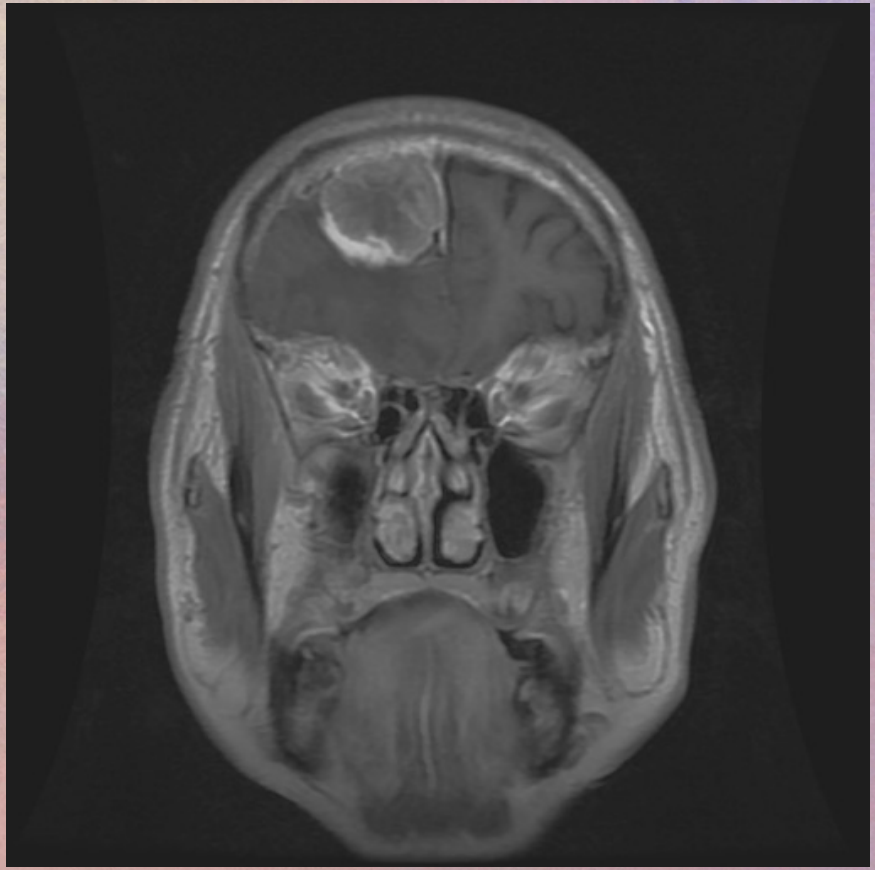
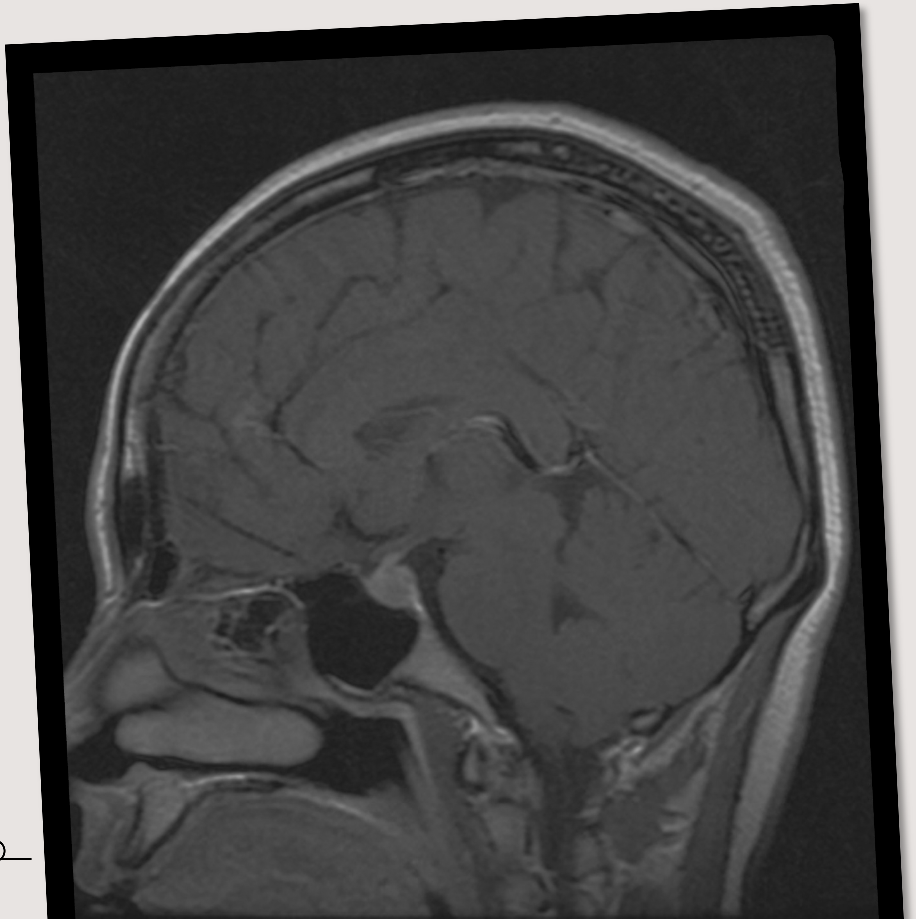
Brain Tumor MRI Classification

