

BRAIN TUMOR CLASSIFICATION SYSTEM

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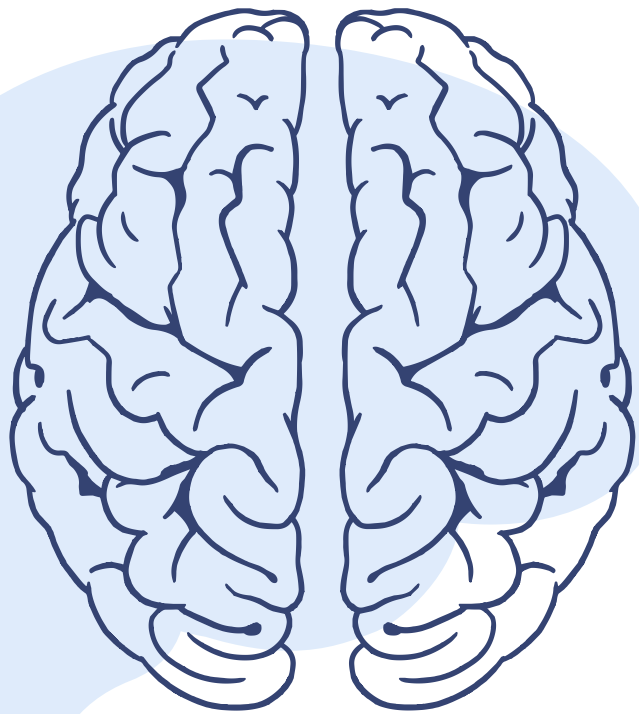
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01

INTRODUCTION

The background features abstract, light blue organic shapes. One large shape is in the top right corner, and another is in the bottom left corner. There are also some smaller, fainter shapes scattered around.

PROBLEM STATEMENT

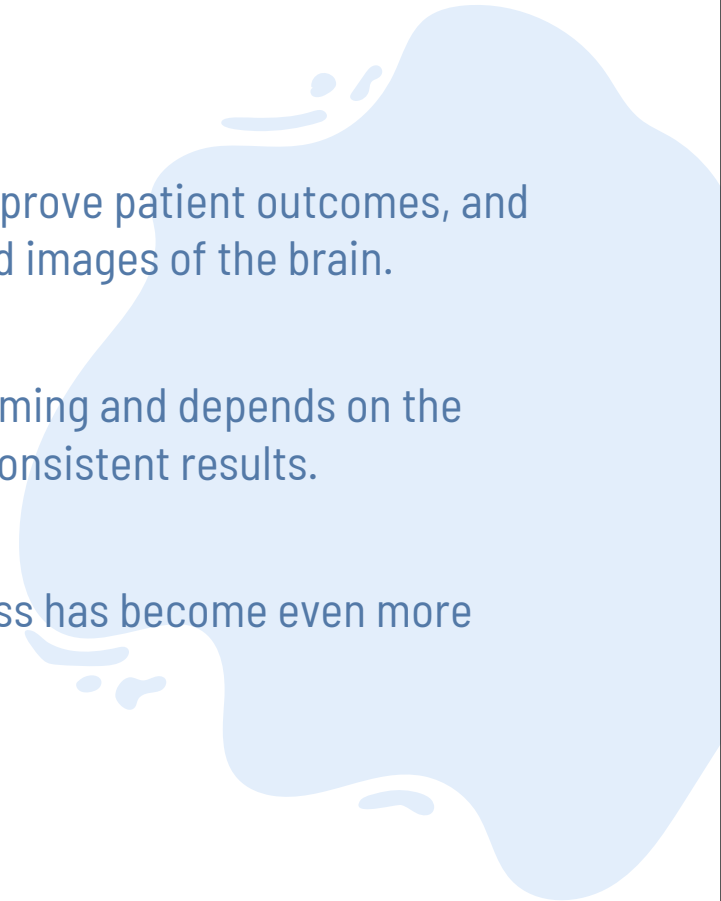
There is a need for an automated system that accurately classifies brain tumors from MRI images to support faster and more reliable diagnosis.

THE ISSUE AT HAND

Brain tumors require early and accurate diagnosis to improve patient outcomes, and MRI scans are widely used because they provide detailed images of the brain.

However, manually analyzing these scans is time-consuming and depends on the radiologist's experience, which can lead to delays or inconsistent results.

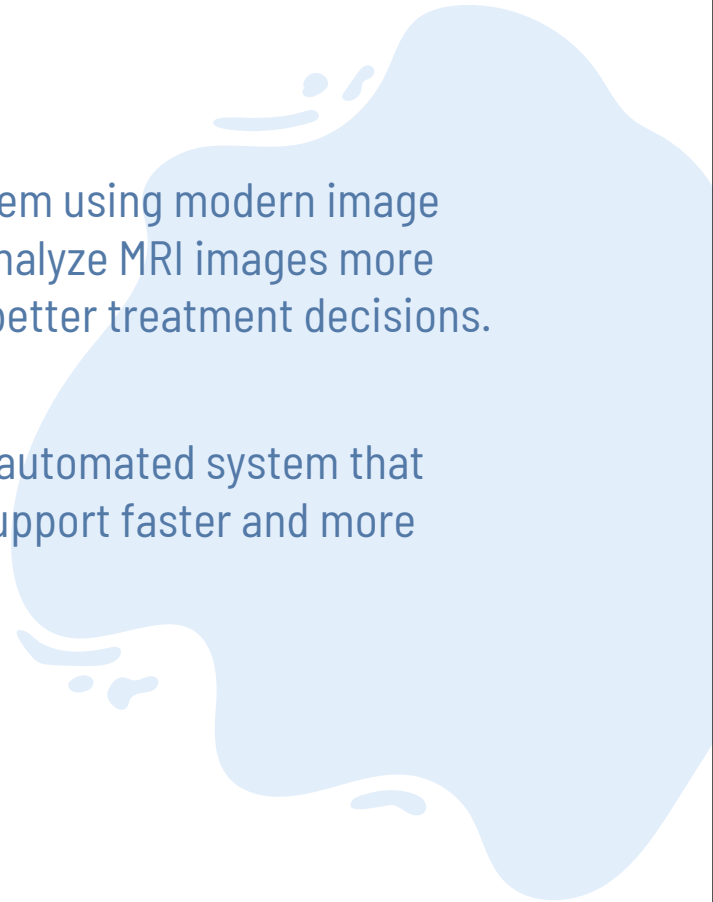
With the growing number of medical images, this process has become even more challenging.

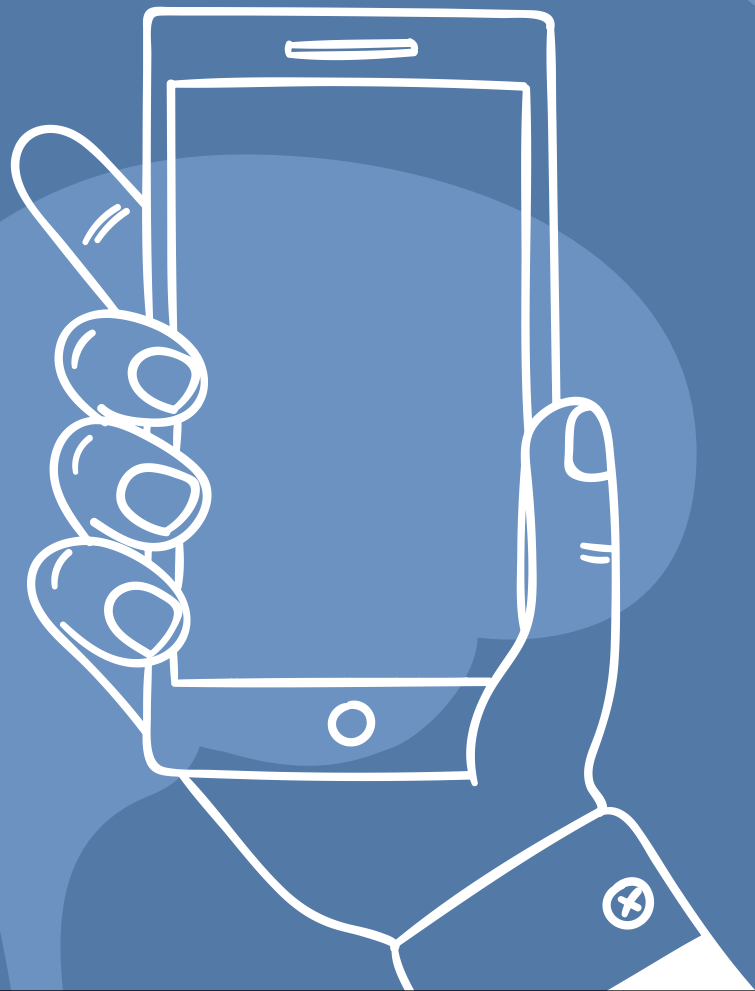


THE SOLUTION

Therefore, an automated brain tumor classification system using modern image processing and deep learning techniques is needed to analyze MRI images more efficiently, reduce errors, and assist doctors in making better treatment decisions.

The next few slides outline our attempt at producing an automated system that accurately classifies brain tumors from MRI images to support faster and more reliable diagnosis.





DATA

DATASET USED

The name of the dataset is Brain Tumor MRI Images 44 Classes. It is a collection of T1, contrast-enhanced T1, and T2 MRI images of brain tumor.

The dataset consists of images without any type of marking or patient identification, interpreted by radiologists and provided for study purposes.

Includes 14 types of brain tumors.

Dataset Link: <https://www.kaggle.com/datasets/fernando2rad/brain-tumor-mri-images-44c/data>

DATASET USED

The dataset included 15 classes;

1. Astrocytoma
2. Carcinoma
3. Ependymoma
4. Ganglioglioma
5. Germinoma
6. Glioblastoma
7. Granuloma
8. Medulloblastoma
9. Meningioma
10. Neurocytoma



