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Brain Tumor Detection & Classification

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INTRODUCTION:

The brain tumor is deadly cancer. The survival chances of the affected human being are very less. However, it is possible to recover from brain cancer, if it is detected early stage. Manual detection using MRI images is computationally complex in cases where the survival of the patient is dependent on timely treatment, and the performance relies on domain expertise. Therefore, computerized detection of tumors is still a challenging task due to significant variations in their location and structure, i.e., irregular shapes and ambiguous boundaries. In this work, I tried to summarize and compare the methods of automatic detection and classification of brain tumors through Magnetic Resonance Image (MRI) used in different Deep Neural Network models such as Convolutional Neural Network (CNN) and a pre-trained model VGG16 for Transfer Learning (VGG16-TF). Different Brain Image classification techniques are studied. Existing methods are classically divided into region-based and contour-based methods. In this work, I used both the large contour detection and Skull segmentation techniques. Simulation results also showed that the proposed system outperforms the state-of-the-art methods. The contour-based method gives us an accuracy of 99.12% for classifying brain tumors.

IMAGE ACQUISITION:

Images used for the experimental purpose are the MRI images collected from Kaggle (details described in the Dataset section). The process of image acquisition is hardware-based. This is characterized by the representation of an object or a scene. The images used have been clinically obtained for the experimentation.

THEORY AND RELATED WORK:

A brain tumor is a fatal disease-causing death to thousands of people around the globe. A brain tumor is mainly caused by abnormal growth in brain tissues. As the skull portion of the human body is inflexible and small, any growth inside the brain may affect the functionality of the human organ depending on its origin and position. Moreover, it may also spread in other parts of the body and affect their functionality. Usually, the brain tumor is categorized into two classes, primary brain tumors begin in brain tissue and continue to remain there. Secondary tumors are also more frequent in the brain. All such cancers begin off elsewhere within the body and then go to the brain. Without clear proof, something can be done to cure a certain disease. Side effects have recent or ever-strong headaches, blurry vision, and loss of balance, depression, and seizures. In certain cases, signs cannot be present. Treatments require surgery, chemotherapy, and radiation. Brain tumor identification stages and Brain tumor segmentation in MRI (magnetic-resonance-imaging) have been an important area of study in the field of image analysis. Detection of brain tumors helps in identifying the exact scale, shape, border, and position of the tumor. The image processing system used to identify brain tumors requires a number of steps. In this work, I used Brightness and Contrast correction of the gray level image then resize the image into 256*256 then the Data augmentation process is done to increase the number of data.

Related works:

In paper [3], they proposed an automated approach for brain tumor detection and segmentation from MRI images. The proposed technique adopts a DL model using a fully convolution neural network, Mask-RCNN [37] with DenseNet-41 backbone and utilizes a multitask loss function to achieve an end-to-end training of deep CNN, increasing the detection accuracy. The motivation behind using a custom Mask-RCNN was to achieve a similar level of accuracy with a comparatively simple model, fewer kernels, and two convolutional layers. To show the efficiency of the proposed approach, they evaluated their model on two free and online available brain tumor datasets [1,2] using various quantitative measures.

Paper [4] showed how preprocessing of images affects the Deep Learning model to achieve higher accuracy. They used Image Enhancement, Segmentation, Feature extraction. After performing the mentioned pre-processing techniques, they used CNN classifier. This CNN deep learning technique, process the image to predict determine whether the given image is a tumor or non tumor and provides the classification accuracy.

DATASET:

My working Brain MRI Dataset collected from [1] and is relatively small. It contains a total of 253 MRI samples of sizes of 845*845 pixels, among which, 155 MRI samples contain tumors. Dataset is publicly available and collected from the Kaggle online community of Data Scientists and Machine Learning practitioners which last updated on 14th April, 2019.

