ED6001 Project Final

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1 Introduction

The goal of the project is to create an algorithm that can detect whether the MRI image of brain has a brain tumor or not. The dataset for the project has been taken from the Kaggle competition. Python with Keras Framework has been used as the coding environment. The main challenge with the above dataset are

- Noise Removal
- Uneven ratio of the height/width of the brain
- Small dataset

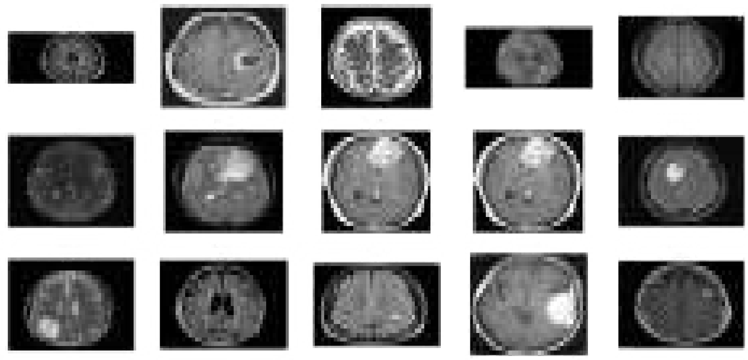
Various combination of technique are used to address the above problem and to detect the Image presence of Tumor in the given image.

2 Overview on the Dataset

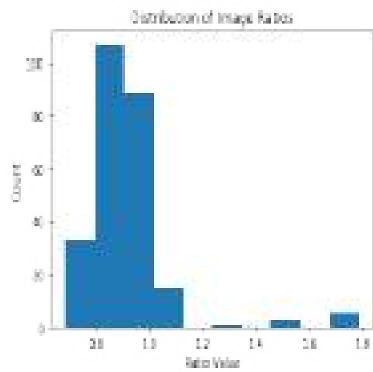
The modality of the image present in the dataset is MRI. The dataset contains a total of 253 image with 155 with tumor and 98 without the tumor. The total number of image is very low considering the usual number of images used to train the Deep Learning Models.

Data	Quantity
With Tumor	155
Without Tumor	98
Total	253

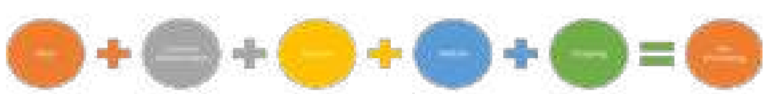
The image given below contains an example of the MRI image with a brain tumor. brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: cancerous (malignant) tumors and benign tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, known as brain metastasis tumors. The goal of the project is to only detect the tumor and not the type of the tumor.



As we can from the image above, images have different width and height and diffent size of "black corners". Since the image size for InceptionResNetV2 layer is (200,200) some wide images may look weird after resizing. Histogram of ratio distributions (ratio = width/height) is given below.



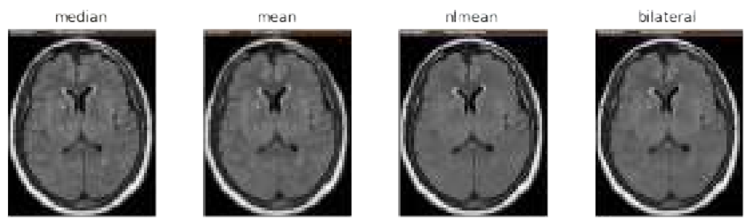
3 Data Preprocessing



3.1 Filters

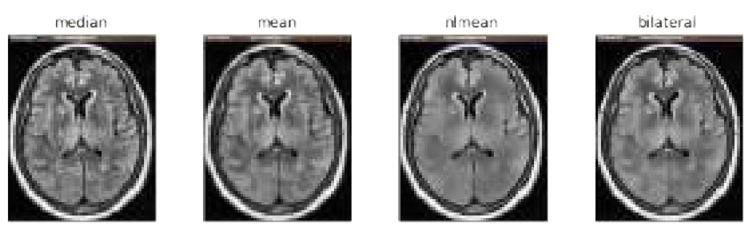
From the modality of the image we made a assumption that the predominant noise of the image present in the image is **Gaussian, Rician and Rayleigh Noises**. The Average PSNR value of the images are calculated for Mean Filter, NL-Mean Filter, Median Filter and Bilateral Filter.

Filter	Average PSNR
NL Mean Filter	35.048
Median Filter	36.251
Mean Filter	30.401
Bilateral Filter	32.976



3.2 Contrast Enhancement

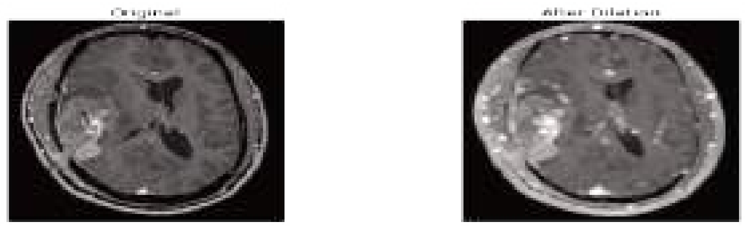
The image is in the format of RGB. The usual CLAHE and Histogram equalizer are performed on the grayscale image but we didn't want the information reduction that happens by converting the image from RGB to grayscale. So we converted the image into LAB format and performed CLAHE on the lightness domain of the image and converted it back to the RGB. This was a better way of preforming compared to perform CLAHE on every channel of the RGB image.