DATASET SAMPLES

_NORMAL



Meningioma



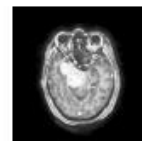
Glioblastoma



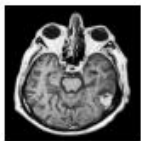
_NORMAL



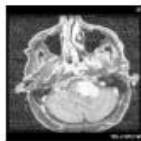
Schwannoma



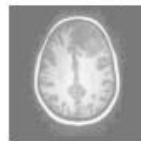
Carcinoma



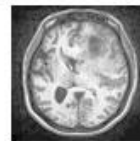
Schwannoma



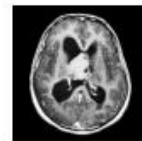
Oligodendroglioma



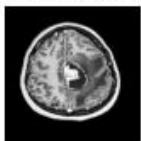
Oligodendroglioma



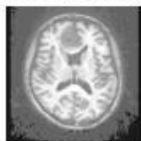
Neurocitoma



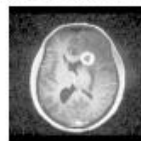
Meningioma



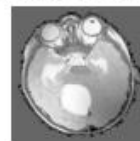
Oligodendroglioma



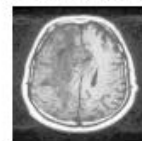
Tuberculoma



Astrocitoma



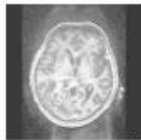
Meningioma



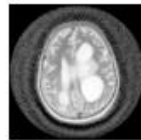
