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Brain tumor segmentation and prediction on MRI images using deep learning network

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Abstract--Brain Tumor is caused when the anomalous cells that form within the brain and these could be of any size, shape in nature, so it is one of the difficult tasks to detect the presence of tumor. This could be found using MRI scans. In this paper, suitable algorithms have been developed to detect the MRI image has a brain tumor or not. The dataset used here has been taken from kaggle competition. Data augmentation is performed to maximize the data in dataset and this could results in having huge data. Since tumor area can overlap with non-tumor area of the MRI image, preprocessing steps is used to differentiate the images. So the proposed idea is to recognize tumors, this utilizes pre-processing strategies like filters, image enhancements, cropping, dilation, erosion, etc and for image classification pre-trained model InceptionResNetv2 is used as an CNN algorithm to detect whether the tumor is present or not. Various combination of pre-processing steps has been performed to find the effective pipeline for the classification. With the image pre processing techniques like cropped , median filter and CLAHE is gives a accuracy of 98.03% after the classification.

Keywords---data augmentation, conventional neural network, Clahe, dialation, erroson.

Introduction

Brain Tumor is an Irregular growth of brain cells. A brain tumor is a collection of tissues in which proliferated cells are at an uncontrollable rate. It comes from a variety of cells, both inside and outside the brain. Basic tumors are those that begin in the brain and spread to other areas of the body, but the developed tumors are those that spread to additional body parts. Tumors can come from a variety of regions, based upon this cell or causes obtained from different kinds of tumors. Headaches, both acute and persistent, muscle abnormalities, dizziness, cognitive difficulties, and other symptoms of a brain tumor might occur. Chemotherapy, radiation, tomotherapy, and surgery are all options for treatment. Although brain tumors are uncommon, they do exist. CNS tumors account for 2% of malignancies in India, with rates ranging from 5 to 10 per 100,000 population on the rise.

Brain Tumor is increasing around the younger generation compared to the elder generations. There are many methods to predict Brain Tumor nowadays. It is very important to the brain tumor at its early stage. Segmentation is a significant interaction in most clinical picture examination and order for radiological assessment or PC supported finding. Fundamentally, picture division strategies can be ordered into three classifications[15] edge-based techniques, district based techniques, and pixel-based strategies.

Magnetic Resonance Imaging (MRI) is used to detect the brain tumor. Abnormal areas in the brain in MRI scans (or any other scan) identify brain tumors[25]. These blobs or areas are typically brighter and have different lighting than that of the rest of the brain. The method of segmenting tumors in MRI scans, on the other hand, is extremely challenging. Tumors come in a variety of sizes, textures, and even locations. If it is tried to segregate the tumor based on attributes like light, it can run into problems like pixels with covering intensities with typical tissues. Segmentation and identification of brain tumors in MRI images[26] is crucial because it exposes the presence of tissues that are abnormal that can be used for curing or hospital patients to get a correct treatment over it. Thus, utilizing various deep learning techniques, proposed an unique brain tumor detection method using MRI scans in this paper.

Thresholding is the most straightforward technique for picture division. Thresholding can be utilized to make binary pictures from grayscale pictures. The morphological activities are fundamentally founded on certain presumptions about the size and state of the growth. These activities are applied on the picture after limit division. The last technique of picture deduction is applied to acquire the specific cancer locale.

Convolutional brain network(CNN) is utilized to handle this information. Inside Deep Learning, a CNN is a sort of counterfeit brain organization, which is generally used to prepare machines/PCs with the goal that they can gain as a

matter of fact, group and perceive information/pictures very much like a human mind does. The term 'Convolution' in CNN indicates the numerical capacity of convolution which is an extraordinary sort of direct activity wherein two capacities are duplicated to deliver a third capacity which communicates how the state of one capacity is altered by the other.

Literature Survey

Related Works

Saravanan Alagarsamy et al proposed the Identification of Brain Tumor using Deep Learning Neural Networks [1]. In this study, a CNN was used in this research, which is created using auto context and global and local picture attributes of 2 dimensional patches of various sizes. Models of several sorts are considered: 1) a voxel-by-voxel method created from two-dimensional routes with multiple directions as well as a three-dimensional picture without the usage of costly convolution networks. 2) A completely automated convolution network based on the U-net design approach. To determine the borders of tumors in the brain and other locations, posterior probability maps are employed in conjunction with networks and compared to the original picture.