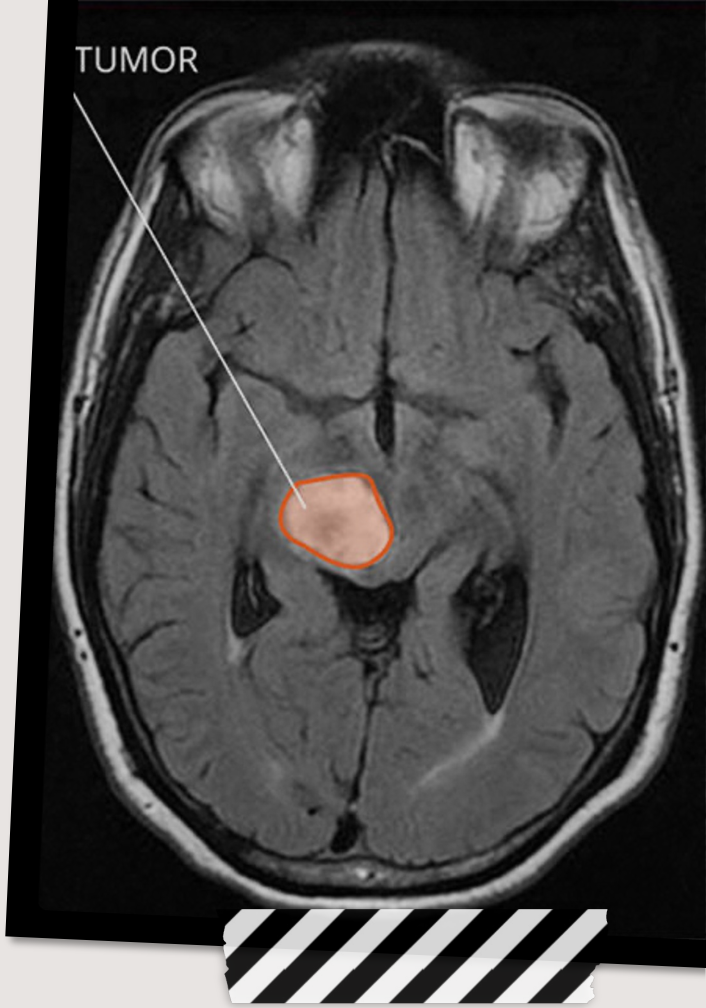
By Nadeem Ahmad



Introduction To The Project



- Brain tumors are abnormal growths in the brain that can be either benign or malignant.
- They are a serious medical condition and require accurate diagnosis and treatment.
- MRI is one of the most used imaging modalities to detect and diagnose brain tumors.
- The main concern is time, as image interpretation by medical professionals can be an arduous and time-consuming affair, which can lead to worse health outcomes for patients
- Machine learning can assist in the diagnosis of brain tumors by analyzing MRI images.
- Our project aims to develop a machine learning model to identify brain tumors in MRI images with high accuracy.