_NORMAL



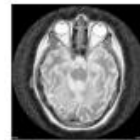
Glioblastoma



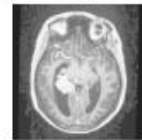
Neurocitoma



Meduloblastoma



Meningioma



Carcinoma



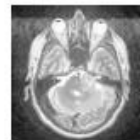
Oligodendroglioma



Neurocitoma



Schwannoma



Astrocitoma

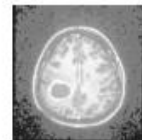


IMAGE PROCESSING

Averaging Filter

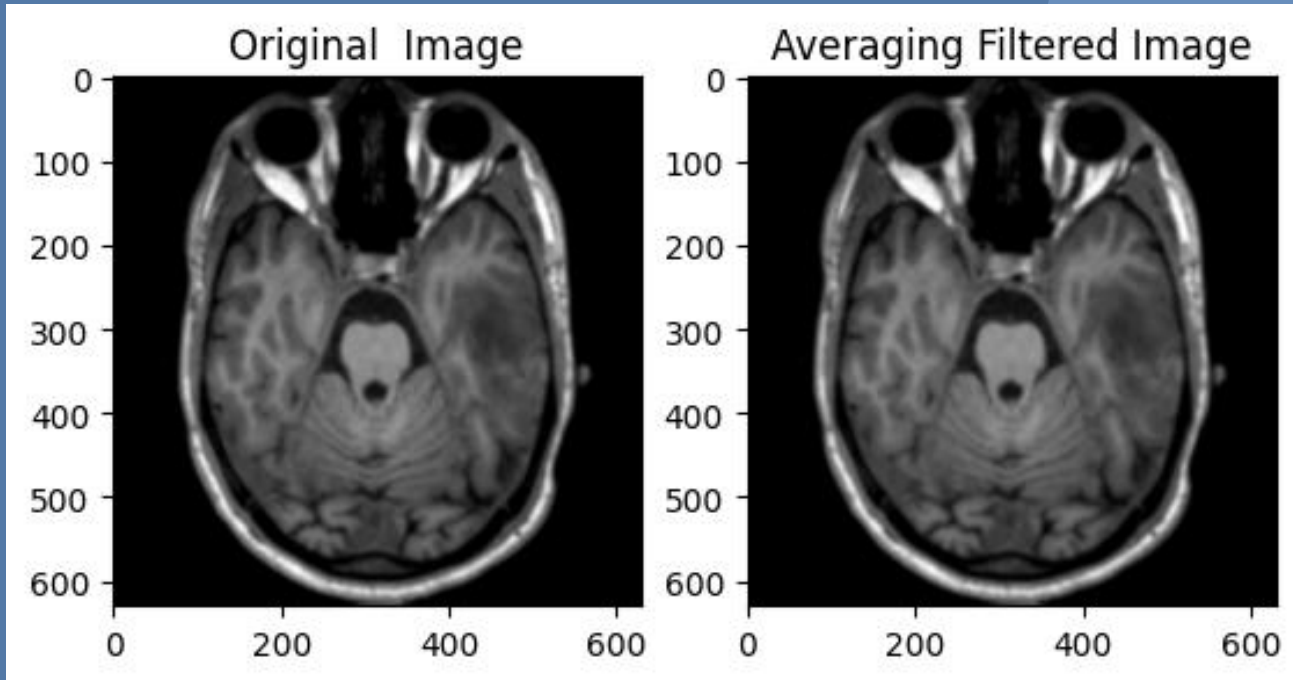


IMAGE PROCESSING

Median Filter

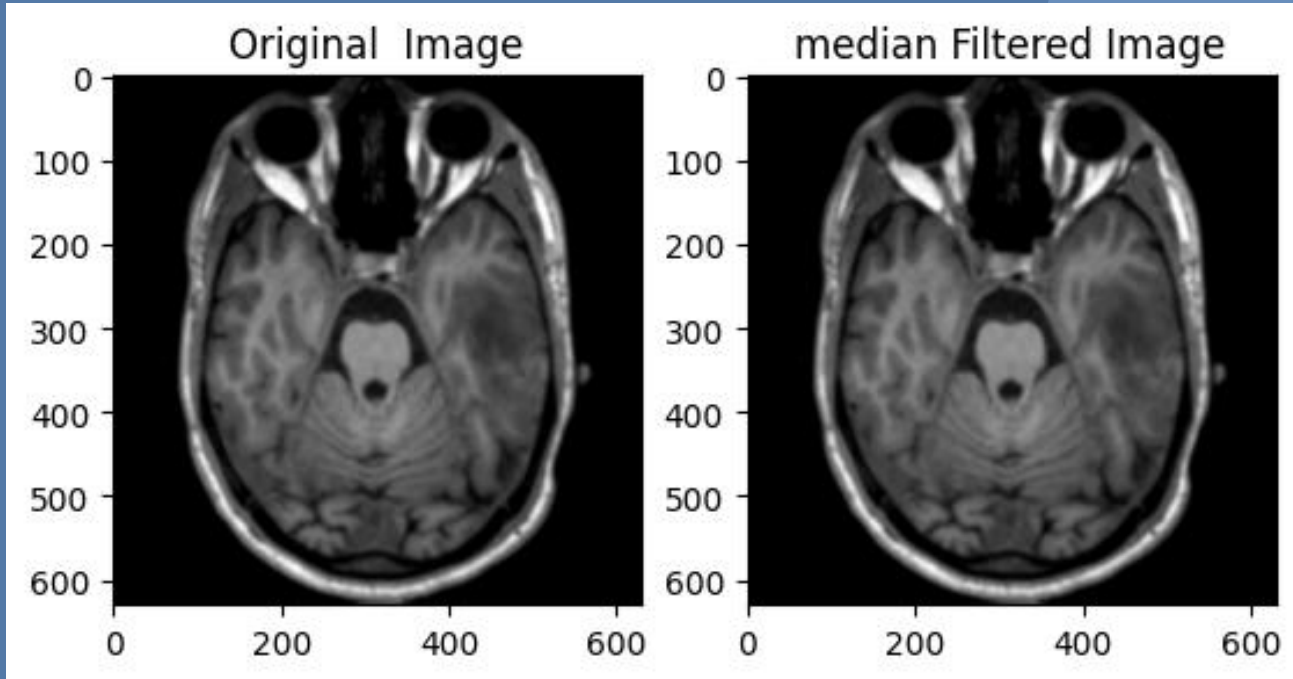


IMAGE PROCESSING

Gaussian Filter

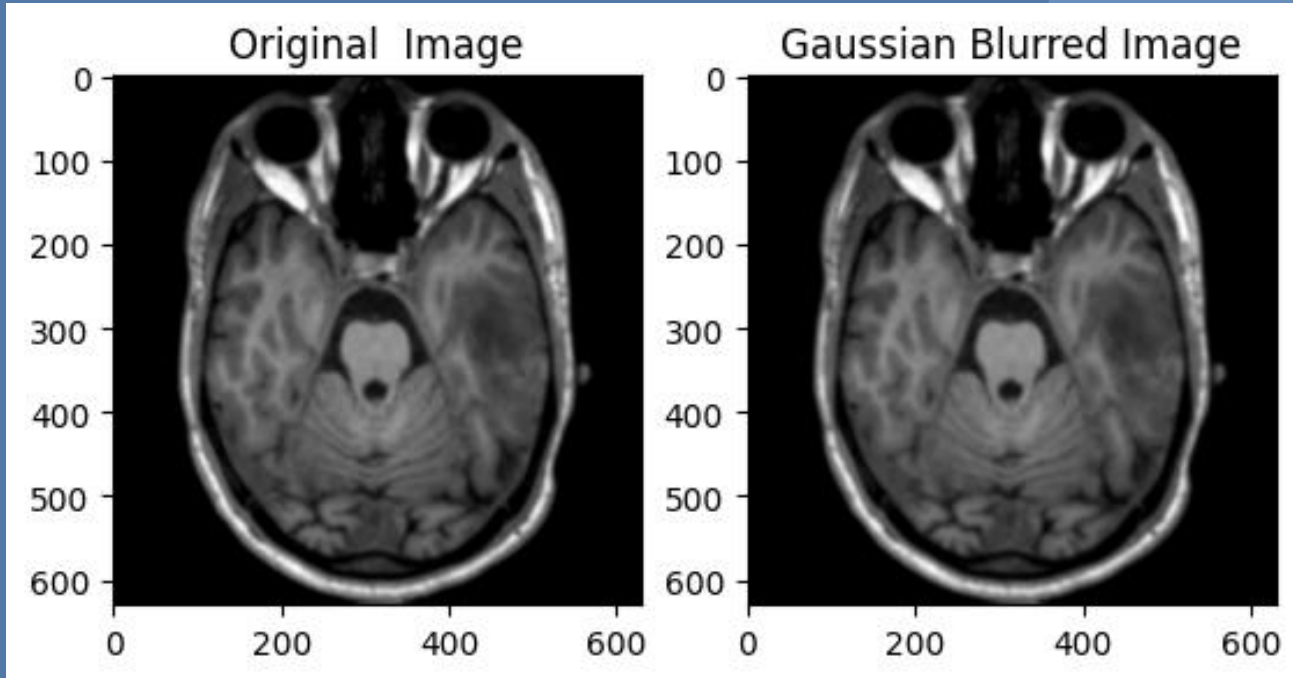


IMAGE PROCESSING

Bilateral Filter

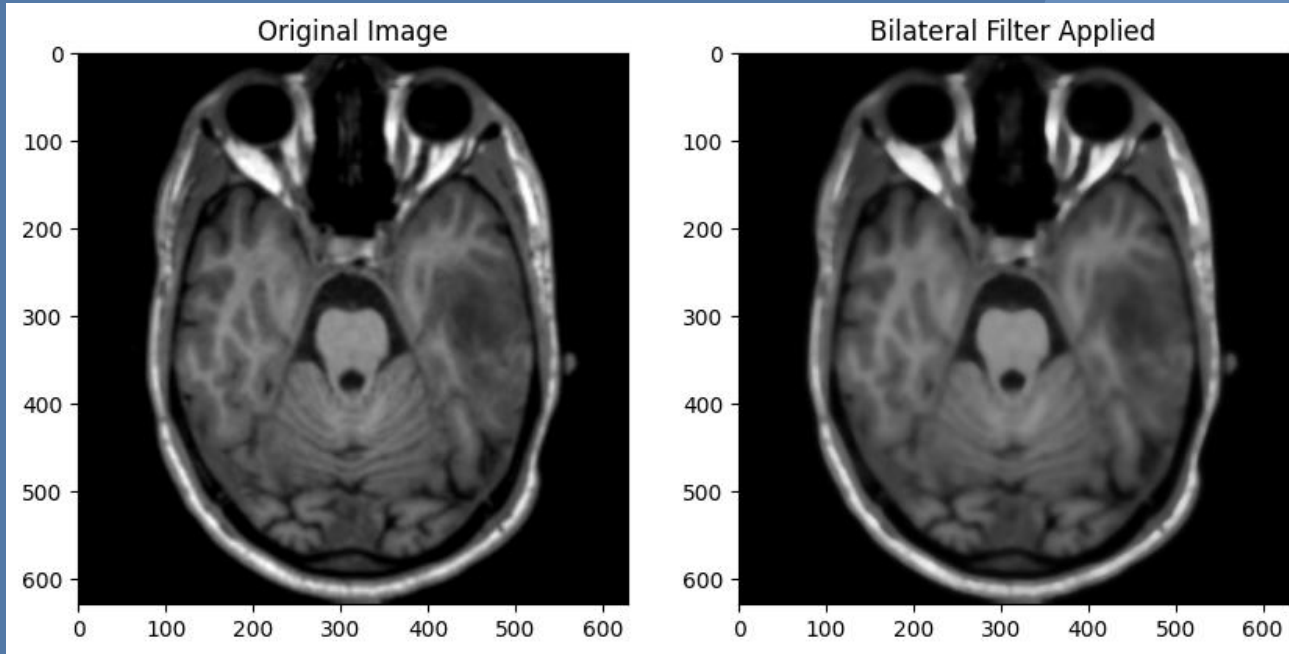


IMAGE PROCESSING

Outlier Method

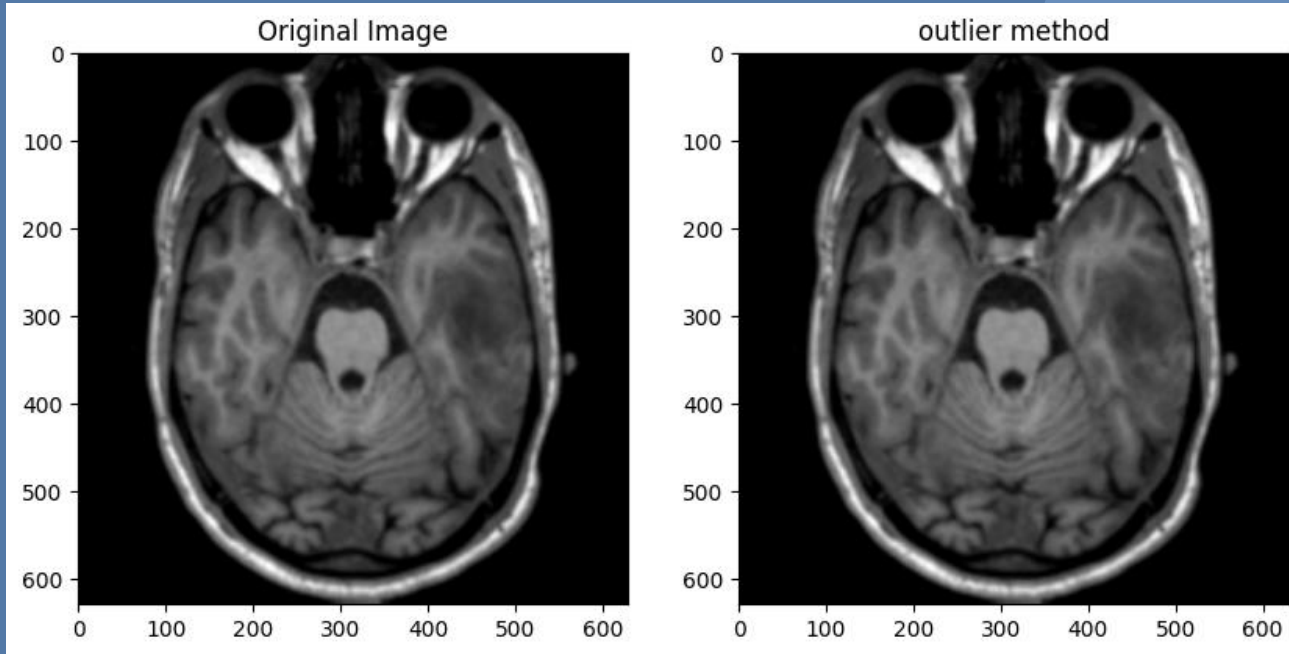


IMAGE PROCESSING

Prewitt Filter