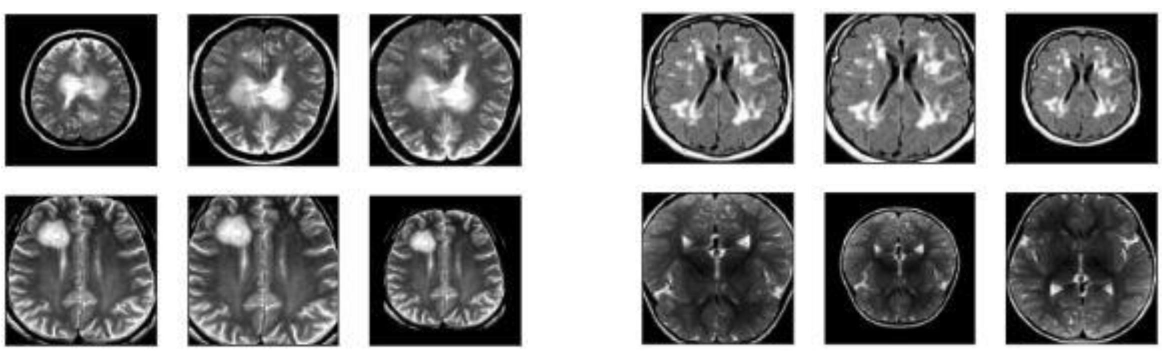

Fig (a) : Brain images with Tumor

Fig (b) : Brain images without Tumor

Fig 1: Dataset

METHODOLOGY:

This work is divided into 7 sections. Such as,

1. Image acquisition and dataset preparing
2. Crop brain contour/ Skull segmentation

3. Preprocessing images
4. Data augmentation
5. Deep Learning Model building
6. Model predictaion
7. Evaluate the methodology

In the image acquisition, the part system acquires the Brain MRI images from the dataset and organized them into two types one for Tumor image and another for non Tumor image. The system acquires all the images in gray level.

As the existing works are based on either cropping the large contour or the skull segmentation I here described the effectiveness of choosing crop large contour instead of skull segmentation on the experimental dataset.

Contour cropping:

Contours detection is a process of joining all the continuous points (along with the boundary), having same colour or intensity. The contours are a useful tool for shape analysis and object detection and recognition. In the fig: 2(b) shows the contour cropping from the same 3 Brian MRI images.

Skull segmentation:

To remove skull portion from the MRI image I used Otsu segmentation as we know If pixels in the image can be classified into two different intensity classes, that is, if they have a bimodal histogram, then Otsu's method can be used to threshold them into a binary mask. Fig: 2(d) depicts the histogram result and fig: 2(c) shows the skull segmentation result from the same 3 Brian MRI images.

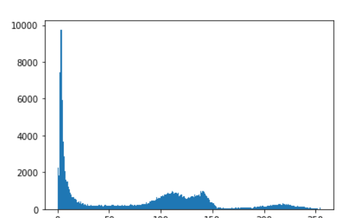

Fig 2 (d): Histogram result of fig 2(a) image

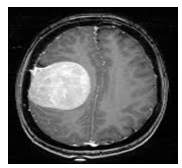

Fig (a): original Brain MRI image with Tumor

Fig (b): Contour cropping

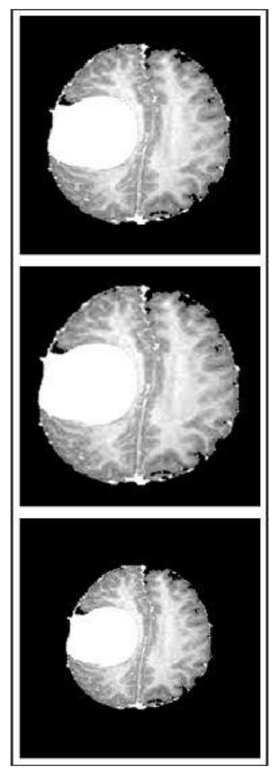

Fig (c): Skull Segmentation

Fig 2: Contour cropping and Skull segmentation

Pre-processing techniques make the image suitable for further processing. It enhances the quality of the image and finally removes the noise present in the image. Pre-Processing techniques aim the enhancement the image without altering the information content. The goal of this step is to reduce artifacts that could mislead the Deep Learning model. Here I tried to correct the brightness and contrast of the images to get better result.