Project Objectives

- To develop a machine learning models for brain tumor detection and identification using MRI images.
- To achieve a high level of accuracy and AUC in the model to ensure reliable identification of brain tumors.
- To evaluate the performance of the model using standard evaluation metrics such as accuracy, AUC, sensitivity, and specificity.
- To compare the performance of the developed model with the existing state-of-the-art methods.
- To explore the potential applications of the developed model in clinical settings for accurate diagnosis of brain tumors.

Data Collection Sources

- The dataset used for this study consisted of brain MRI images obtained from multiple hospitals and medical centers.
- The data was obtained from data set sites such as Kaggle, OpenNeuro, The Cancer Imaging Archive and the Brain Imaging Data Structure (BIDS)
- sagittal, coronal, and axial photos were taken in even distributions to allow for a robust model to be made.
- A Variety of patients was also targeted to make sure that the model didn’t overfit to a specific type of person

Data Collection and Preprocessing

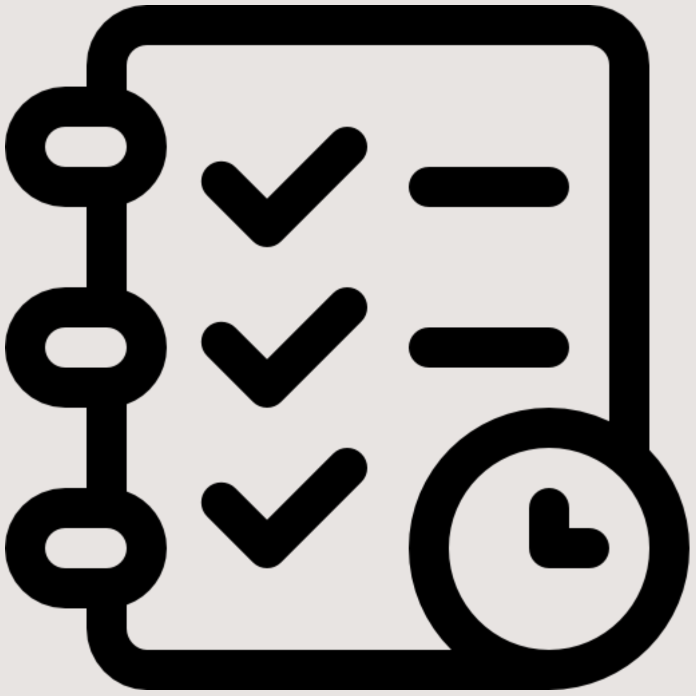
- The dataset consisted of over 22,000 images of unhealthy brains and 600 images of healthy ones.
- Techniques used for data augmentation included translations, rotations, and flips.
- The data was split into separate training, validation, and test sets with 64%, 16%, and 20% in each, respectively.
- The unhealthy folder had further subdirectories, each representing a different type of tumor that was possible.
- The images were preprocessed by rescaling them to a uniform size of 224 x 224 pixels and normalizing the pixel values between 0 and 1.
- The data was loaded into a data generator using the Keras ImageDataGenerator class to efficiently feed the data to the model during training and evaluation.

Methodology

- To prevent class imbalance, a subset of 600 unhealthy images was selected, and an equal number of photos were taken from each tumor type directory to ensure balanced classes, for the training of the tumor detection model.
- Two separate model's convolutional neural networks (CNN) were created using the Keras library: a binary classification model for tumor detection and a multi-class classification model for tumor identification.
- The models were evaluated using metrics such as accuracy, F1 score, and AUC, as well as graphical methods such as confusion matrices and ROC curves.
- The models were adjusted by modifying the number of convolutional layers, changing activation functions, and adjusting data organization. These adjustments were based on evaluations.