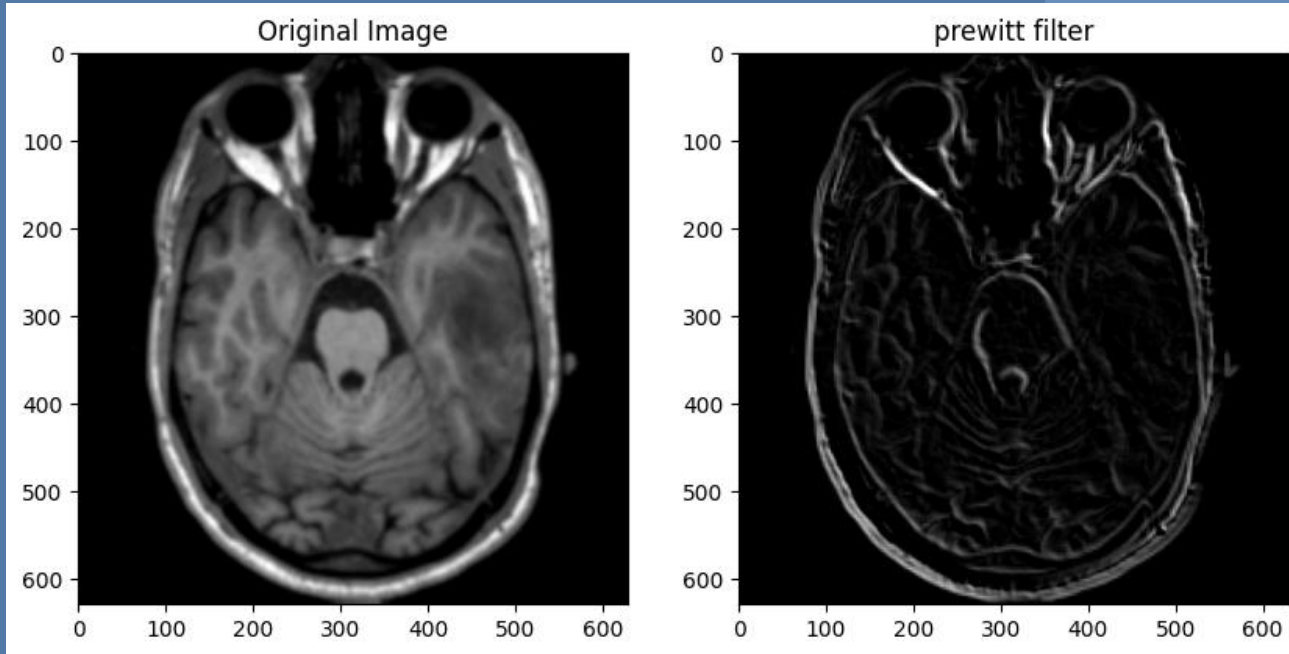


IMAGE PROCESSING

Sobel Filter

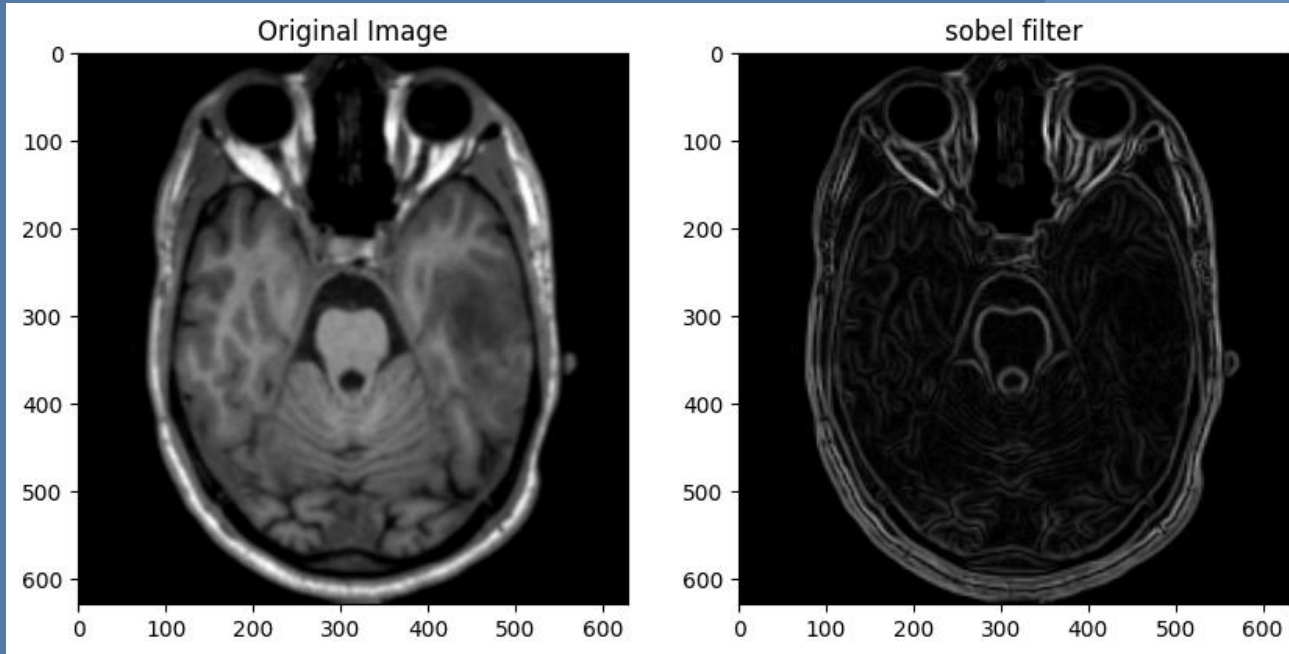


IMAGE PROCESSING

Contrast Stretching

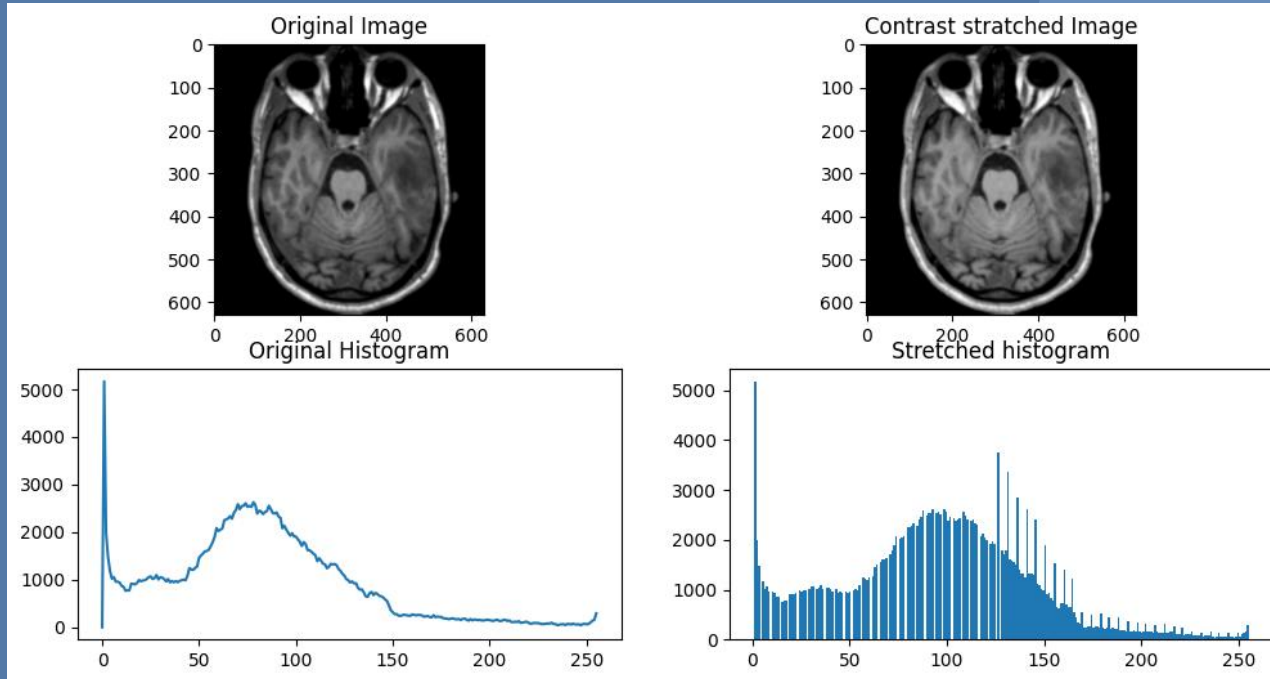


IMAGE PROCESSING

Thresholding

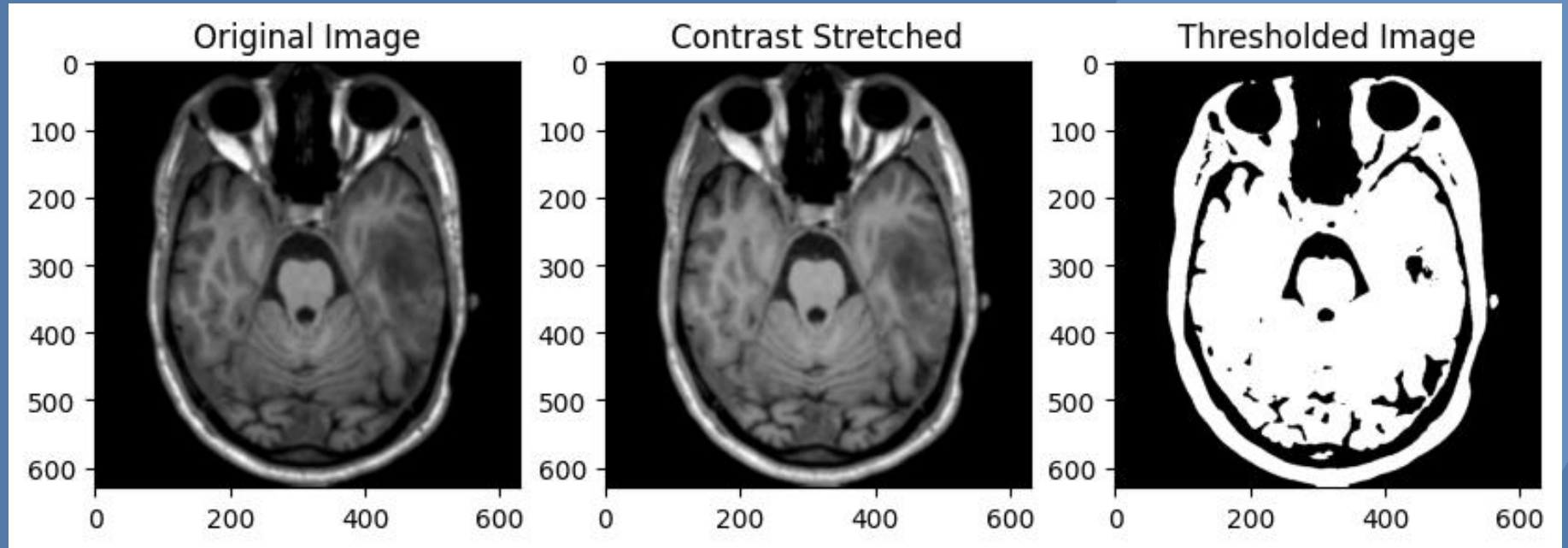


IMAGE PROCESSING

Histogram Equalization

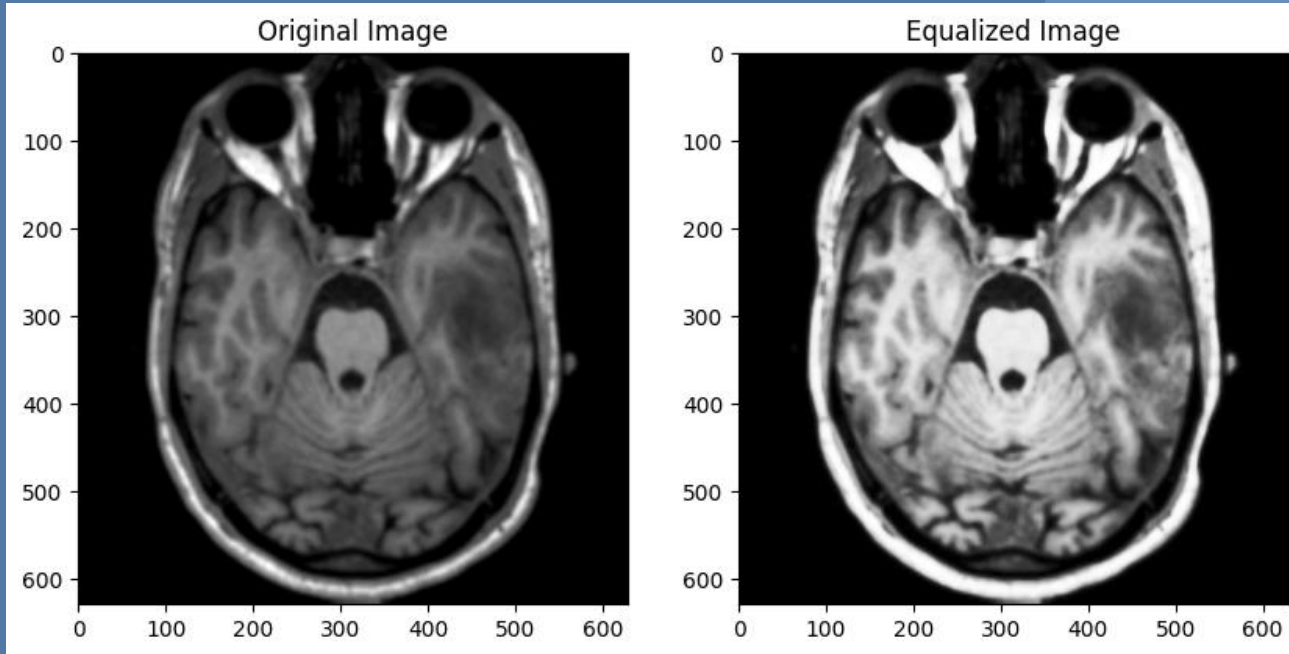


IMAGE PROCESSING

Negative Transformation

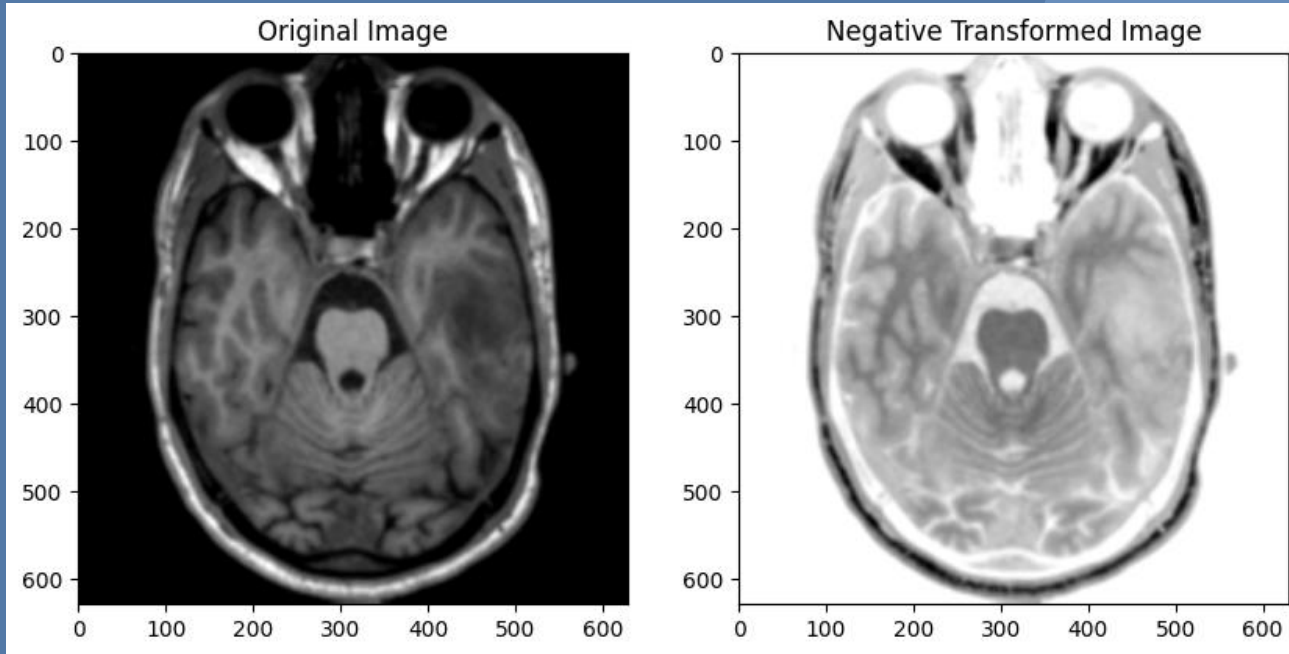
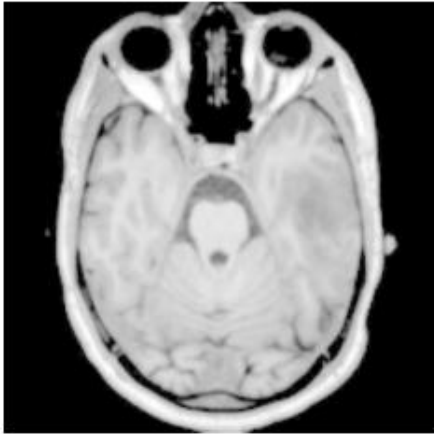


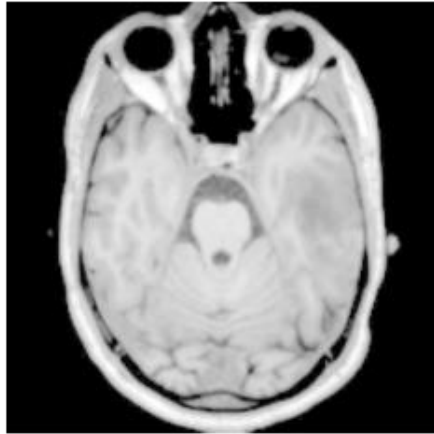
IMAGE PROCESSING

Logarithmic Transformation

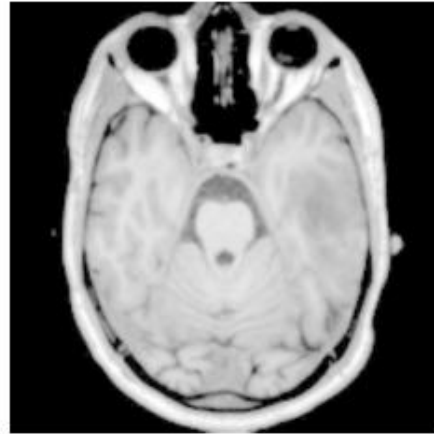
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$c = 1$



$c = 5$



$c = 10$

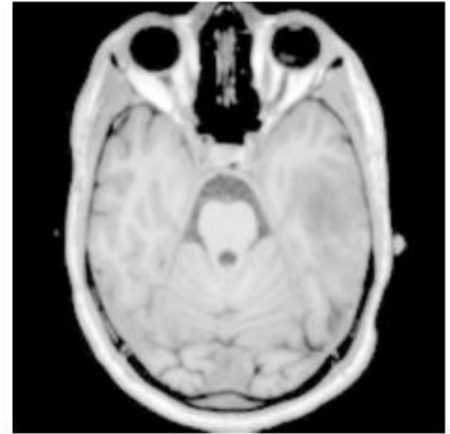
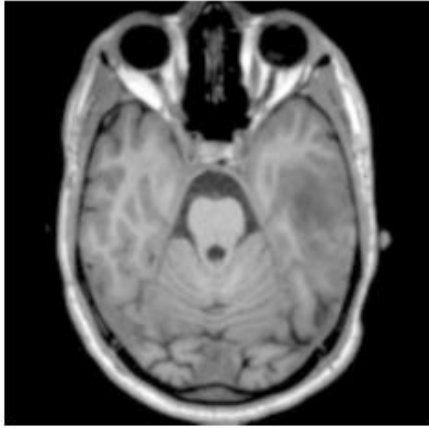


