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Deep Learning based Brain Tumor Detection

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***Abstract:** In current technology era, to sustain and provide healthy life to humans it is necessary to detect the diseases in early stages. We are focused on Brain tumour detection process, it is very challenging task in medical image processing. Through early diagnosis of brain, we can improve treatment possibilities and increase the survival rate of the patients. Recently, deep learning plays a major role in computer vision, using deep learning techniques to reduction of human judgements in the process of diagnosis. Proposed model is efficient than traditional model and provides best accuracy values. The experimental results are clearly showing that, the proposed model outperforms in the detection of brain tumour images.*

***Keywords:** Deep Learning, Data Augmentation, Normalization, Transfer Learning.*

I. INTRODUCTION

In the medical image processing, Brain tumor detection is very challenging task. With the early diagnosis there are many chances in improvement of treatment possibilities and survival rate of patients. Due to the revolution in big data, huge number of MRI images are generating every second. For the radiologist, it is very time consuming task to process these images and finding insights in this clinical activity. So that we used deep learning techniques to identify the disease and early diagnosis of these diseases. [1] used segmentation based approach, K means with combined C means to improve the accuracy in segmenting the tumor stage. To display the stage of tumor which is the area calculated from the cluster. [2] Developed technique of 3D segmentation of brain tumor using water shed and thresholding techniques with morphological operation. This method is not suitable for color based segmentation. By using the appropriate method for classification to find the 3D objects into various feature classes, these properties are helpful in better diagnosis of brain images. [3] Uses thresholding and level based segmentation with the integration of K means and fuzzy c means algorithms. Due to this accuracy is improved a bit but processing time is increased in the large data set of images.

[4] combined thresholding with sobel method and find the regions using closed contour algorithm. By using intensity information with in closed contours these tumors are extracted.

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The drawback of this method is producing less false edges. By decreasing boundary lines of regions we can increase the region area. [5] used CNN approach to exploit both local and global features. The model used fully convolution layer with forty fold speed up and improved accuracy. This method is tested on brats 2013 dataset of images. [6] used histogram equalization for contrast enhancement of MRI images. And region growing algorithm for region labeling with level set method to find the segmented boundary of tumor region. [7] suggested three level backpropagation neural network to contrast between benign and malignant tumor types of 165 patients data analyzed with thirteen features. [8] used region of interest (ROI) technique for better classification of brain tumors. [9] Used intensity histogram, gray level co-occurrence matrix and bag-of-words model for feature extraction to identify the tumor. [10] [11] used rectangular window based image cropping technique for classification. In this model, they used discrete wavelet transform as feature extraction, principle component analysis for dimensionality reduction and support vector machine for classification. From the literature survey, few methods are used thresholding techniques and morphological operations to classify the disease with less data set of images. After that used machine learning techniques for classification like support vector machines. Later few models are based on deep learning techniques for deeper insights in disease detection and diagnosis of patients. But they trained models on brats 2013 data set with reasonable accuracy. Various techniques used in this area, still there are gaps in accuracy levels, usage of data sets. So that we proposed a model which uses light weight architecture for identifying of brain tumor images.

II. METHOD FOR CLASSIFICATION

We used VGG-16 model for tumor classification. VGG-16 is a convolutional neural network architecture.It contain 16 layers. It's layers consists of convolutional layers, max-pooling layers, Activation layers, Fully-connected layers. There are 13 covolutional layers, 5 Max pooling layers and 2 Dense layers which sums up to 21 layers but there are only 16 weighted layers.

A. Data set Description

We used brats 2018 data set of 193 train images, 10 test images and 50 validation set of images. We consider an Input image size of 224X224. We prepared data with data preprocessing techniques like data augmentation, cropping and normalization. In data augmentation, by using rotation, width_shift and height_shift of 0.05 with rescale and shear operations. Finally, 3990 of train images,210 of test images and 1050 of validation images are used for processing. The following section displays sample set of Input images.