Methodology

- The final models were then employed using cascading prediction, where the detection model would first make a prediction on an image, returning a floating-point number between 0 and 1, and if the number was greater than 0.5, the MRI would be passed onto the tumor identification model.
- The outputs were again evaluated using metrics from earlier, to ensure that the models were performing at a high level.
- Overall, methodology involves a combination of data preprocessing, model building, training, evaluation, and visualization techniques to develop accurate and reliable deep learning models for brain tumor classification.



Results/Experimental Analysis

- The output of the model can be classified into two categories: healthy or unhealthy. In the case of an unhealthy classification, the model will further identify the specific tumor type.
- The Cascading prediction code was designed so that a user can input one photo, or they can add a directory of photos, allowing for many to be processed at once.

```
Image 1933: The brain scan is healthy.
Image 1934: The brain scan is healthy.
Image 1935: The brain scan is unhealthy.
The predicted tumor type is: meningioma
```

```python
predictions = binary_model.predict(test_generator)
tumor_keys={0:'glioma', 1:'meningioma', 2:'pituitary_tumor'}
for i in range(len(predictions)):
    if predictions[i] > 0.5:
        print(f"Image {i+1}: The brain scan is unhealthy.")
        img = tf.image.resize(test_generator[i][0], (224, 224))
        tumor_prediction = multi_class_model.predict(img,verbose=0)
        print('The predicted tumor type is:', tumor_keys[np.argmax(tumor_prediction)])

        print()
    else:
        print(f"Image {i+1}: The brain scan is healthy.")
```

Results/Experimental Analysis (Metrics)

Table 1. Performance Metrics for MRI model stages

Type	Evaluation	F1-Score	AUC
Tumor Detection Model	*0.91*	0.89	0.99
Tumor Identification Model	*0.94*	0.87	0.96
Cascading Prediction	*0.88*	0.84	0.89

- The trained tumor detection model achieved an accuracy of 91% on the test set, with an F1 score of 0.89 and an AUC of 0.99.
- The trained tumor identification model achieved an accuracy of 94% on the test set, with an F1 score of 0.87 and an AUC of 0.96.
- The cascading prediction method combining both models achieved an accuracy of 88% on the test set, with an F1 score of 0.84 and an AUC of 0.89.