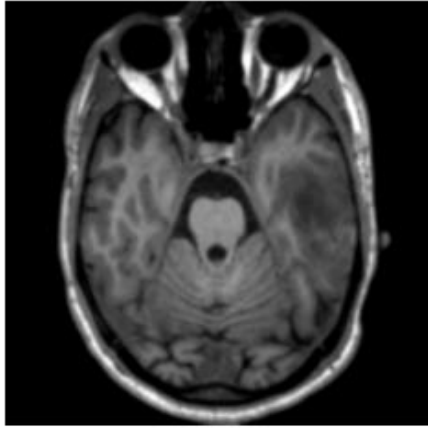
IMAGE PROCESSING

Gamma Transformation

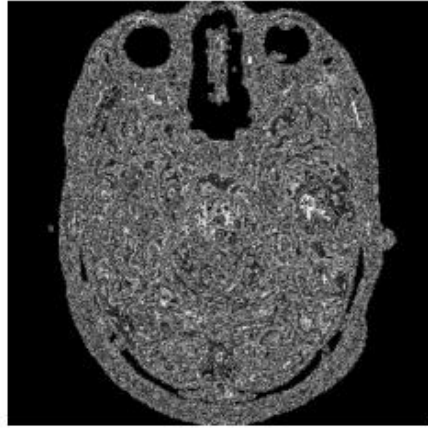
$c = 0.5$



$c = 1$



$c = 5$



$c = 10$

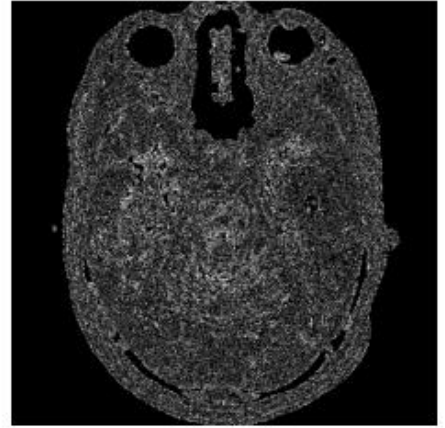


IMAGE PROCESSING

Low Pass Filtering

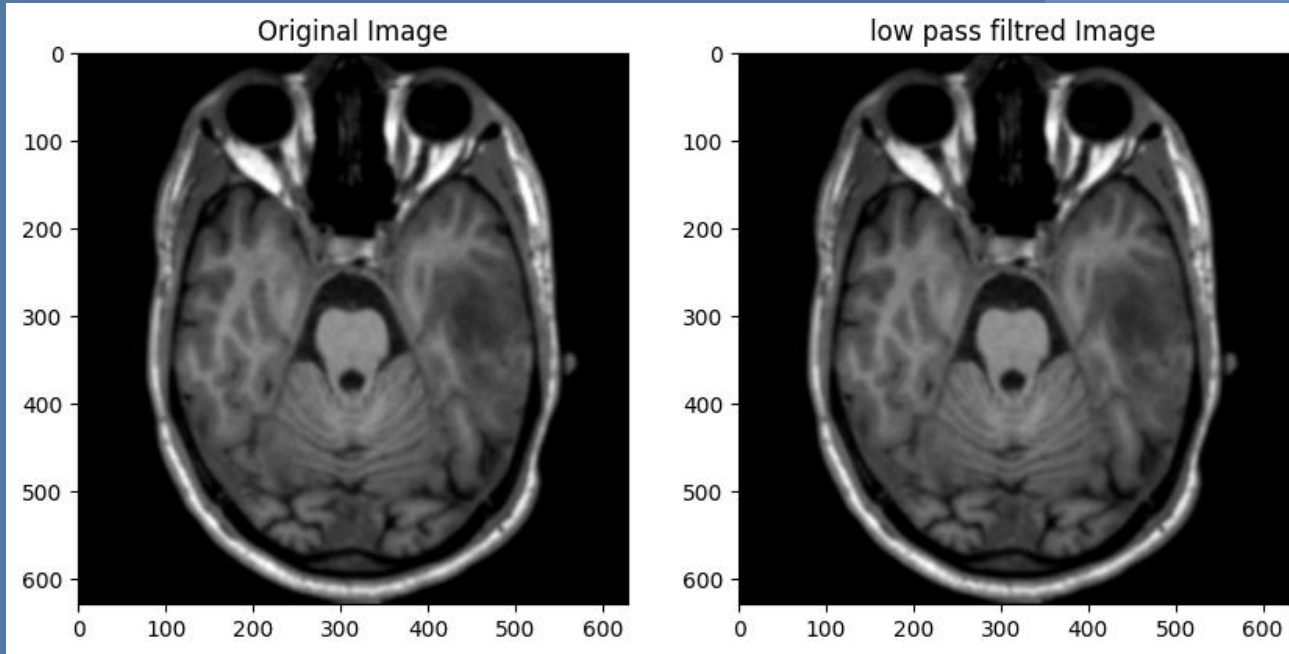
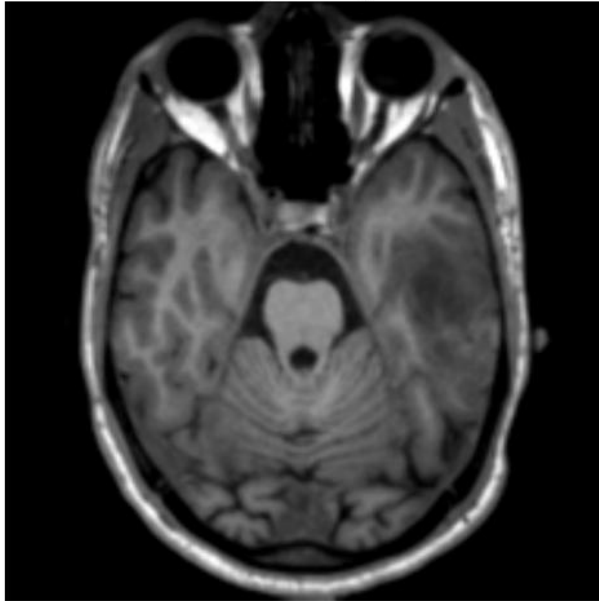


IMAGE PROCESSING

Butterworth Lowpass Filtering

Original Image



Butterworth Lowpass Filtered Image

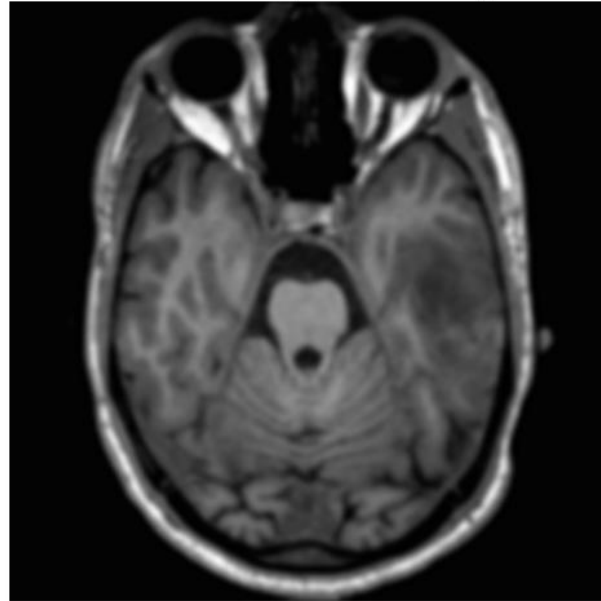


IMAGE PROCESSING

High Pass Filter

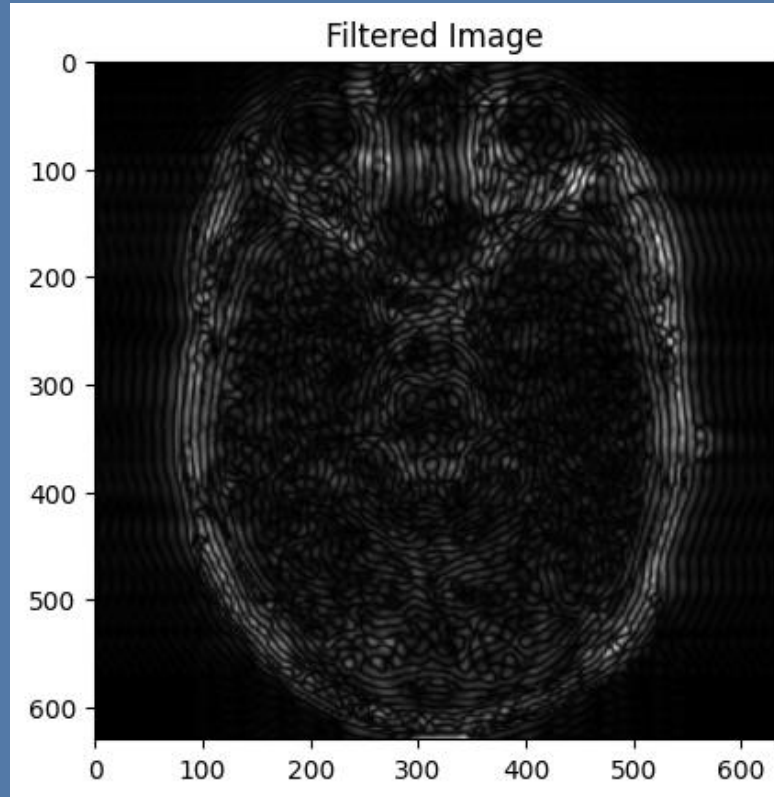
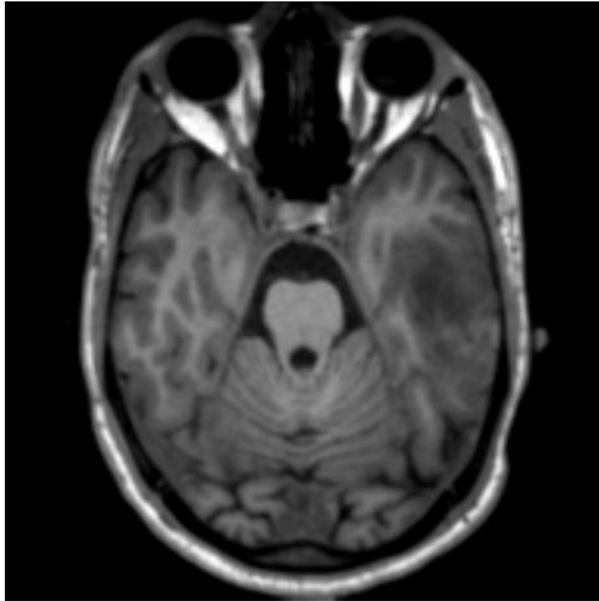


