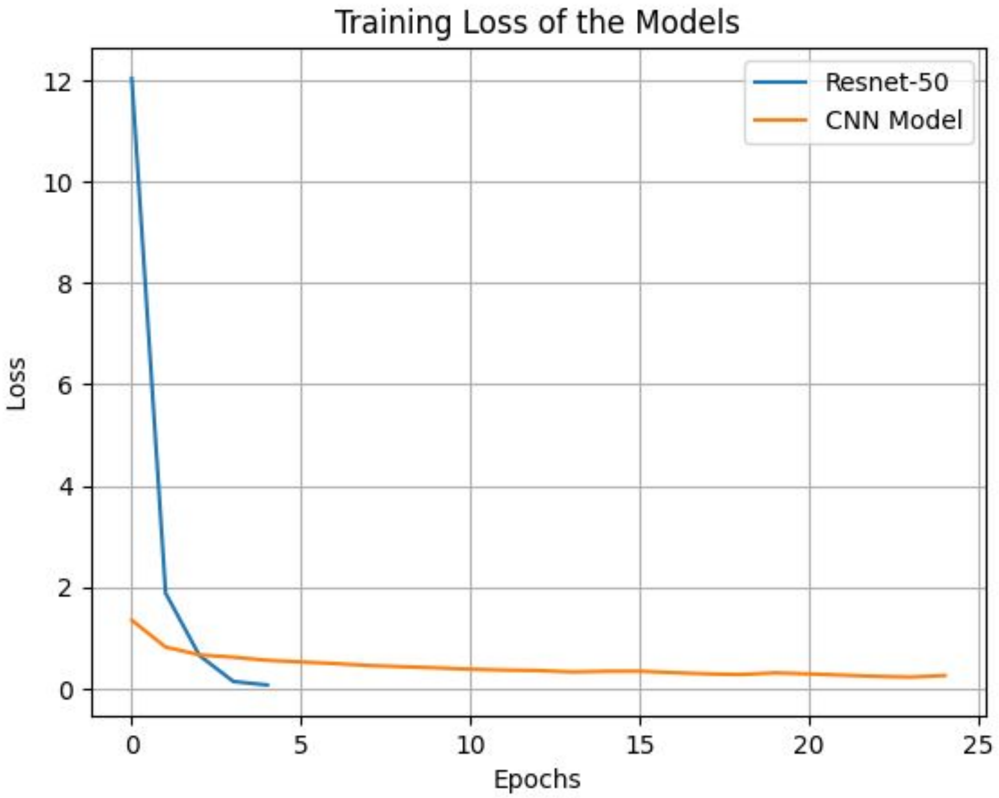
1. Learning Rate: 0.001
2. Epochs: 25
3. Batch size: 128
4. Momentum = 0.9
5. Loss Function: Cross Entropy Loss
6. Optimiser Function: Stochastic gradient descent

Hyper-parameters of the Resnet-50 model are the following:

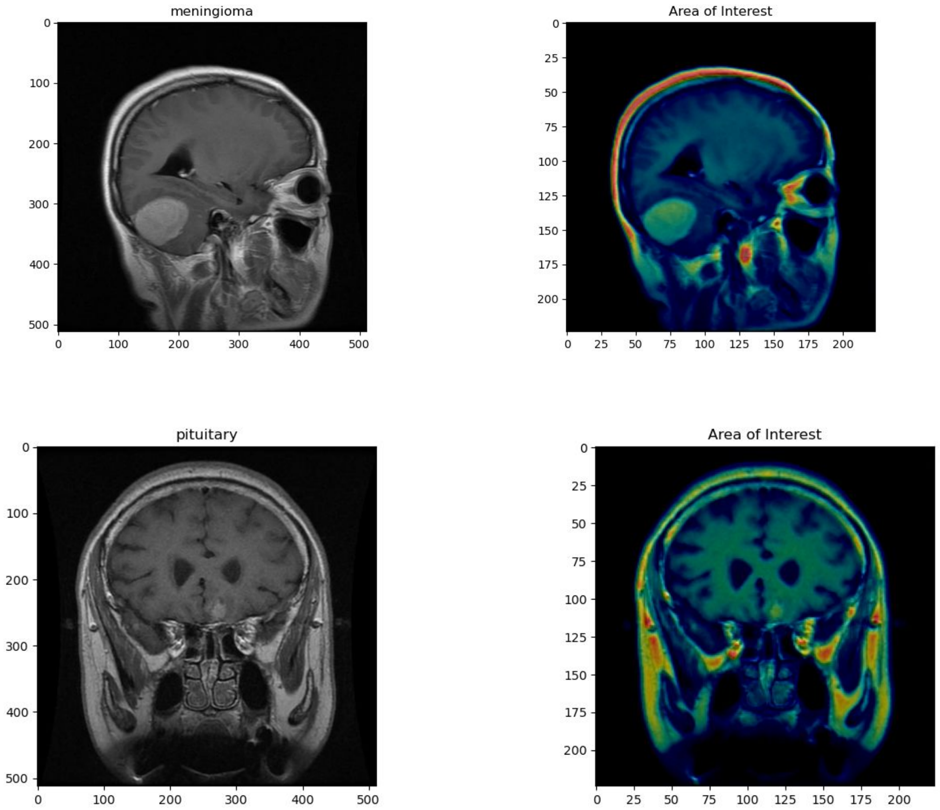
1. Learning Rate: 0.0001
2. Epochs: 5
3. Batch size: 32
4. Loss Function: Cross Entropy Loss
5. Optimiser Function: Stochastic gradient descent