Yakub Bhanothu et al proposed the Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network [2]. Meningioma, pituitary, and Glioma tumors are among the three primary brain malignancies included in the MR image dataset. The suggested technique uses the VGG-16 architecture for both the region proposal network and the classifier network. The algorithm's detection and classification findings show that it can detect glioma with an average precision of 75.18 percent, meningioma with an average precision of 89.45 percent, and pituitary tumor with an average precision of 68.18 percent. The method attained a average mean accuracy of 77.60 percent across all class as a performance metric.

S.Deepak et al proposed the Brain tumor classification using deep CNN features through transfer learning [3]. In this approach deep learning has been performed with CNN as the algorithm and it also used googLeNet as the pre-trained model to extract the data from the MRI images. This approach performed five fold patient level validation strategy on the dataset. The accuracy gained on this approach is 98%.

Nadim Mahmud Dipu et al proposed the Deep Learning Based Brain Tumor Detection and Classification [4]. Using YOLO and FastAi, this research provides deep learning-based techniques for brain tumour identification and classification. This research used a BRATS 2018 dataset, which included 1,992 collection of brain MRI images. The YOLOv5 classification model was 85.95 percent accurate, while the FastAi classification model was 95.78 percent accurate. These two models can be used to identify brain tumours in real time and diagnose brain cancer early

Abhishek Anil et al proposed the Brain Tumor detection from brain MRI using Deep Learning [5]. The proposed technique uses a classification network to divide

the input MR images into two categories: one with tumor and one without. The model is again retrained using transfer learning [28] app from the classifier to identify the brain tumor.

Tariq Sadad et al proposed the Brain tumor detection and multi-classification using advanced deep learning [6]. On the data set, the study provides segmentation using Unet with ResNet50 as a technique, achieving a level of 0.9504 of IoU. To improve the classification rate, some preprocessing steps with data augmentation are used. InceptionV3, DenseNet201, V2, MobileNet, and ResNet50 are among the deep learning algorithms used.

Deipali Vikram Gore et al proposed the Comparative Study of various techniques using Deep Learning for Brain Tumor Detection [7]. To detect the tumor, the picture of the brain is detected. Several sounds, as well as latency, have an impact on image accuracy. Image segmentation, MRI methods have become useful related to medical tools [16]. It is used deep learning techniques to give a comprehensive review of brain disorders in this study. This study considers the examination and comparison of new information linked with brain illness identification utilizing deep learning techniques.

Sidra Sajid et al proposed the Brain Tumor Detection and Segmentation in MR Images Using Deep Learning [8]. When predicting output labels, the hybrid convolutional neural network method employs a patch based method and considers both basic and text information. The suggested network addresses the problem of overfitting by combining a dropout regularizer with batch normalization, while the problem of data imbalance is addressed by a two-phase training approach. On BRATS 2013 dataset, the suggested method achieves scores of 0.91, 0.86, and 0.86 in terms of specificity, dice score and sensitivity over the entire tumor area.

Heba Mohsen et al proposed the Classification using deep learning neural networks for brain tumors [9]. A Deep Neural Network classifier was used to separate dataset of 66 brain MRIs into four categories: sarcoma, metastatic, normal, and glioblastoma bronchogenic carcinoma tumours, which is one of the Deep learning architectures. The new methodological design is equal to CNN [29], but it requires less hardware requirements and processes large pictures in a fair period of time. DNN classifier has a maximum level of accuracy when compared to conventional classifiers. The results gained with DWT might be used with CNN to compare and get good results.

Sunil Maharjan et al proposed the Novel Enhanced Softmax Loss Function for Brain Tumor Detection using Deep Learning [10]. In this it is noted that they used to boost classification accuracy by lowering other risks and encouraging multi class categorization. This system involves a CNN with a regularization and modification of some functions. The processing time and classification accuracy for different types of cancers were calculated using the probability score of the labelled data and their execution duration. When the proposed system was put to the test with various MRI image samples, different accuracy were identified. When compared to the other systems, the suggested method outperforms them.

A. Keerthana et al proposed the Brain Tumour Detection Using Machine Learning Algorithm [11]. From this paper , early diagnosis of a brain tumor allows for more effective medical treatment[19]. MRI images give more obtained details than Computed Tomography images. Brain tumours or neoplasms can be detected using a variety of approaches. This examines the most competent and effective algorithms[22] after examining more relevant research publications. Methods performed are pre-processing, segmenting , clustering and tumor detections.