IMAGE PROCESSING

Butterworth Lowpass Filtering

Original Image



Butterworth Lowpass Filtered Image

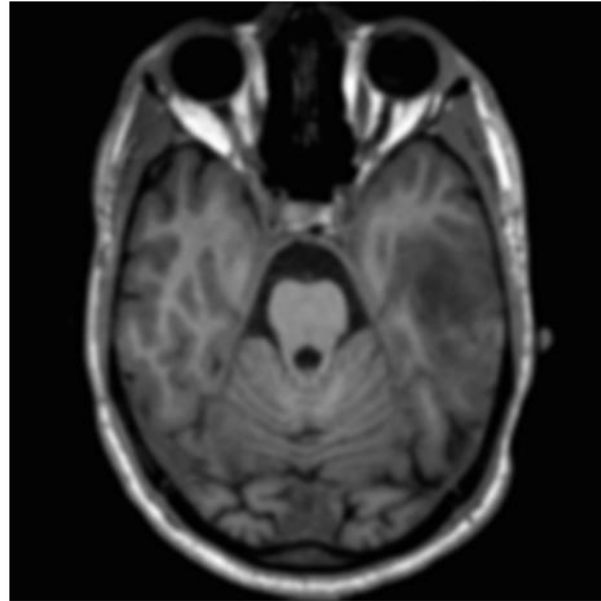
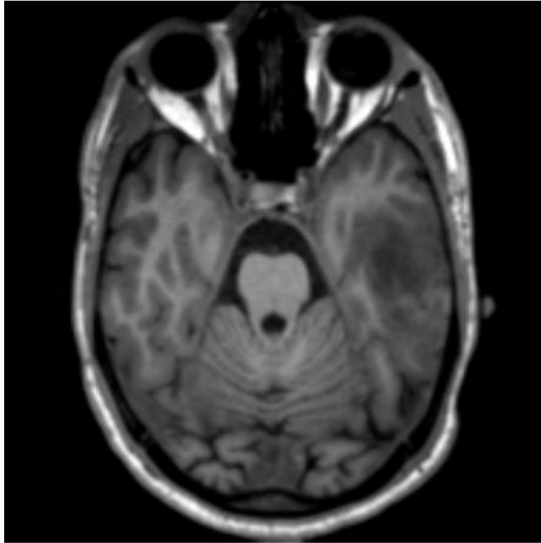


IMAGE PROCESSING

Dilation Filter

Original Image



Dilated Image

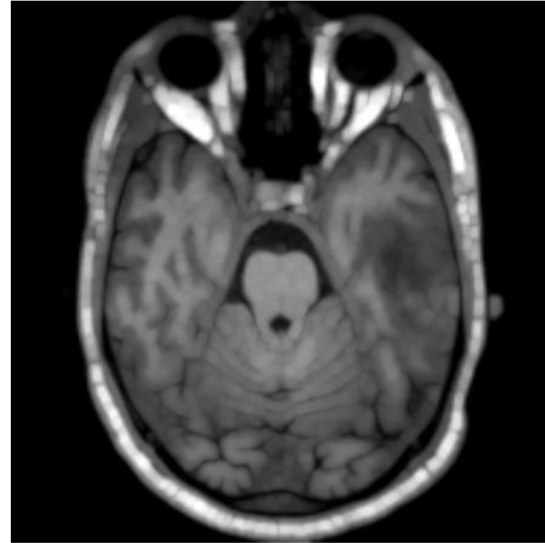
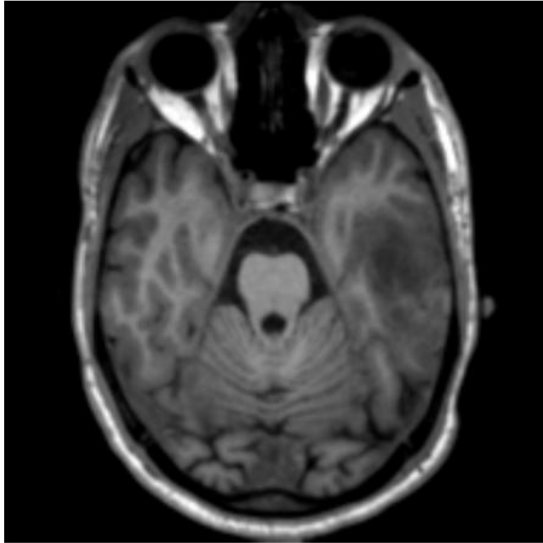


IMAGE PROCESSING

Erosion Filter

Original Image



Eroded Image

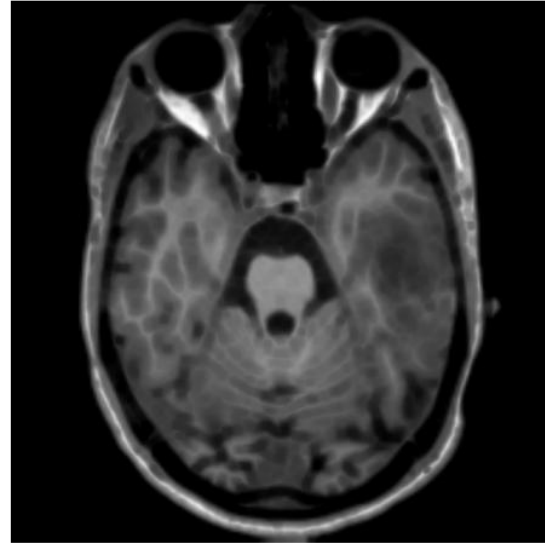
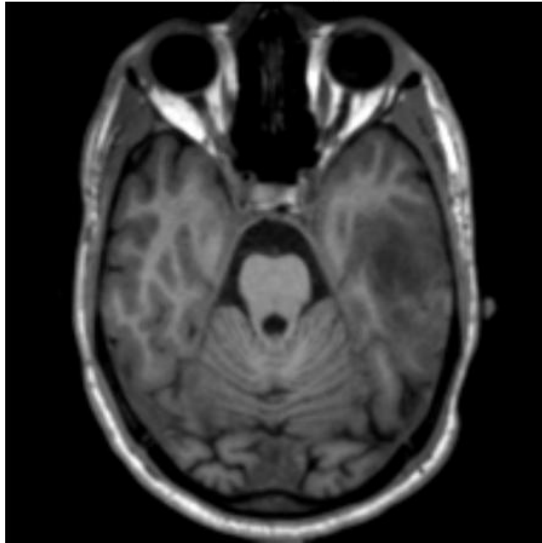


IMAGE PROCESSING

Closing Filter

Original Image



Closing Filter

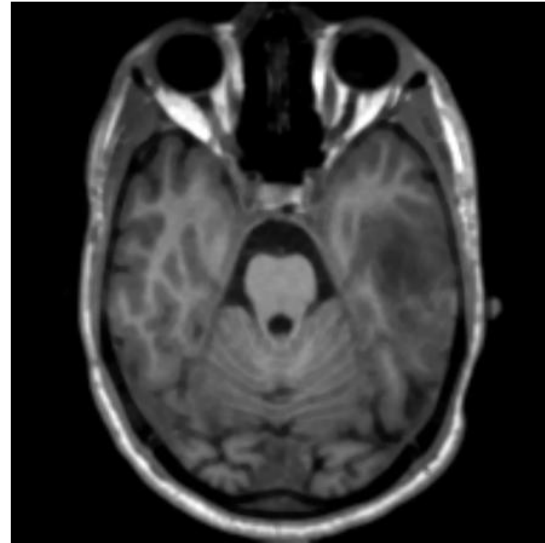
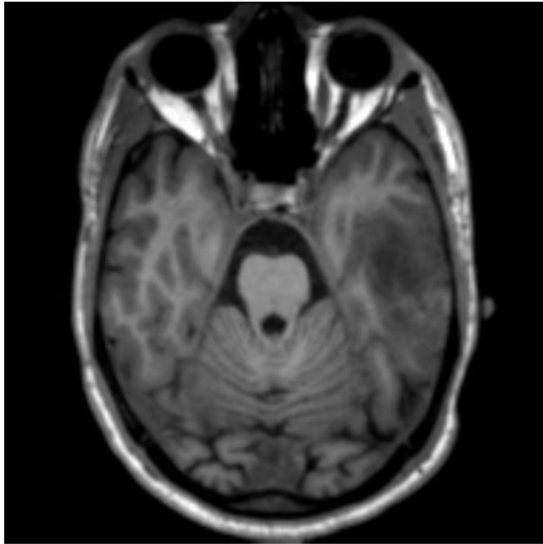