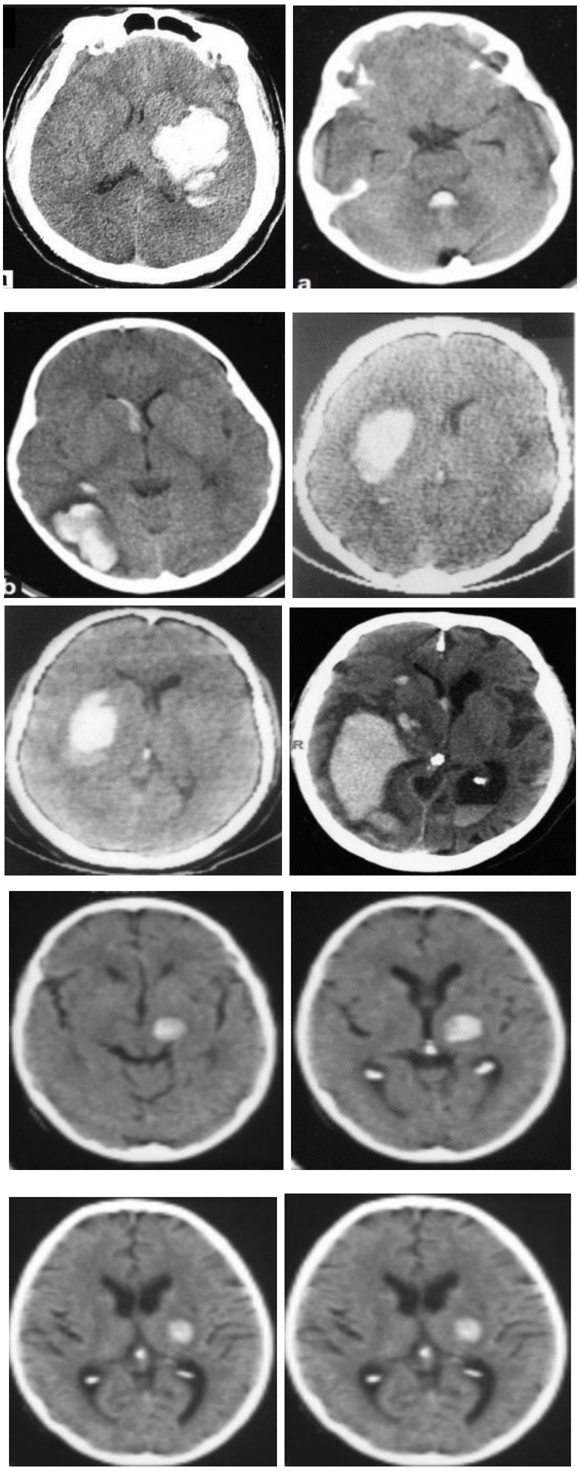
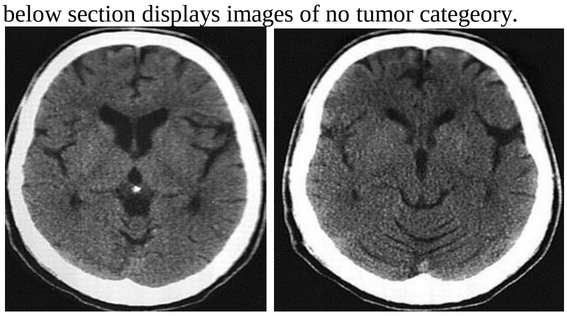


Figure 1: Data set of images - tumor category images

The below section displays images of no tumor categeory.