Tonmoy Hossain et al proposed the Brain Tumor Detection Using Convolutional Neural Network[12]. In this study, Author proposed utilising the Fuzzy C-Means clustering technique to track the brain tumours from MRI, followed by conventional classifiers and CNN. The study used a dataset that included tumours of varying sizes, locations, shapes, and intensities. Method utilised six basic classifiers built in scikit-learn in the conventional classifier section. CNN, which are built with Keras and Tensorflow and yield better results than traditional neural networks. In this paper, CNN has a remarkable accuracy rate of 97.87 percent.

D suresha et al proposed the Detection of Brain Tumor Using Image Processing [13]. This study proposes a system that uses a mix of K-Means and support vector machine Algorithms to evaluate whether a brain image has a tumor or is tumor-free. In the first stage, the input picture is converted to grayscale using binary thresholding, and the spots are recognised. Tumors are classed as malignant or benign when they arise. Because tumours can be life-threatening, it's vital to discover and identify their presence in brain scans. The discovered spots are shown in terms of their intensities to distinguish between normal and cancerous brains. Following that, the K-Means approach is used to define the collection of returned characteristics, followed by tumor recognition.

Observations

The Methodologies that were used from the other related works were Global Thresholding, Adaptive Thresholding, Sobel filter, High Pass Filter which are considered to be inefficient. But Median Blur , Histogram Equalization , Dilation methodologies were considered to be more efficient in comparison to other methods.

Proposed Methodology

Overview of dataset

The modality of the image present in the dataset is MRI. The dataset contains a total of 819 images with 325 with tumor and 494 without the tumor. The total number of images is very low considering the usual number of images used to train the Deep Learning Models.

Table 1 Dataset

Data	Quantity
With Tumor	325
Without Tumor	494
Total	819

The image given below contains an example of the MRI image with a brain tumor. When uncommon cells grow in brain, a brain tumour develops. Benign tumors and benign tumours are the two most common forms of tumours. Primary brain tumours and secondary brain metastasis tumours are two types of cancerous tumours. The goal of the project is to only detect the tumor and not the type of the tumor.



Fig 1. Sample image with Tumor

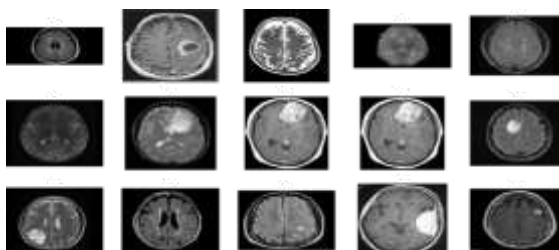


Fig 2. Image with different ratio

As seen from the image above, images have different sizes of 'black corners', height and width. The images may look weird after resizing, due to some image size that is (200,200) for InceptionResNetV2 layer. The ratio distributions of Histogram(ratio = width/height) is given below.

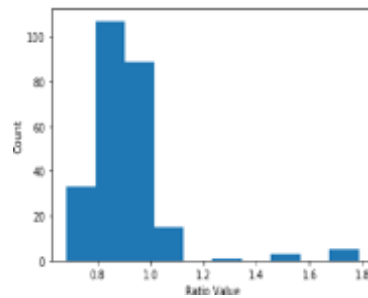


Fig 3. Distribution of image ratio

From the Fig. 3 the x-axis describes the count of the image and the y-axis describes the ratio with which the images are present in the dataset.

Architecture

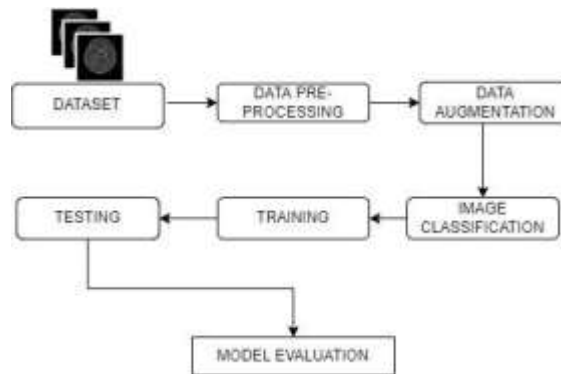


Fig 4 working flow of the proposed system

Fig. 4 This explains the steps in the proposed system. It starts with the preprocessing of the dataset, which is a collection of MRI image. The preprocessing steps which involve filters, dilation, contrast enhancement, etc are being carried out. Once the pre-processing is completed the data augmentation step is carried out. The data has been trained and tested using image classification. And finally the model is evaluated on the basis of accuracy.