Above images contain the result of the image after performing a filter + CLAHE.

3.3 Dilation and Erosion

Dilation adds pixels to the boundary of objects so white regions such as tumors grow in size after dilation due to the addition of white pixels on the boundaries.



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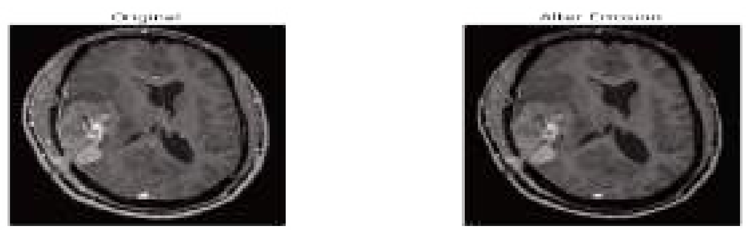
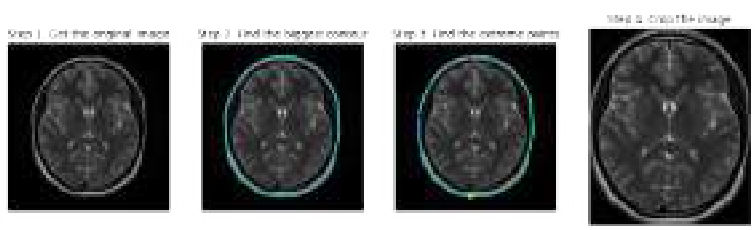
While erosion removes pixels to the boundaries of objects so white regions such as tumors reduces in size after dilation due to the removal of white pixels on the boundaries.



3.4 Cropping

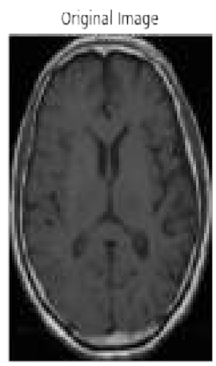
The image cropping is performed on the image to normalize the height and width of the image. At first the image is converted to grayscale and then the contours of the given image is founded. With the contour of the given image the maximum point of the contour is found to make them the final edge after cropping. Then using this point cropping is performed on the final image.

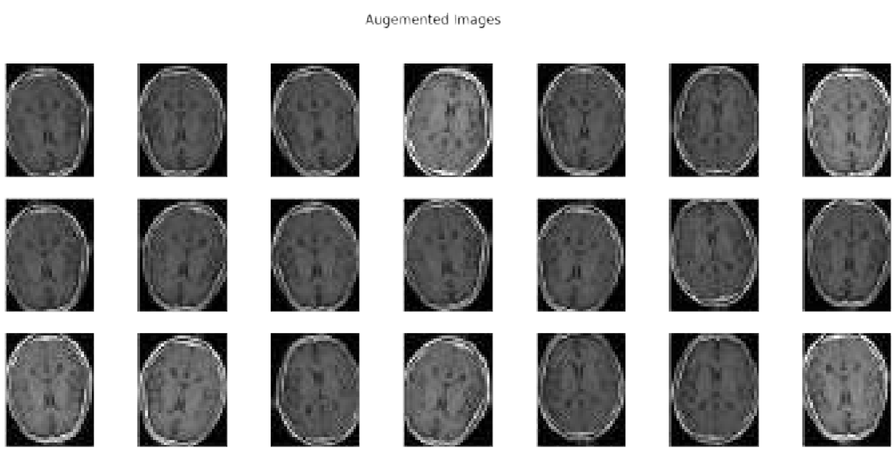


4 Data Augmentation

To solve the small dataset issue Data Augmentation is used to create synthetic data from the existing data to increase the present dataset. The synthetic dataset is obtained by performing combination of scaling, rotating, flip, shear and translation.

Geometric Transformation	Range
Re-scale	1.0/255.0
Rotation Range	15
Width Shift Range	0.05
Height Shift Range	0.05
Shear Range	0.05
Horizontal Flip	180^o
Vertical Flip	180^o





5 Model Evaluation

Accuracy is the basic evaluation metric that measures how correct our predictions were. In this case we simply compare predicted labels to true labels and divide by the total. Further we construct a confusion matrix which is a 2x2 matrix.