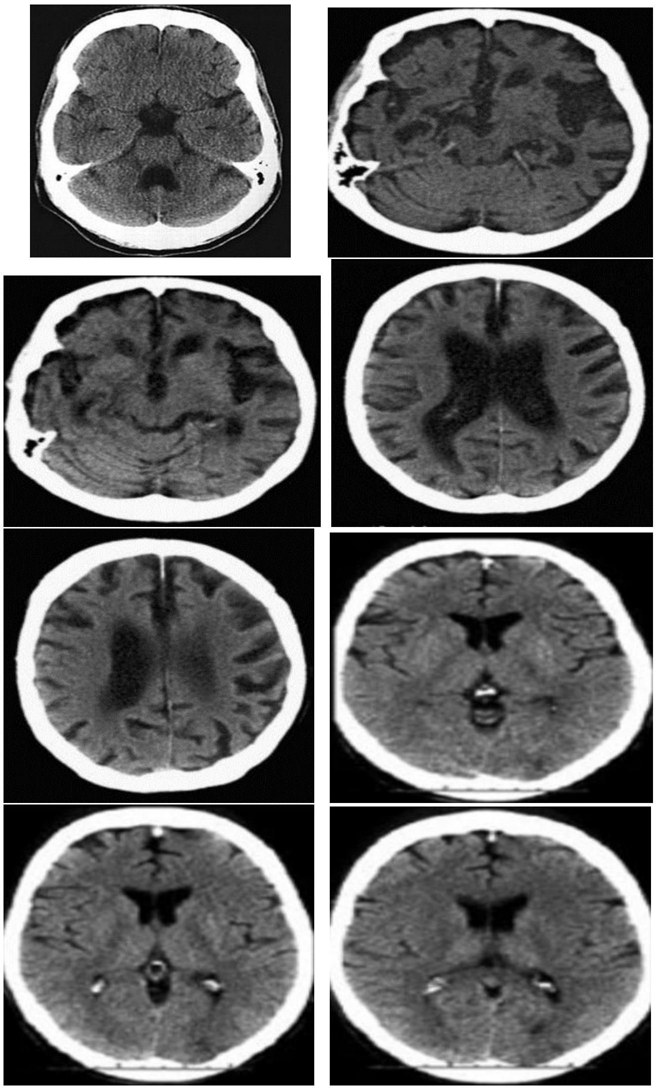


Figure 2: Data set of images – no tumor category images

Normalization - There wide images are look weird after resizing, so that we used cropping technique to get the clear brain contour from input image. The contour and final crop image is shown in below section.

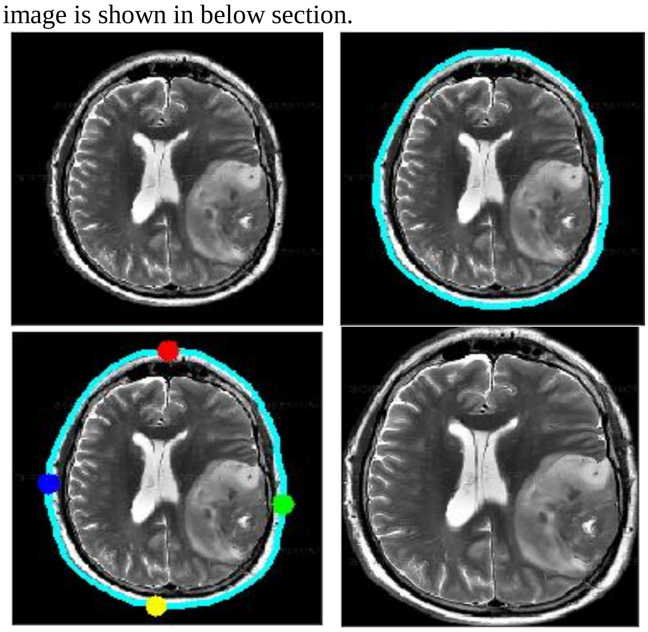


Figure 3: Images after cropping which are : Input image, largest contour, extreme points and cropped image.

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The cropping process applied on all the train, test and validation data set of images. Initially we have collected less number of images, so that through augmentation (shift, shear, rotate and flip operations) we have been creating 21 images from each of the image, finally we considered 3990 train set of images and five percent are used in test and twenty percent in validation sets.