Figure 1. ROC curve after tumor detection and identification models

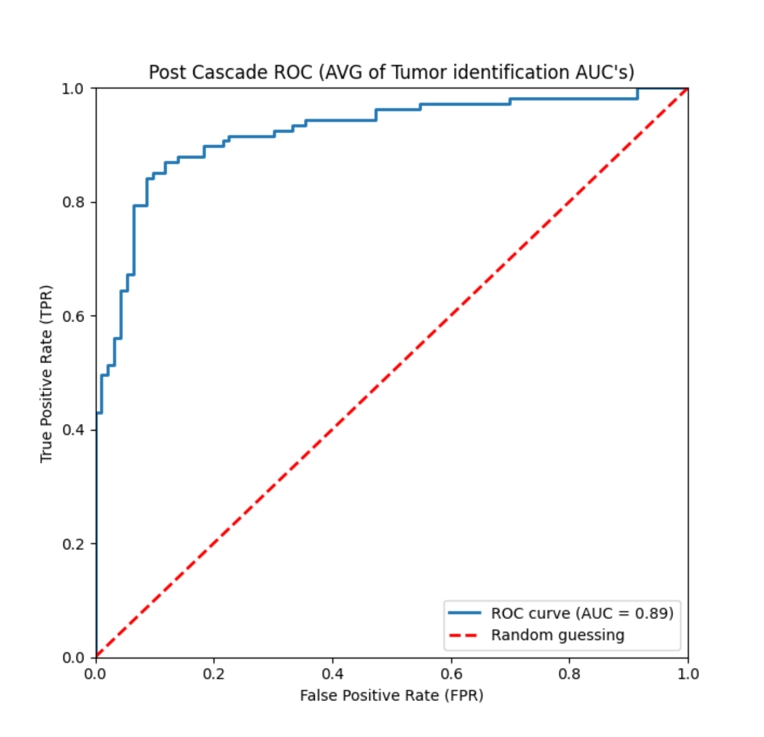
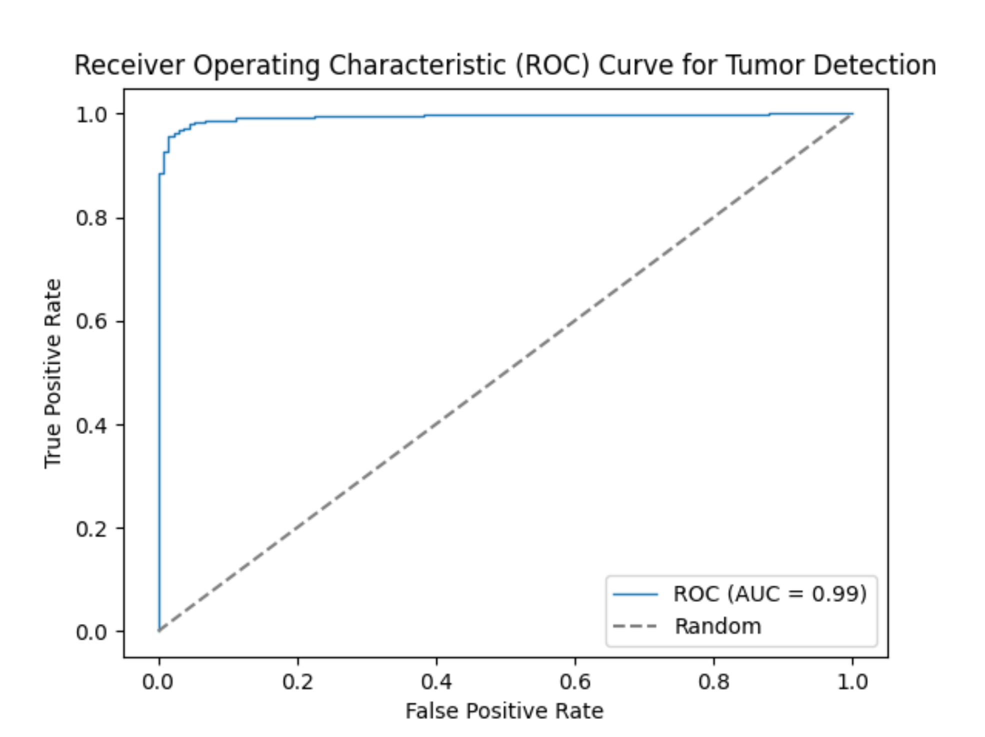


