Deep Learning based Automatic Brain Tumor Analysis using Multimodal Fusion

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Abstract - *Multi-modality is extensively used in medical imaging, because it can provide multiple information about a target (tumor, organ or tissue). Recently, deep learning-based approaches have presented the state-of-the-art performance in image classification, segmentation and object detection. Brain Tumors are intricate and it's really challenging to detect. The process of diagnosing the brain tumors by manual segmentation is not only time overwhelming but also prone to human error, and its performance depends on pathologists' experience. Hence, trusted and automatic analysis of tumor is essential to prevent the death rate of human. In this paper, we propose Multimodal fusion using Principal Component Analysis. Then we implement Tumor Classification and Segmentation using the fused result obtained from Multimodal fusion. The method presented is based on a Convolutional neural network for Classification and Otsu thresholding for segmentation of the tumors. The whole brain tumor analysis is designed and executed in MATLAB App designer. Experimental results demonstrate that the proposal outperforms other existing methods qualitatively and quantitatively.*

***Key Words*: Multimodal fusion, Deep learning, Brain tumor, Convolutional Neural Network (CNN), Segmentation, Magnetic Resonance Imaging (MRI), Computed Tomography (CT)**

1. INTRODUCTION

Brain tumor is one of the most fatal diseases which occur due to abnormal growth of cells inside the brain or central spine that can disrupt the normal functioning of brain. An effective and efficient analysis is always a key concern to detect the disease at early stage and to save human life. Automated disease detection in multimodal medical imaging using deep learning has become the emergent field in several medical applications. Its application in the detection of brain tumor using MRI & CT scan image is very crucial as it provides necessary information for planning treatment.

Automatic computerized detection and diagnosis of the disease based on multimodal medical image analysis could be a good alternative as it would greatly aid in clinical management of brain tumor and also obtain a tested accuracy. In this paper, we use MRI and CT scan images. The premise is that various imaging modalities encompass abundant information which is different and complementary to each other. MRI scans are more detailed and considered as best way to detect tumor. MRI is a non-destructive, non-invasive and non-ionizing method in nature. They provide high resolution images which are commonly used in brain imaging purpose. CT scans are preferred next to MRI .They are faster and provide details of bone structure near the tumor. Multimodal fusion is performed using MRI and CT scans by Principal Component Analysis.

Convolutional Neural Network plays an important role to detect the disease providing a feasible alternative to manual classification for brain tumors. We detect and classify the type of tumor and then segment the tumor region.

Segmentation is the partition of an image making it more meaningful and easier to analyze. In this work, Segmentation of tumor is done using Otsu Thresholding. This helps by locating tumor region from healthy tissue which is necessary for planning treatment and patient follow-up. The whole tumor analysis process is implemented at user friendly App designer in MATLAB.

1.1 Objective

- To contribute the medical domain with the deep learning technology to make tumor analysis more accurate and efficient.
- To implement an algorithm for automatic tumor classification and segmentation through Multimodal fusion results for further analysis.
- To display the overall tumor analysis process using App designer in MATLAB.

2. MATERIALS AND METHODS

The brain tumor analysis process is a difficult task because of the complex structure of brain. The tumor analysis process involves four modules: Pre-Processing, Multimodal fusion, Classification and Segmentation of tumor. Finally the modules are implemented in MATLAB 2020b using App designer which is attractive and easy to use.

2.1 Dataset

We used publicly available Kaggle dataset with the training set employed to train the models and the validation set for the evaluation of the proposed ensemble. The training set consists of 395 no-tumor images, 826 Glioma, 822 Meningioma and 827 Pituitary tumor affected images. We used Testing dataset of MRI and CT scan images of 38 patients.