$$accuracy = \frac{(a+d)}{(a+b+c+d)} \quad (1)$$

Table 1: Confusion matrix

	Target Positive	***Target Negative***
Model positive	a	b
Model negative	c	d

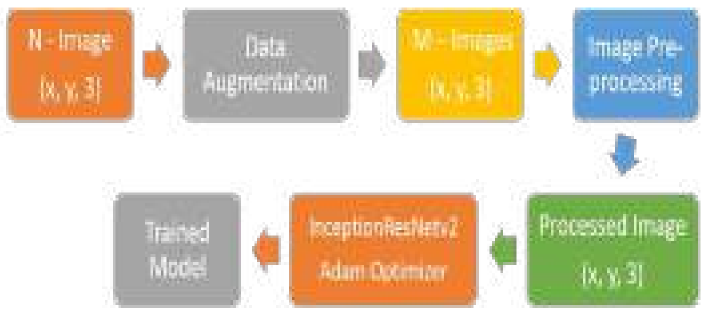


Figure 1: Training Pipeline

- **Precision** : the proportion of positive cases that were correctly identified.

$$precision = \frac{a}{(a+b)} \tag{2}$$

- **Recall** : the proportion of actual positive cases which are correctly identified.

$$recall = \frac{a}{(a+c)} \tag{3}$$

If we are trying to get best precision and recall at the same time for our model, we use F1 score which is the harmonic mean of precision and recall.

$$F1 = 2\frac{(precision \times recall)}{(precision + recall)} \tag{4}$$

6 Image Classification

Pre-trained model InceptionResNetv2 was used as the CNN algorithm to classify the given image as Tumor cs Not a Tumor. An average pooling layer and a fully connected layer with 128 perceptron was added to the end of the algorithm for training the transfer learning model.

The various combination of pre-process step is trained and tested to find the most effective pipeline that can be used for classification.

Figure 2: Output Pipeline

6.1 Model 1 - Without Pre-Processing

- **Observation** : This model has very high precision, all images having tumor were classified correctly. The model without any pre processing performs fairly well in classifying tumor and non-tumor images.

6.2 Model 2 - Histogram equalization

- **Observation** : This models performs very poor, it failed to classify any images with the presence of tumor correctly. Histogram equalization used was global, this increased the overall brightness of the image, this could be a reason for the inability of the model to classify the images.

6.3 Model 3 - CLAHE

- **Observation** : The model with CLAHE as pre-processing is observed to perform better than normal histogram equalization. CLAHE is applied locally, and does better than histogram equalization. the model is able to achieve good classification with CLAHE. But it is not performing better when compared to model without pre-processing. A possible explanation could be that the pre-processing failed to highlight some tumor regions that were notable in model 1.

6.4 Model 4 - Median filter

- **Observation** : Median filter yielded high PSNR values when tested with the images from dataset. hence it was tested in pre-processing pipeline. The model was a good classifier, but still does not beat the performance of model 1.

6.5 Model 5 - Dilation

- **Observation** : This model has high precision although the overall accuracy was less. Dilation increases the size of tumor. So the classifier might have predicted a few non-tumor as positives.

6.6 Model 6 - Erosion

- **Observation** : The overall accuracy of this model is very high. And this model has very high recall. The tumor size is reduced due to erosion and the number of wrong classifications are reduced. The model is seen to classify a few tumors as negatives.

6.7 Model 7 - Cropped

- **Observation** : The model is observed to have high precision. Images with tumors are classified correctly. Unwanted parts of the image is removed when cropped and resized this reduces processing unwanted parts of the image. This model has less accuracy than model 1 but does very well in finding if a image has tumor.

6.8 Model 8 - Median filter + CLAHE

- **Observation** : Although the precision of this model is better than some of the other models, the precision and recall are comparatively less than many previous models. The model lacks good precision in identifying the tumors. We can also observe here that applying CLAHE after applying a filter to the image provides much better results than just CLAHE.

6.9 Model 9 - Erosion + CLAHE

- **Observation** : Model 6 provided very good accuracy. CLAHE was added to pre-processing pipeline to check if this could improve results further. Though the model had good precision the overall accuracy of the model decreased. The model was classifying many negatives as positives.

6.10 Model 10 - Cropped + Median filter

- **Observation** : Model 7 and model 4 were models with high precision. Model was trained with cropping and median filter. The model has high accuracy and high recall. The model performs relatively better than all the above models.

6.11 Model 11 - Cropped + Median filter + CLAHE

- **Observation** : CLAHE was added in the pipeline to test if it provides any better results. The results were similar to Model 10. Not many differences was observed.

7 Results

	Precision	Recal	F-Score	Accuracy
Model 1	1	0.92	0.96	0.941
Model 2	0	0	0	0.294
Model 3	0.97	0.86	0.91	0.882
Model 4	0.92	0.92	0.92	0.921
Model 5	1	0.94	0.97	0.96
Model 6	1	0.86	0.93	0.901
Model 7	0.97	1	0.99	0.9803
Model 8	0.97	0.94	0.96	0.941
Model 9	1	0.72	0.84	0.803
Model 10	1	0.86	0.93	0.901
Model 11	0.97	1	0.99	0.9803
Model 12	0.97	1	0.99	0.9803

8 Conclusion

A model with excellent precision and very good accuracy should be chosen for the above problem statement. High precision will ensure that tumors are not wrongly classified, which will be very vital in real life cases. Hence model () seems satisfying and provides good results.