B. Proposed Architecture

The following section describes Proposed Architecture

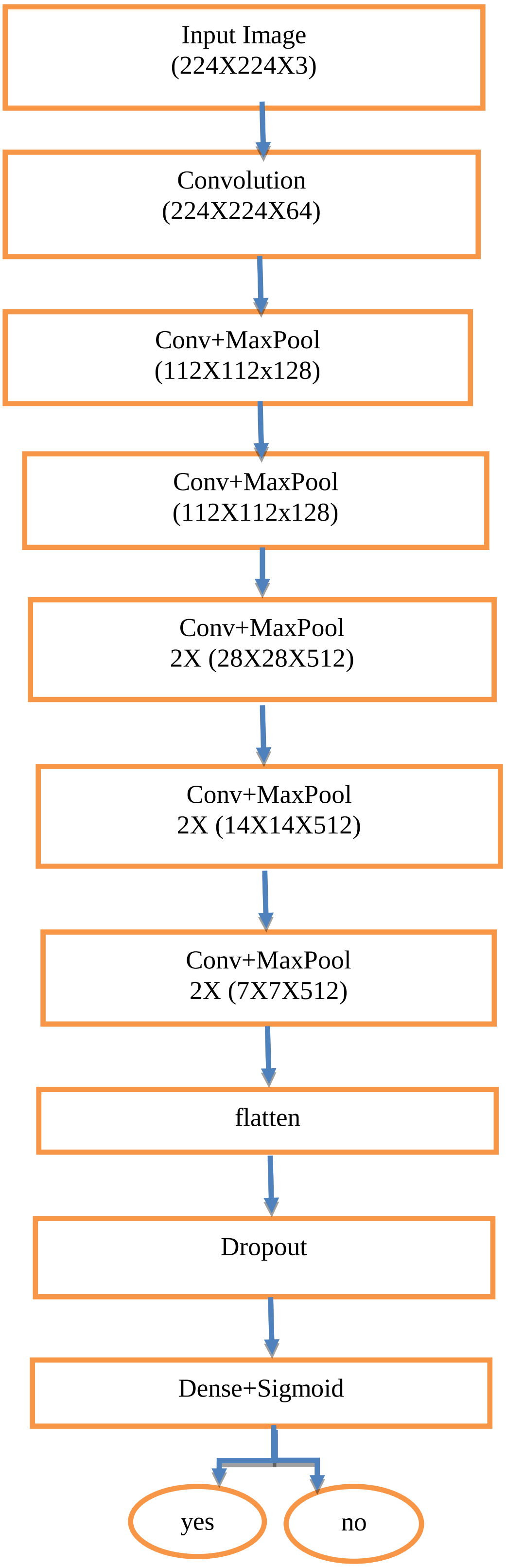

Figure 4: Proposed Architecture

. We implemented a model with eight convolution layers and five pooling layers with three fully convolution layers as a base model. Furthermore, to improve the accuracy along with base model, we proposed transfer learning technique with one dropout layer with 0.5 value and extended to dense layer with sigmoid function. This model achieves high accuracy in classifying images having tumor or not.

III. RESULTS AND DISCUSSIONS

In this paper, obtained results are compared with base model. Using transfer learning, the proposed model is improved value accuracy by more than ten percentage than base model. In the medical im aging field, the classification accuracy plays major role to diagnosis the patient in more efficient manner. Here, we presented results in tabular format and Graphical representation. Experimental results are clearly saying that the proposed model is more efficient than state-of-the art methods.

Table1: Value and test accuracy values

Model	Vgg16	Proposed Model
Value Accuracy	88	90
Test Accuracy	80	100

The following graph describes the Comparative study between existing and proposed systems.

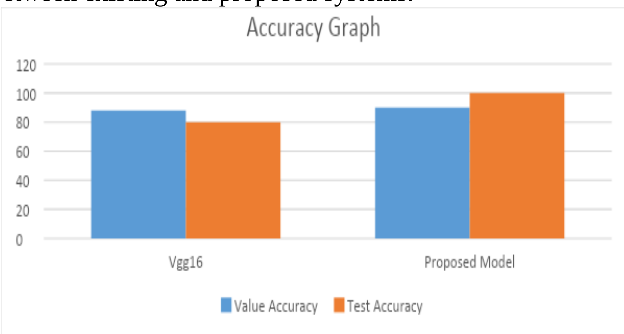

Figure 5: Value Accuracy and Test Accuracy Graph

IV. CONCLUSION

In this paper, we addressed brain tumor detection on recent BRATS dataset of images. We proposed transfer learning based classification model to classify the given image having tumor or not. Obtained results are compared with state-of-the art models, our model gives high accuracy upon those. Experimental results are clearly depicting that, proposed method is efficient than base models. Further, we may extend this model with segmentation of tumor part from yes-category images.

REFERENCES

1. Selvakumar J, et al. Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and Fuzzy C-mean algorithm, IEEE Explore, 2012.
2. N Mong, et al, An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation, Int Jounal of Image graphics and signal processing, 2012.
3. Eman Adbel, et al, Brain tumor segmentation based on a hybrid clustering technique, Egyptian Informatics journal,march 2015.

4. Aslam A, Ekram Khan, M M Sufyan,Improved Edge Detection Algorithm for Brain Tumor Segmentation, procedia computer science, 2015.
5. M havaei, et al, Brain Tumor Segmentation with Deep Neural Networks, Medical image Analysis, jan 2017.
6. hardeep kaur,jyoti rani, Mri brain image enhancement using histogram Equilization Techniques, ieee conference on wispnet,2016.
7. I Cabria, I Gondra, MRI segmentation fusion for brain tumor detection, Information Fusion, july 2017.
8. X Zhao, et al, A deep learning model integrating FCNNs and CRFs for brain tumor segmentation,Medical Image Analysis, jan 2018.
9. K Sudharani, et al, Advanced Morphological Technique for Automatic Brain Tumor Detection and Evaluation of Statistical Parameters,Procedia Technology,May 2016.
10. Z Sobhaninia, et al, Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images, corpus id-52336157, sep 2018.
11. Multi-grade brain tumor classification using deep CNN with extensive data augmentation, M Sajjada, et al, Journal of Computer Science, 2018

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