Figure 2. ROC curve for tumor detection model

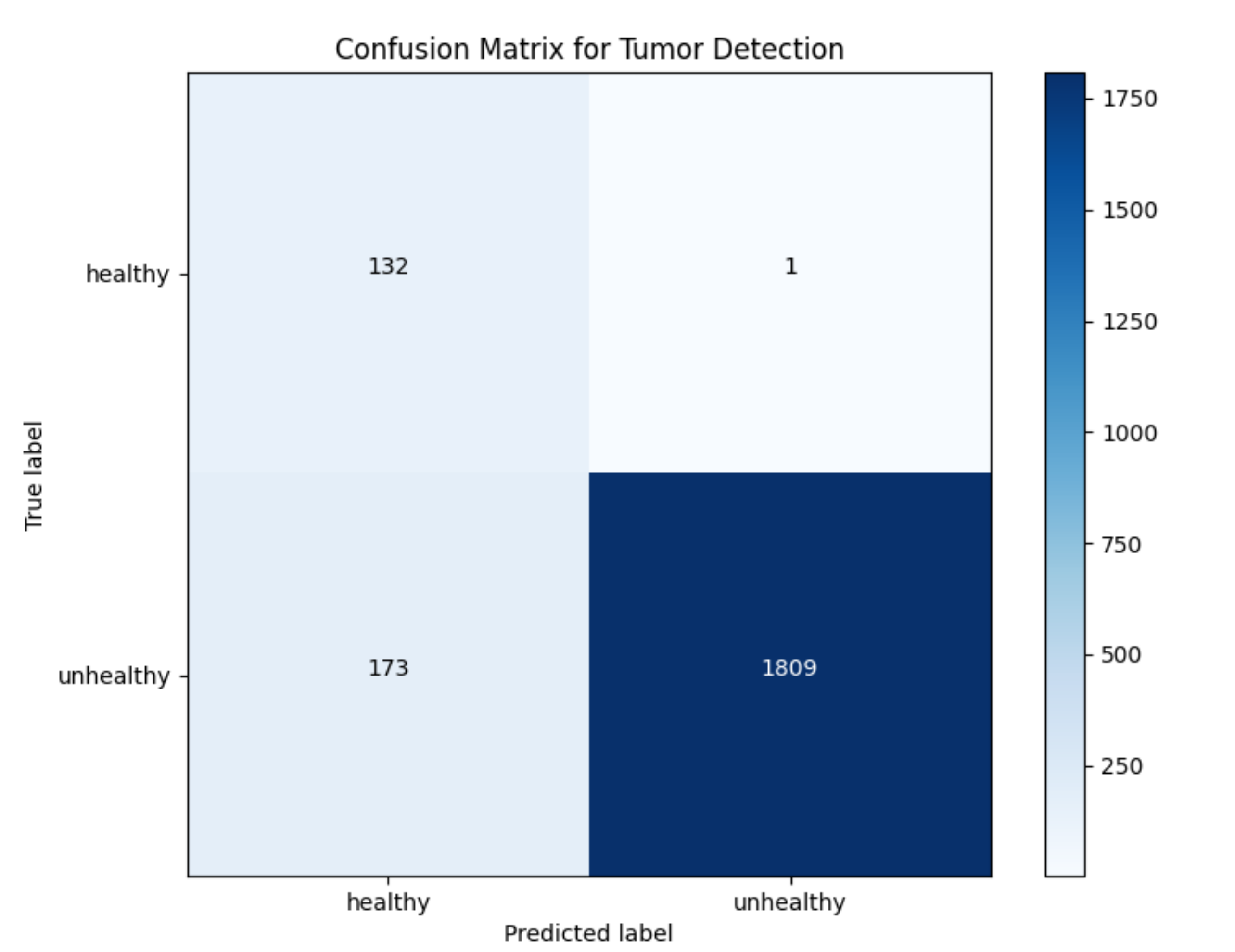


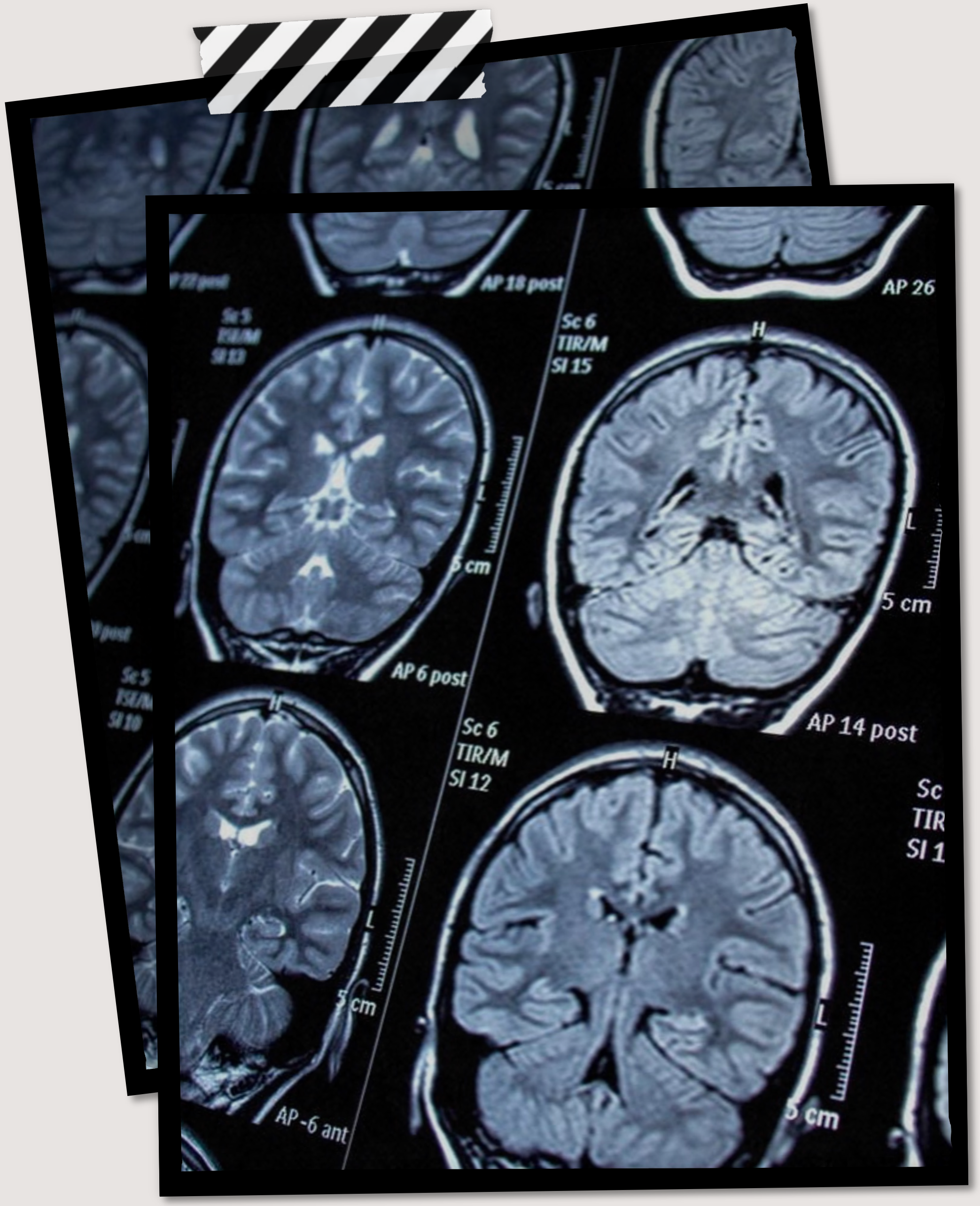
Results/Experimental Analysis (ROC Curve)

Confusion matrix

- I used confusion matrices to help in identifying trends and patterns in the data.
- This allowed for models and data to be adjusted accordingly to return expected results
- An example would be the tumor detection matrix, it allowed me to see that the model has some struggles classifying healthy scans.

Figure 3. Confusion Matrix for Binary Classification Model





Limitations

- Data sets could not be uploaded to GitHub as they consisted of multiple GB of photos. This means that models won't be able to run by those who are marking.
- Model Training time: Model training time was a limitation as each creation of a model would take about an hour and a half, meaning only so many iterations could be made
- Data: Although the data set is satisfactory, it could be further segmented to allow more granular decisions to be made
- Limited interpretability: Deep learning models can be difficult to interpret and understand. While the models developed in this study demonstrated high accuracy rates, it can be difficult to understand how the models are making their predictions.

Model Demo

Thank You