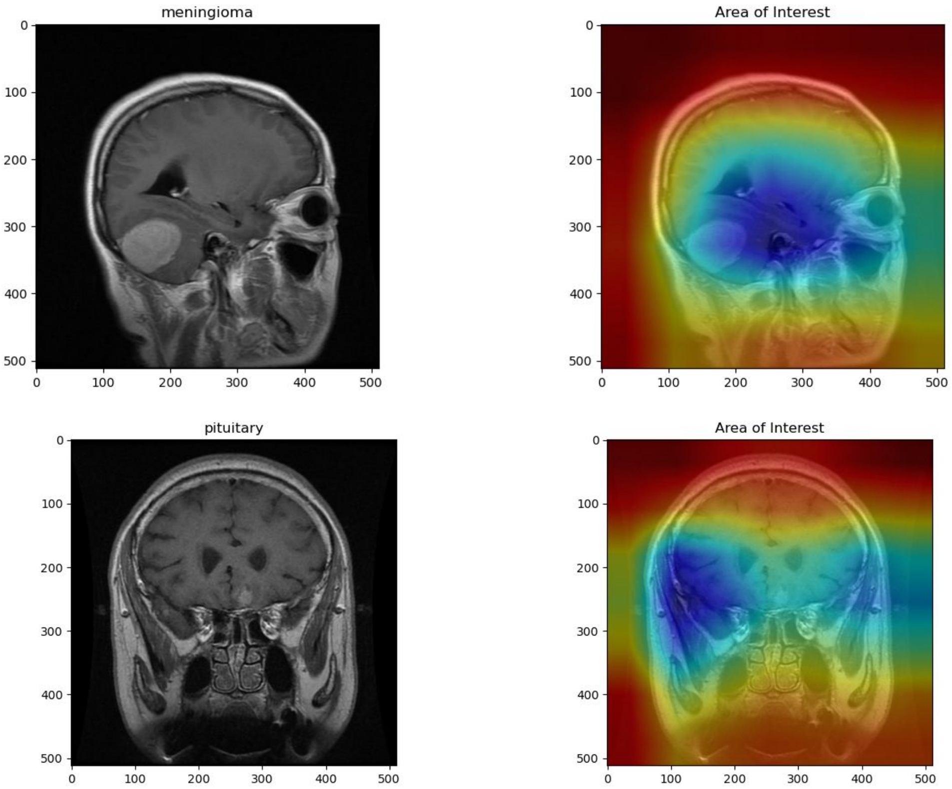
Accuracy Metrics (2/2)



Explainable AI-XAI (1/2)



Explainable AI-XAI (2/2)



Conclusion

In conclusion, both the custom CNN and the pre- trained ResNet-50 models demonstrated exceptional performance in the given task.

- The ResNet- 50 model showcased near-perfect accuracy within a short period, leveraging its pre-trained weights and learned representations.

- On the other hand, the custom CNN model achieved an impressive accuracy of 90% after a slightly longer training duration.

Although the performance of both models was remarkable, the custom CNN model exhibited a slight advantage in terms of the Grad-CAM im- plementation.

Thank you !