Data augmentation is a strategy that increases the diversity and amount of data significantly from available data to train a model without collecting new data. Cropping, Padding, Flipping, Zooming, Varying the im-age size are the techniques that are used to augment the data. It also helps to avoid overfitting. In this work, I used zoom in, zoom out techniques to augment the data.

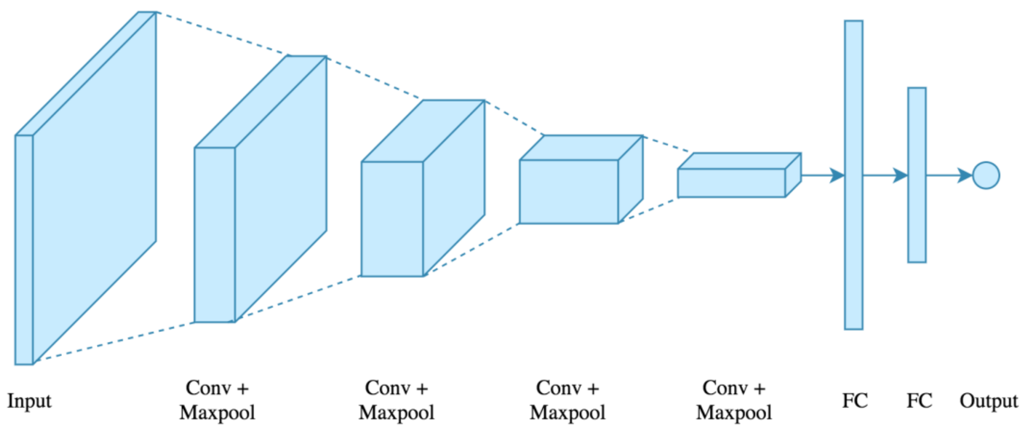

Fig 3: CNN model architecture

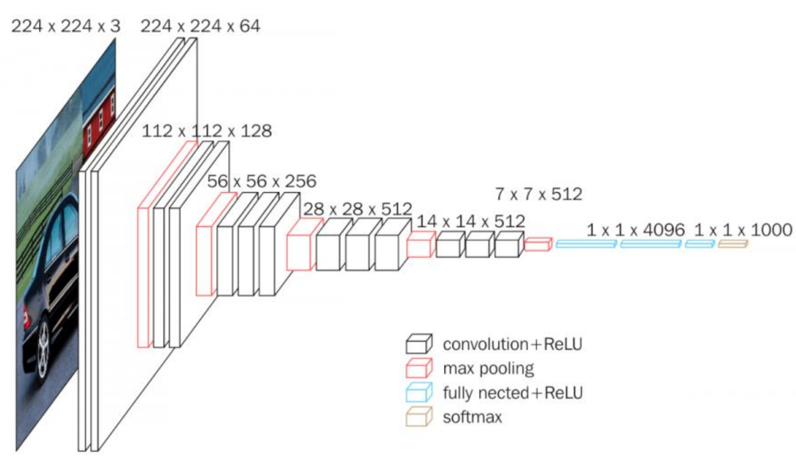

Fig 4: VGG16 model architecture

The deep learning models here I used are CNN and VGG16 pre-trained models. In the CNN model (fig: 3), I used 4 dropout layers to avoid overfitting the model. Output layer predicts whether the image contains tumor or not, using Softmax function. The model used Adam optimizer. Where

Adam optimization is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments.

VGG16 (fig: 4) is a CNN model which is pre-trained on imagenet dataset. In this work, I put the first 15 layers as not trainable and added 4 additional layers to train on the experimental dataset. To avoid overfitting I added 3 dropout layers to the model.

Finally, the pre-processed images are feed into the model to evaluate the model performance and compare them.

The model evaluation metrics here I used, Sensitivity, Recall, precision, Negative predictive value (NPV), Accuracy, and F1 score.