Data Preprocessing

The data preprocessing steps involve Filtering of images, Contrast enhancement, Erosion, Dilation and Cropping. All the above mentioned steps are performed as data processing.

Filters

From the modality of the image it is made an 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.

Table 2 Filters with PSNR

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

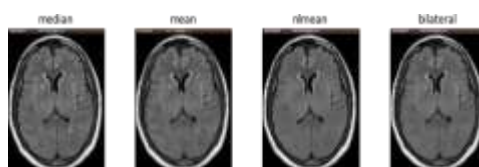


Fig 5. Images with different filters

From the Table 2 Median filter has the highest PSNR value than the other filter, with mean filter as the lowest PSNR value.

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 performing compared to perform CLAHE on every channel of the RGB image.

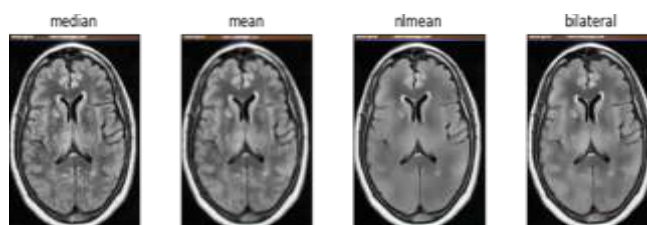


Fig 6 Images contain the result of the image after performing a filter + CLAHE.

Dilation and Erosion

Dilation builds pixels on boundaries of the object so that the white region where the tumor actually present grows in size after this process because of the addition of some white white range of pixels.



Fig 7. Image before and after dilation

While erosion removes those added pixels in the boundaries of that object, hence the added white pixels in dilation will be removed and the original MRI image will be used.



Fig 8. Image before and after erosion

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 are found. With the contour of the given image the maximum point of the contour is found to make them the final edge after cropping[18]. Then using this point cropping is performed on the final image.

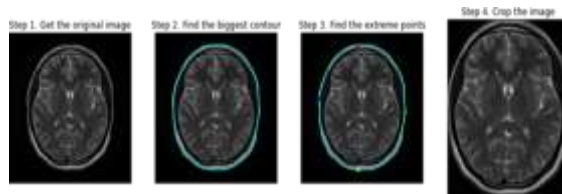


Fig 9. Results of cropped image

Data Augmentation

Table 3 Filters with PSNR

Geometric Transformation	Range
Re-scale	1.0/255.0
Rotation Range	15

Height Shift Range	0.05
Width Shift Range	0.05
Shear Range	0.05
Horizontal Flip	180°
Vertical Flip	180°

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 a combination of scaling, rotating, flip, shear and translation[20].

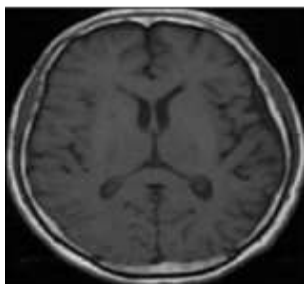


Fig 10. Original image for augmentation

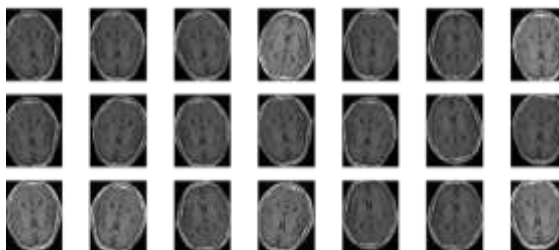


Fig 11. Augmented image

Model Evaluation

A greatly improved method for assessing the presentation of a classifier is to check out at the disarray framework. The overall thought is to count the times occurrences of class A are named class B. For instance, to know the times the classifier perplexed pictures of 5s with 3s, you would thoroughly search in the fifth line and third segment of the Confusion Matrix. Further we construct a confusion matrix which is a 2x2 matrix.