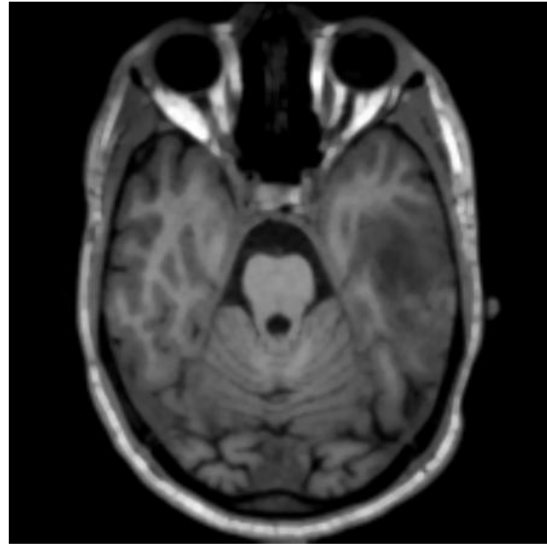
IMAGE PROCESSING

Opening Filter

Original Image



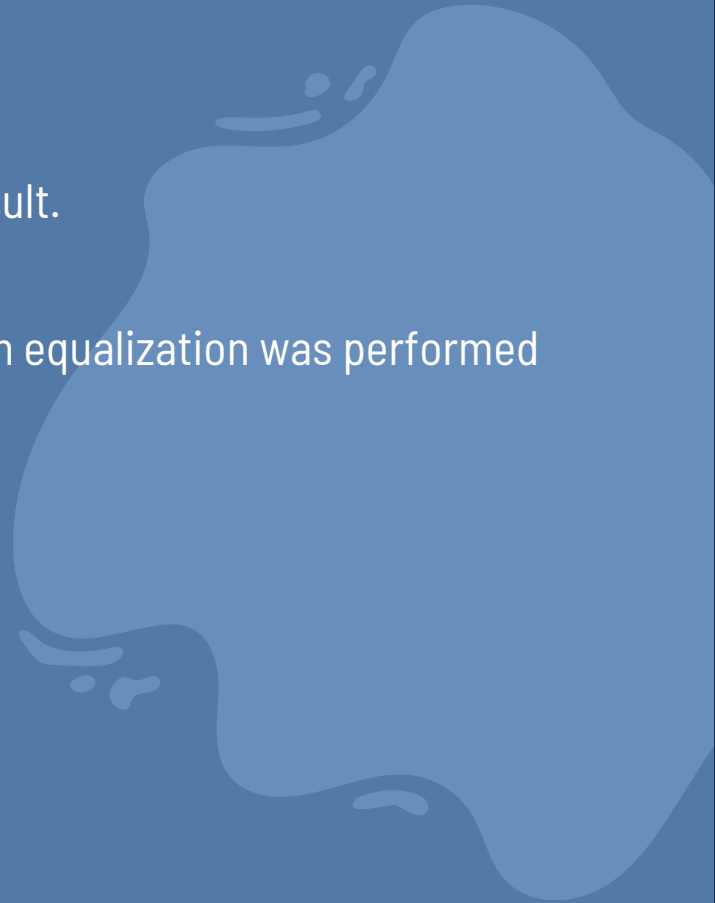
Opening Filter



PRE-PROCESSING

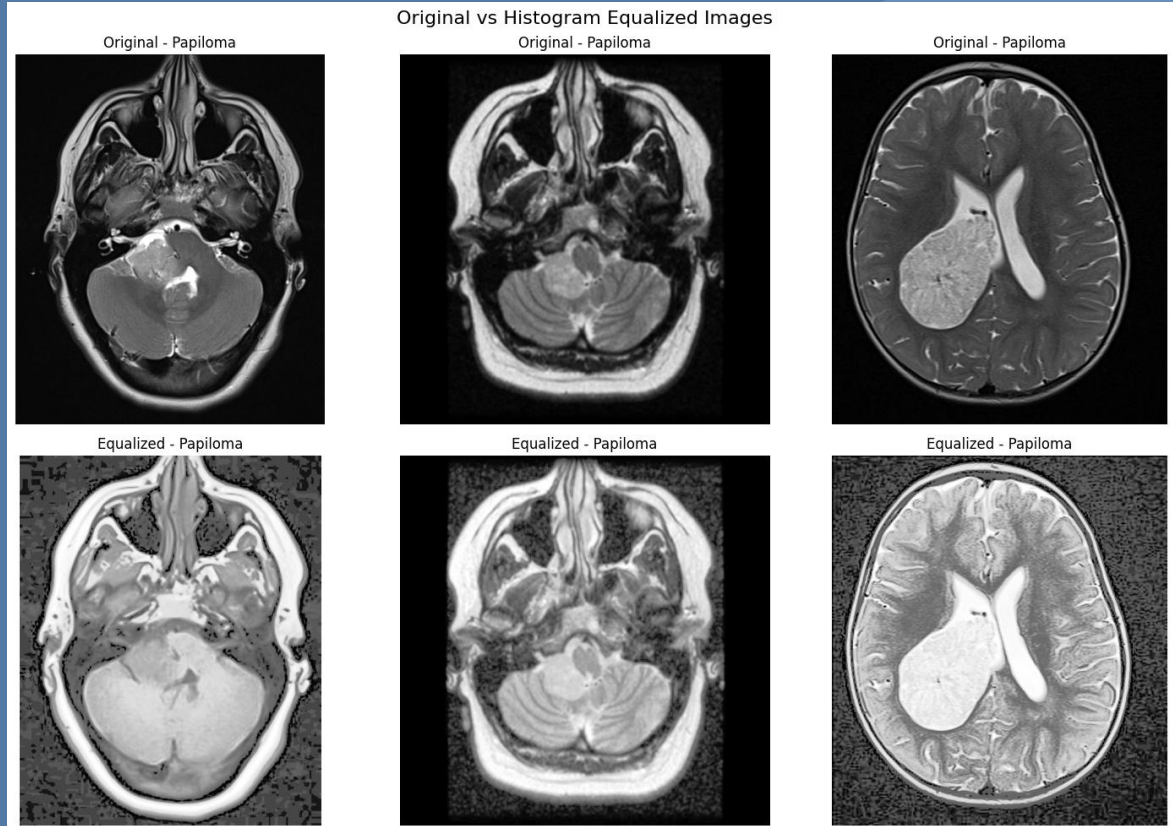
Histogram Equalization provided the most satisfying result.

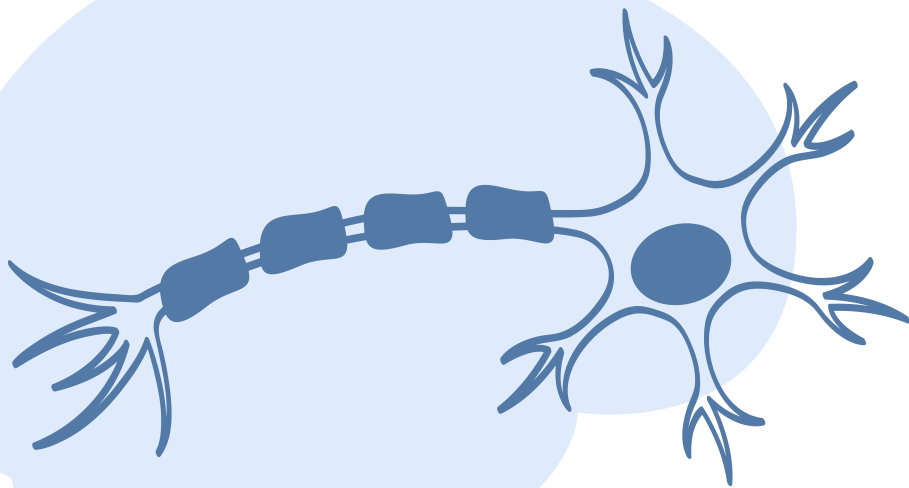
The dataset was turned into a Data Frame and histogram equalization was performed on the entire Data Frame.



PRE-PROCESSING

Samples of
preprocessed data





03 MODEL

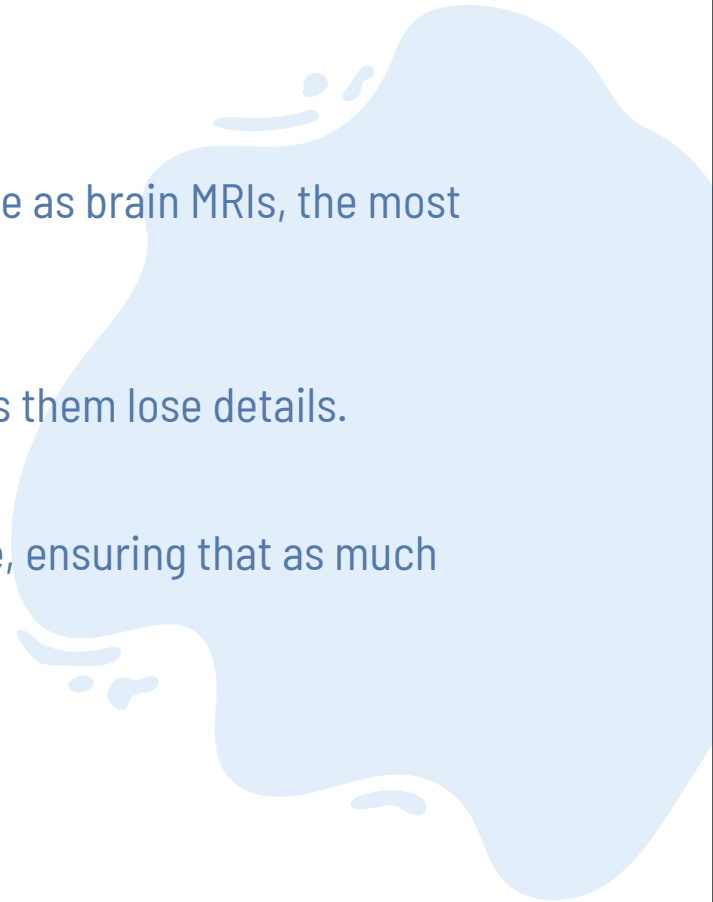
MODEL SELECTION

To perform deep learning on medical imagery as intricate as brain MRIs, the most details have to be preserved.

Dense Neural Networks flatten images first which makes them lose details.

However, CNNs work by moving a filter across the image, ensuring that as much detail as possible is considered.

EfficientNetB5 is one such CNN.

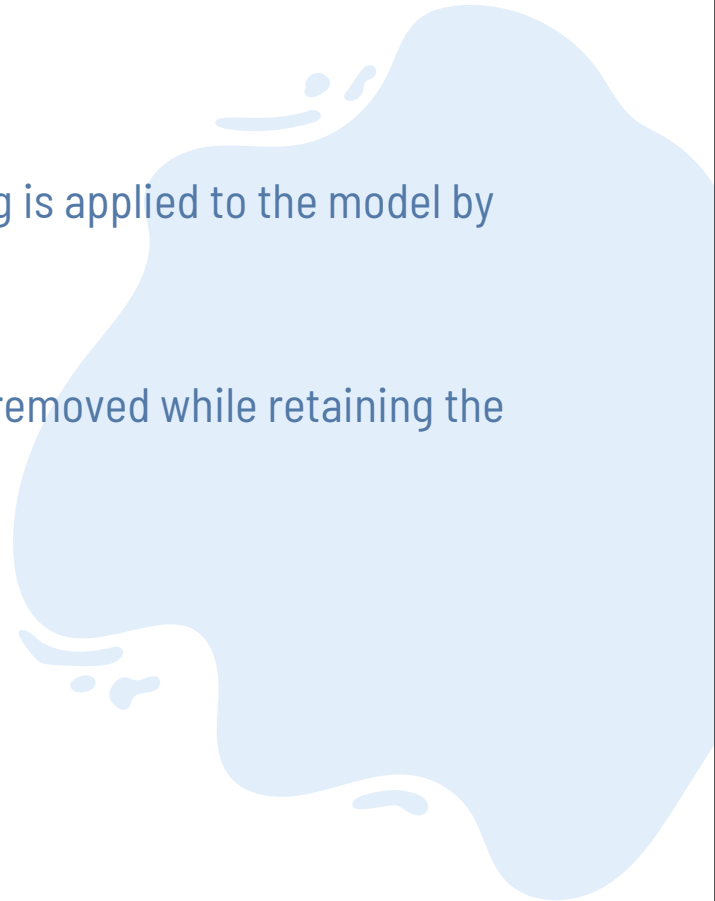


LOADING MODEL

EfficientNetB5 is a pretrained model so transfer learning is applied to the model by training it on the brain MRI images.

However, this meant that the original classes had to be removed while retaining the weights by using;

```
Include_top=False  
weights='imagenet',
```



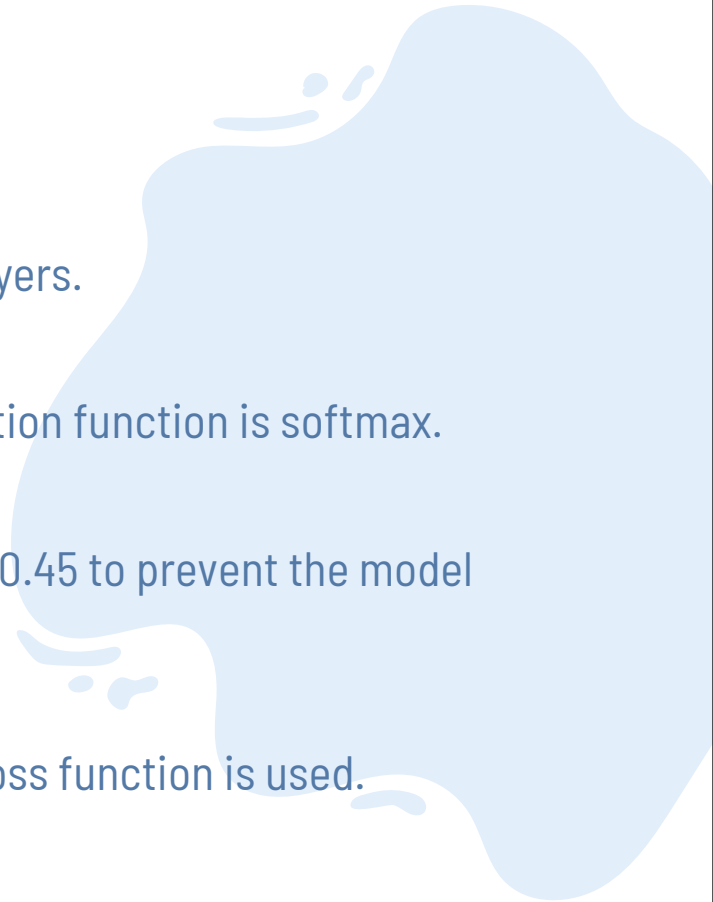
ALTERING MODEL

Three layers were added;

1. Flatten Layer to turn data into 1D vector for dense layers.
2. Dense layer, 256 nodes with activation relu
3. Dense layer, 15 nodes the classification layer, activation function is softmax.

Batch Normalization is used as well as a dropout rate of 0.45 to prevent the model from depending on some nodes.

Adam optimizer is used and Categorical Crossentropy Loss function is used.