The proposed methodology depicted in fig: 5.

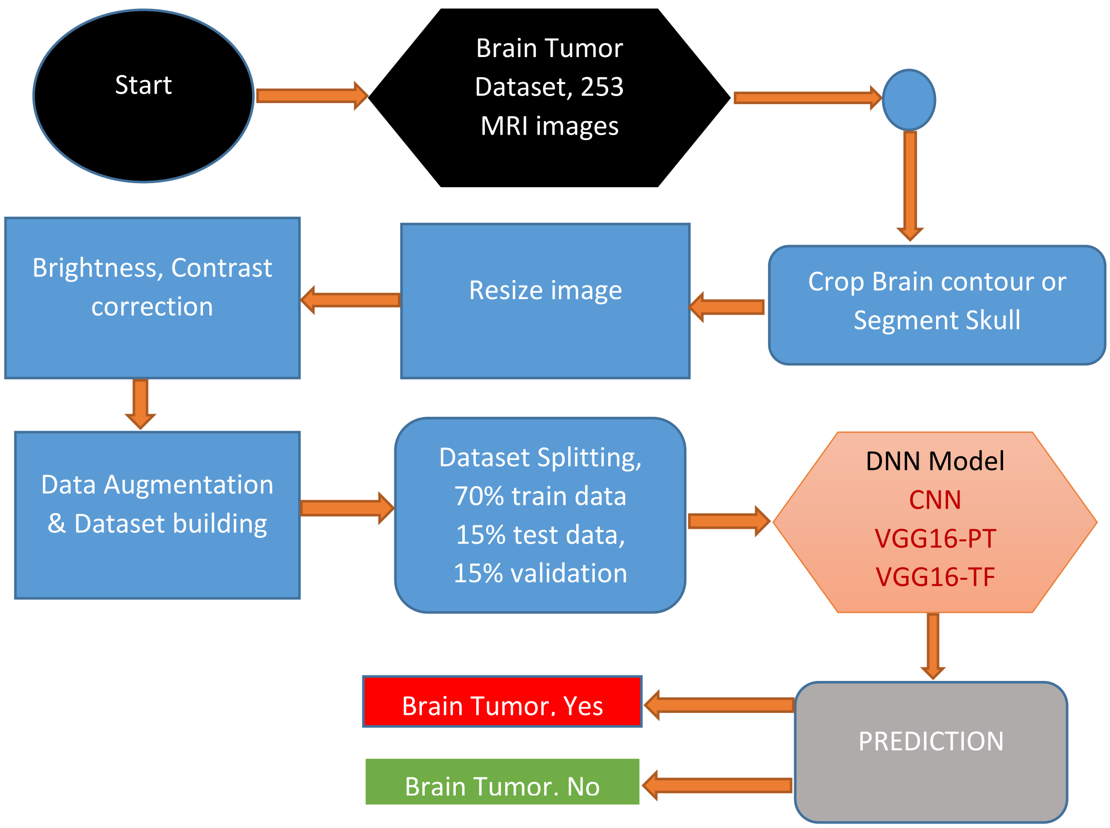

Fig 5: PROPOSED METHOD

RESULT DISCUSSION:

In this section, the proposed method is evaluated on a publically available dataset of MRI Brain Tumor images [1]. I split the dataset in 3 sections.

1. 70% data is used for training purpose.

2. 15% used for validation &
3. 15% used for testing purpose.

The proposed methodology implemented on google colab notebook.