Accuracy : It is the basic evaluation metric that measures that the correctness of the process. Here it is compared to predicted labels to true labels and divide by the total. It is a measurement for assessing arrangement models. Casually, accuracy is the small part of expectations that the model was correct. Officially, accuracy is the quantity of right expectations per complete number of expectations. The Accuracy acquired is

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

Precision : It is a metric that measures the quantity of right certain expectations made. Precision, subsequently works out the exactness for the minority class. It is determined as the proportion of accurately anticipated positive models divided by the total number of positive models that were anticipated. Equation (2) portrays precision as the proportion of genuine true positives and the addition of genuine true positives and misleading false positives.

$$Precision = \frac{a}{(a+b)} \quad (2)$$

Recall : Sensitivity evaluates the quantity of right certain expectations made from all positive predictions that might have been made. Dissimilar precision that main remarks on the correct positive expectations out of every single positive forecast, Sensitivity gives a sign of missed positive expectations. Equation (3) portrays the sensitivity as the proportion of genuine true positives and the addition of genuine true positive and genuine false negative.

$$Recall = \frac{a}{(a+c)} \quad (3)$$

F1 Score : It is a proportion of a model exactness on a dataset. The F1-score is an approach to consolidating recall and precision of the model, and it is characterized as the consonant mean of the model's precision and recall. Hence, this score considers both misleading false positives and bogus false negatives. Naturally it isn't as straightforward as Accuracy, yet F1 is typically more valuable than exactness, particularly assuming that you have an unevenly distributed class. Equation (4) depicts the F1 score as two times the proportion of duplication of precision and recall to the addition of precision and recall.

$$F1\ Score = 2 * \left(\frac{(precision * recall)}{(precision + recall)} \right) \quad (4)$$

Image Classification

Pre-trained model InceptionResNetv2 was used as the CNN algorithm to classify the given image as Tumor or Not a Tumor [23]. An average pooling layer and a fully connected layer with 128 perceptrons was added to the end of the algorithm for training the transfer learning model [30].

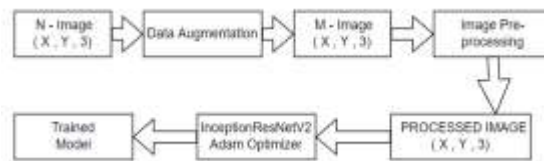


Fig 12. Training Pipeline

The different combinations of pre-process steps are trained and tested to find the most effective pipeline that can be used for classification[24].

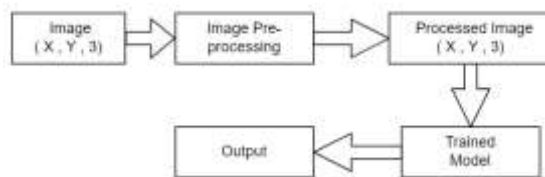


Fig 13. Output Pipeline

The various combinations of pre-processing steps that were used were described in the upcoming section as models.

Without Pre-Processing

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

Model 2 - Histogram equalization

Observation : This model with Histogram equalization as pre-processing method performs very poorly, 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.

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 without pre-processing.

Model 4 - Median filter

Observation : In this model with median filter yielded high PSNR values when tested with the images from the dataset. Hence it was tested in a pre-processing pipeline. The model was a good classifier, but still does not perform the performance of model without pre-processing.

Model 5 - Dilation

Observation : This model with pre-processing method as dilation has high precision although the overall accuracy was less. Dilation increases the size of the tumor which in turn has the accuracy but as per medical report this increase in size could cause other problems thus this model fails to perform. Also this classifier might have predicted a few non-tumor as positives.

Model 6 - Erosion

Observation : The overall accuracy of this model with pre-processing method as erosion 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.

Model 7 - Croppe

Observation : This model with pre-processing method as cropping is observed to have high precision. Images with tumors are classified correctly. Unwanted parts of the image are removed when cropped and resized, this reduces processing unwanted parts of the image. This model has less accuracy than model without pre-processing but does very well in finding if an image has a tumor.

Model 8 - Median filter + CLAHE

Observation : Although the precision of this model with pre-processing methods as median filter and CLAHE 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.

Model 9 - Erosion + CLAHE

Observation : Model with erosion provided very good accuracy. CLAHE was added to the 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.

Model 10 - Cropped + Median filter

Observation : Model 7 which is cropping as pre-processing method and model 4 which is median filter as pre-processing 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.

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 previous model . Not many differences were observed.As per the results this model with pre-pocessing steps as Cropped, Median filter and CLAHE has higher accuracy than compared to other models.