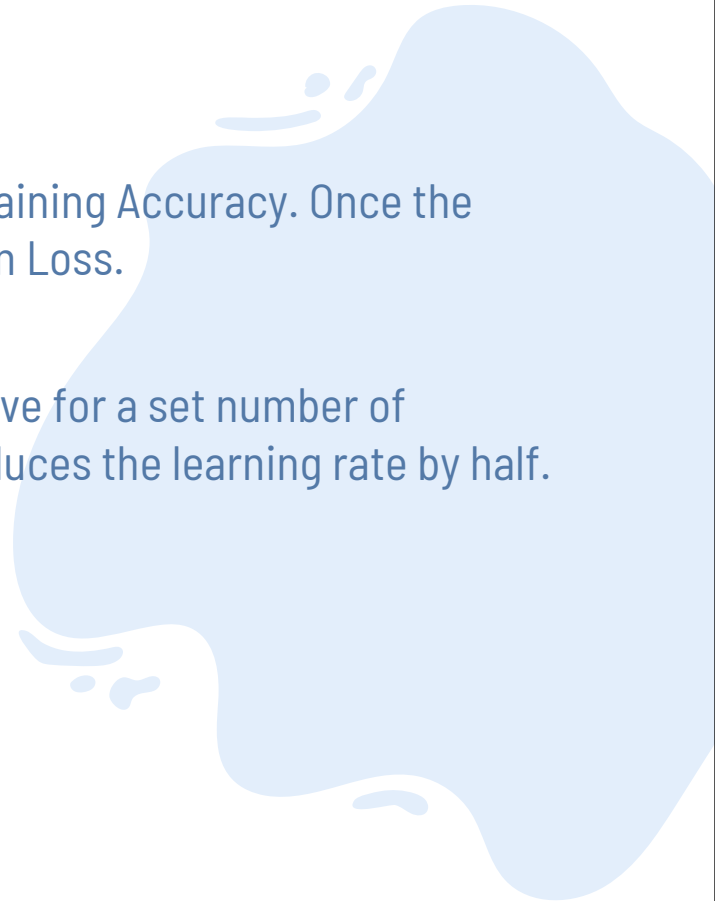


CALLBACKS

While accuracy is below 90%, the callback prioritizes Training Accuracy. Once the model hits 90% accuracy, the priority shifts to Validation Loss.

If the metric (Accuracy or Validation Loss) doesn't improve for a set number of epochs the callback assumes the model is stuck and reduces the learning rate by half.

Best weights are saved to prevent any late overfitting.

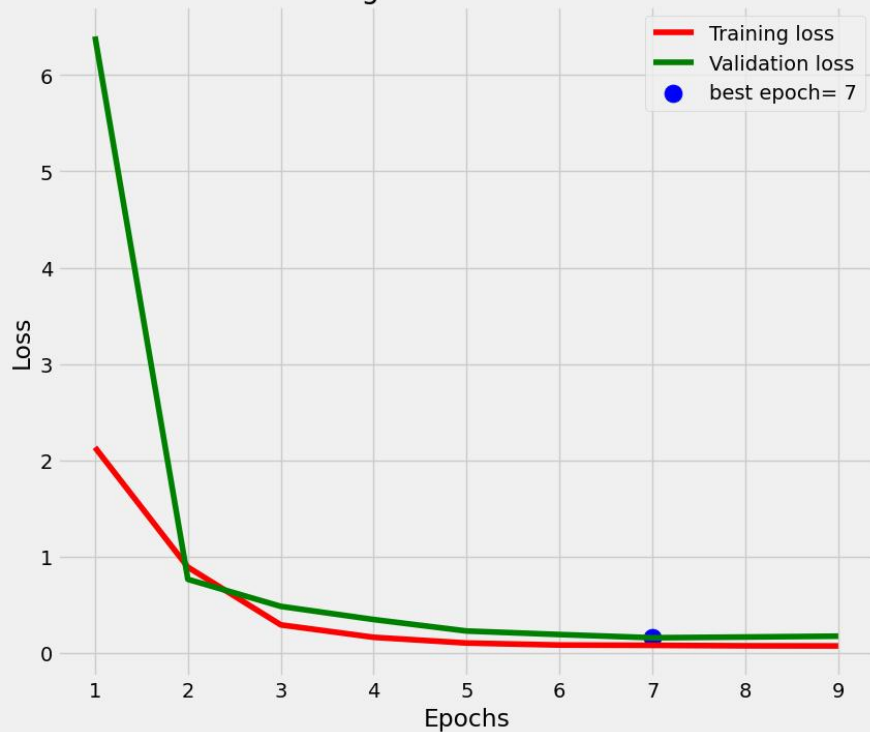




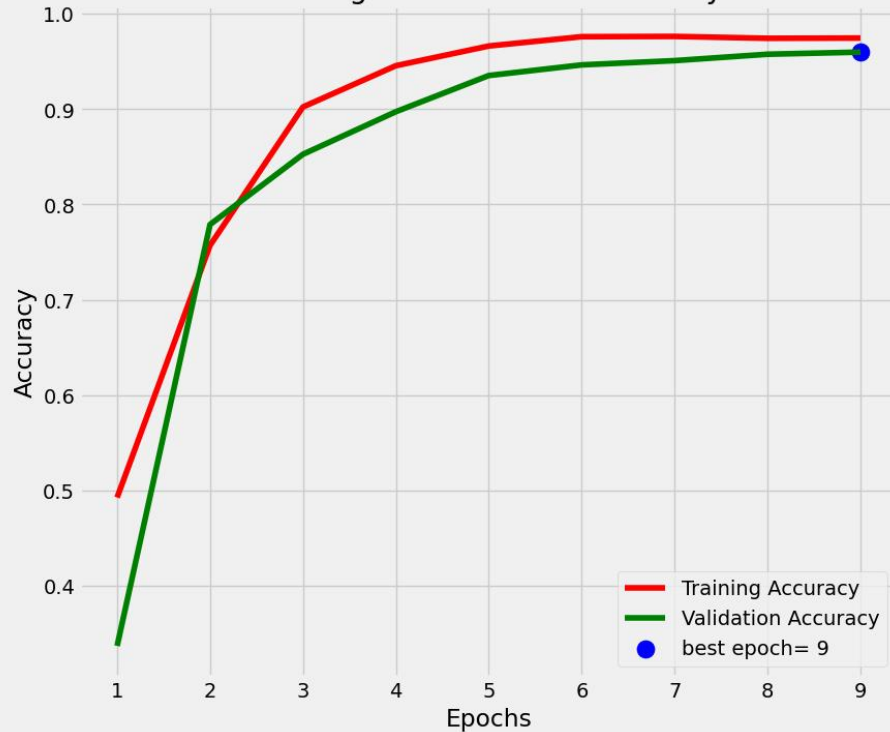
RESULTS

LOSS AND ACCURACY CURVES

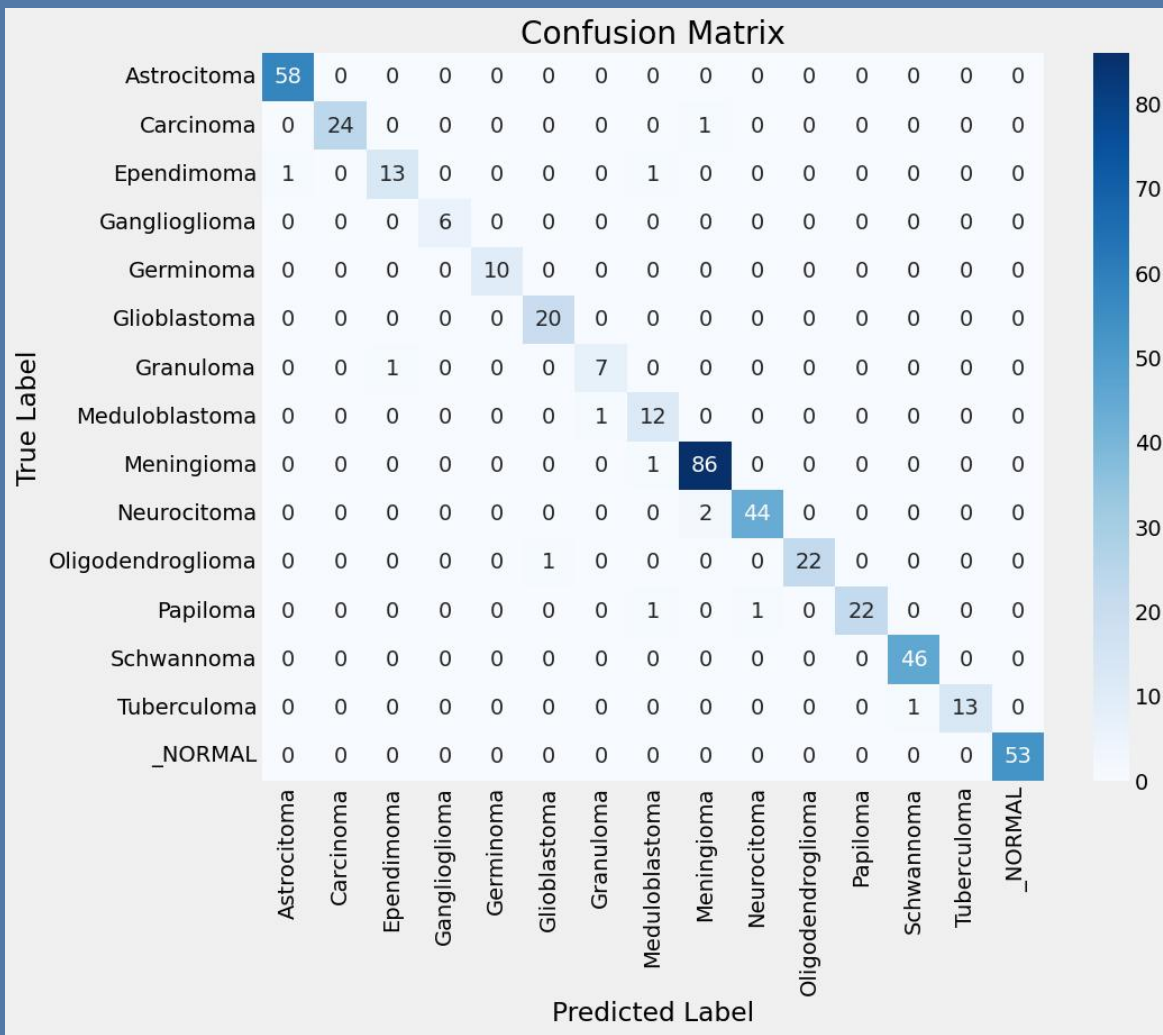
Training and Validation Loss



Training and Validation Accuracy



CONFUSION MATRIX



CLASSIFICATION REPORT

Evaluating model: EfficientNetB5

Classification Report:

	precision	recall	f1-score	support
Astrocitoma	0.98	1.00	0.99	58
Carcinoma	1.00	0.96	0.98	25
Ependimoma	0.93	0.87	0.90	15
Ganglioglioma	1.00	1.00	1.00	6
Germinoma	1.00	1.00	1.00	10
Glioblastoma	0.95	1.00	0.98	20
Granuloma	0.88	0.88	0.88	8
Meduloblastoma	0.80	0.92	0.86	13
Meningioma	0.97	0.99	0.98	87
Neurocitoma	0.98	0.96	0.97	46
Oligodendroglioma	1.00	0.96	0.98	23
Papiloma	1.00	0.92	0.96	24
Schwannoma	0.98	1.00	0.99	46
Tuberculoma	1.00	0.93	0.96	14
_NORMAL	1.00	1.00	1.00	53
accuracy			0.97	448
macro avg	0.96	0.96	0.96	448
weighted avg	0.97	0.97	0.97	448

References

[Automated multi-class MRI brain tumor classification and segmentation using deformable attention and saliency mapping | Scientific Reports](#)

[Brain Tumor Detection and Prediction in MRI Images Utilizing a Fine-Tuned Transfer Learning Model Integrated Within Deep Learning Frameworks](#)



THANK YOU

Project Link: <https://github.com/fady-bakheet/Brain-Tumor-MRI-Classification/tree/main>