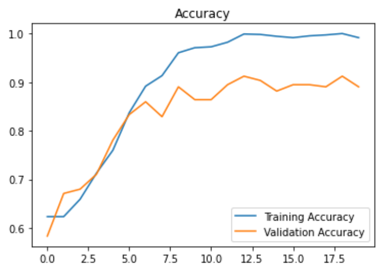

Fig (a): CNN result plot

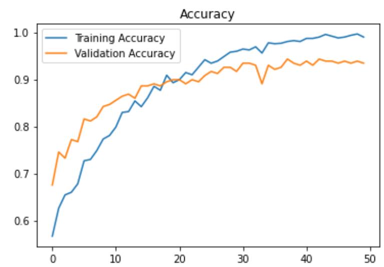

Fig (b): VGG16-PT result plot

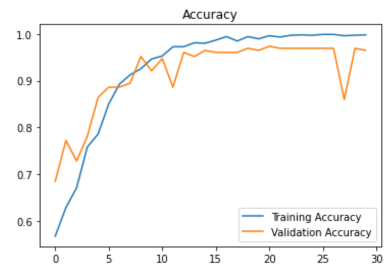

Fig (c): VGG16-TF result plot

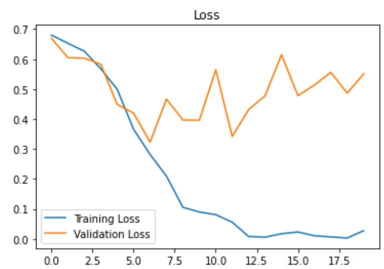

Fig (d): CNN result plot

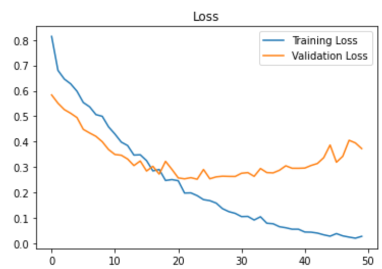

Fig (e): VGG16-PT result plot

Fig (f): VGG16-TF result plot

Fig 6: Model performance analysis using Skull Segmentation.

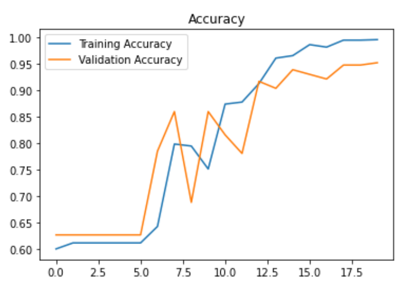

Fig (a): CNN result plot

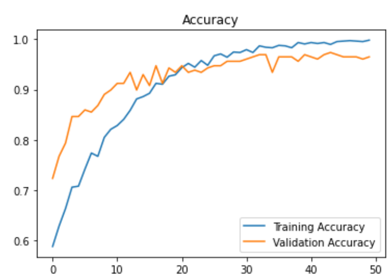

Fig (b): VGG16-PT result plot

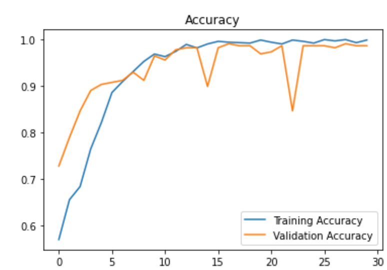

Fig (c): VGG16-TF result plot

Fig (d): CNN result plot

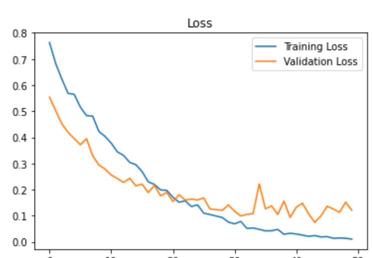

Fig (e): VGG16-PT result plot

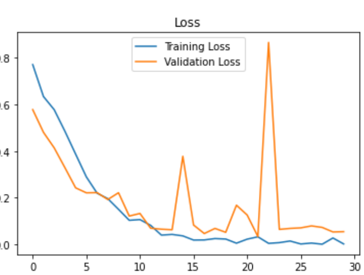

Fig (f): VGG16-TF result plot

Fig 7: Model performance analysis using Contour cropping.