Results

	Precision	Recall	F-Score	Accuracy
Without Preprocessing	1	0.92	0.96	0.941
Histogram equalization	0	0	0	0.294
CLAHE	0.97	0.86	0.91	0.882
Median filter	0.92	0.92	0.92	0.921
Dilation	1	0.94	0.97	0.96
Erosion	1	0.86	0.93	0.901
Cropped	0.97	1	0.99	0.980
Median filter + CLAHE	0.97	0.94	0.96	0.941
Erosion + CLAHE	1	0.72	0.84	0.803
Cropped + Median filter	1	0.86	0.93	0.901
Cropped + Median filter + CLAHE	0.97	1	0.99	0.9803

The below bar graph shows the accuracy obtained from the different models that were performed and the model with the pre-processing steps cropped + median filter + CLAHE has the highest accuracy with 98.03%.

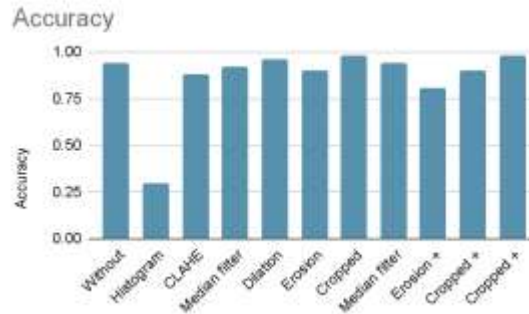


Fig 14. Accuracy of models

Results of Loss

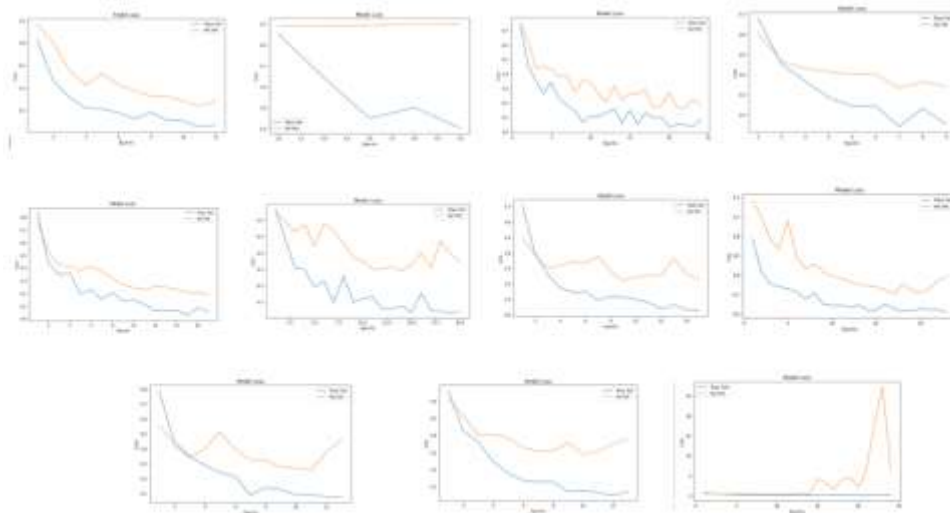


Fig.15. Graph results (a) Without Preprocessing; (b) Histogram equalization; (c) CLAHE; (d) Median filter; (e) Dilation; (f) Erosion ; (g) Cropped; (h) Median filter + CLAHE; (i) Erosion + CLAHE; (j) Cropped + Median filter; (k) Cropped + Median filter + CLAHE;

From the fig.1, x-axis gives the Epochs and y-axis gives the loss of the different models. The graph consists of two lines, in which the orange line denotes the validation set and the blue line indicates the training set. Each graph describes the wrong prediction that is discovered during the training and validation of the images in different model.

Conclusion and Future Works

A suitable preprocessing model with excellent precision and very good accuracy should be chosen for the above mention statement to find the tumor with higher accuracy . High precision will ensure that tumors are not wrongly classified, which will be very vital in real life cases to detect the tumor without any

variations in the position or shape. Hence model with the preprocessing steps which include cropped , median filter and CLAHE seems to provide a good precision and accuracy with 98.03% . This can also be extended in various other medical application like skin disease classification, and other similiar classification[21]. In the future it could also be extended for calculating the percentage of brain tumor present in the brain with the correct identification of tumor area. Thereby could be very useful in the hospitals to treat the patients according to the percentage of the brain tumor present in the brain.

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