In Fig. 6 plot shows the model performances using Skull Segmentation. Fig. 6(d) plot shows the training loss and validation loss. Where the validation loss increases gradually after 6 epochs which indicates overfitting the model. I ran the VGG16 pre-trained (PT) model till 50 epochs. Fig. 6(e) shows after 20 epochs the validation loss started to increase gradually which also indicates that the model gets overfitting but comparatively less than the CNN model. Fig. 6(f) shows the VGG16-TF model does not get overfitting. From the three Deep Neural Network models using Skull segmentation VGG16-TF achieves better result than the other two models in Fig. 6(a), Fig. 6(b) comparative less epoch. After completion of training the VGG16-TF, model successfully predicts with 97.81% accuracy which outperforms other two methods.

Fig. 7(d) (e) (f) shows that all the models are trained well and does not get overfitted. Fig. 7(f) shows the VGG16-TF model performance with only 30 epochs and Fig. 7 (c) shows the VGG16-model using Contour cropping achieves better result than the other two models Fig. 7(a), Fig. 7(b) in comparative less epoch. After completion of training the VGG16-TF, model successfully predicts with 99.123% accuracy which outperforms other two methods.

From the two methodologies VGG16-TF with the Skull Segmentation and the Contour cropping we can see that the VGG16-TF model with Contour cropping shows better result. I also showed the comparative analysis of these models and methods in Table 1, Table 2.

Table, 1: Experiment Result Analysis using Brain Skull Cropping

Evaluation Metric	**VGG16-Transfer Learning**	**VGG16-Pretrained model**	**CNN model**
Sensitivity or Recall	**100.0%**	99.25%	82.96%
Specificity or TN	**94.62%**	**94.62%**	92.47%
Precision or PPV	**96.42%**	96.40%	94.12%
NPV	**100.0%**	98.88%	78.90%
Accuracy	**97.81%**	97.37%	86.84%
F1 score	**98.18%**	97.81%	88.19%

Table, 2: Experiment Result Analysis using Brain Contour Cropping

Evaluation Metric	VGG16-Transfer Learning	VGG16-Pretrained model	CNN model
Sensitivity or Recall	**100.0%**	97.24%	98.54%
Specificity or TN	97.59%	**98.80%**	89.01%
Precision or PPV	98.64%	**99.30%**	93.12%
NPV	**100.0%**	95.35%	97.59%
Accuracy	**99.123%**	97.81%	94.74%
F1 score	**99.32%**	98.26%	95.75%

Table, 3: Comparative Result Analysis

Evaluation Metric	(Proposed) VGG16-Transfer Learning	VGG16-Pretrained model	[6] DNCC method (2020)	[5] using SVM classifier (2017)	[13] Custom-Mask RCNN (2021)
Sensitivity or Recall	**100.0%**	97.24%	-	97.72%	-
Specificity or TN	97.59%	**98.80%**	-	94.2%	-
Precision or PPV	98.64%	**99.30%**	-	-	-
NPV	**100.0%**	95.35%	-	-	-
Accuracy	**99.123%**	97.81%	97.3%	96.51%	98.34%
F1 score	**99.32%**	98.26%	-	-	-

Table 3, shows the comparative analysis of this work with the existing methodologies. Where the proposed VGG16-TF model better than DNCC method [6], SVM classifier [5], Custom Mask RCNN [13] interms of all Deep Learning model evaluation metrices.

CONCLUSION:

Brain tumor is dangerous. It can happen at any age. The chances of affected human beings survival is less. Here we used kaggle MRI Brain tumor image dataset from kaggle website. In this work, a computational complex method based on deep learning was implemented on MRI image dataset to detect and classify Brain Tumor. This system was capable of detecting Tumor images and Non Tumor images. We were able to increase the accuracy of the system by sending images through brightness and contrast correction that increased the discrimination capability of the system. Our proposed methodology VGG16-TF with contour cropping shows better result than state-of-the-art methods. Thoug the proposed model performs better but there few noticeabl thing 1. The proposed methodology need to test on different dataset with large amount of data to make sure the data diversity. 2. There are many new methodologies to segment skull correctly other than Otsu method.

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[1] Brain MRI Images for Brain Tumor Detection. Available online: https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection (accessed on 1 April 2021)

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[4] Megha, H. C. Evaluation of Brain Tumor MRI Imaging Test Detection and Classification.

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