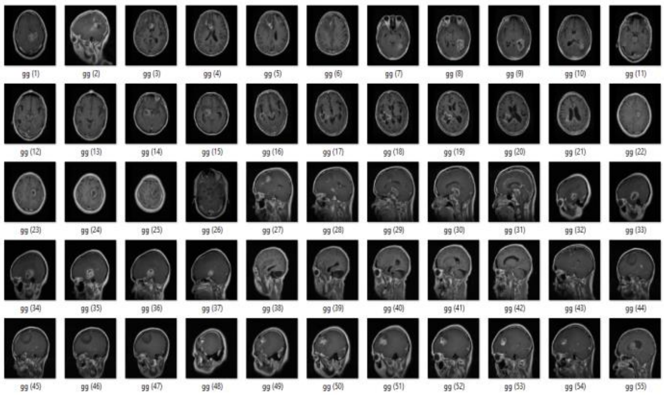


Fig -2.1: Dataset used in our proposed work

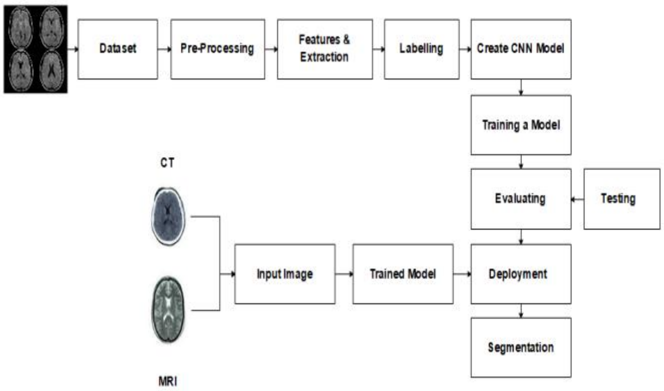


Fig -2.2: Proposed Architecture

2.2 Pre-Processing

Images cannot be fed directly as the input for Multimodal fusion. Therefore Pre-processing is required because there are variant intensity, contrast and noise in the images. Therefore, to make the images appear more similar and make the process smooth and quantifiable, pre-processing techniques are applied before feeding to the proposed framework. It aims to improve the image by suppressing unwanted distortion and enhancing important features. Our pre-processing includes rescaling, noise removal to enhance the image and applying morphological operations like erosion.

2.3 Multimodal Fusion

Use of Multimodality images are increasing now-a-days. In the field of biomedical imaging, use of more than one modality on the same target has become promising. In our work we used two modalities for getting fused image of Brain Tumor. We used MRI & CT scans which provide details on anatomic structures and spatial resolution to better characterize tumor. In this paper, we mainly focus on the MRI-CT multimodal medical image fusion task.

Principal Component Analysis (PCA) is used for Multimodal Fusion combining two different modalities MRI and CT. The first principal component indicates the most amount of variance. Each additional component expresses less variance and more noise, so representing the data with a smaller subset of principal components preserves the signal and discards the noise.

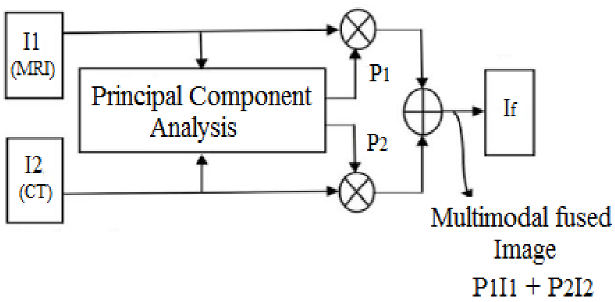


Fig -2.3: Schematic Diagram of PCA Multimodal Fusion

The number of feature combinations is equal to the number of dimensions of the dataset. Eigen vectors and Eigen values are measures used to quantify the direction and the magnitude of the variation captured by each axis. Eigen vector describes the angle or direction of the axis through the data space. The correlation between each principal component should be zero as subsequent components capture the remaining variance. Correlation between any pair of Eigen value/Eigen vector is zero so that the axes are orthogonal. High variance axes are treated as principal components, while low variance axes are treated as noise and discarded. Steps involved in PCA Multimodal Fusion are given below:

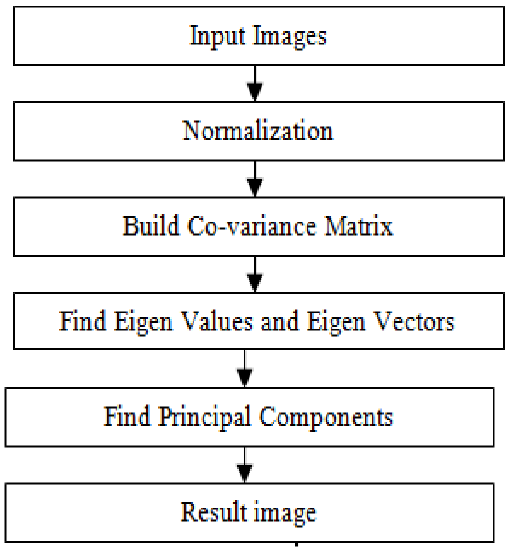


Fig -2.4: Flowchart for PCA Multimodal Fusion

2.4 Classification of tumors

In our paper, we have used the Convolutional Neural Network architecture for Brain tumor Detection and Classification. CNN automatically learns mid-level and high-level representations from the input training data.

The main building block used to construct a CNN architecture is the Convolutional layer. Input Layer takes in the raw pixel value of input image. Convolutional Layer is the first layer to extract features from an input image and preserves the relationship between pixels by learning image features using squares of the input data. Activation Layer produces a single output based on the weighted sum of inputs. Pooling layers would reduce the number of parameters when the images are too large but retains important information. We use Max Pooling which take the largest element in the feature map. Fully connected layer involves weights, biases, and neurons. It is used to classify images between different categories by training. Logistic is used for binary classification and SoftMax is for multi-classification. Output layer contains the label which is in the form of one-hot encoded.

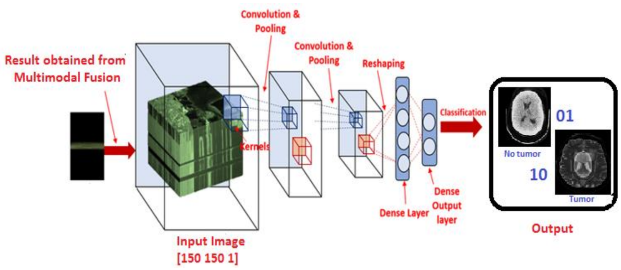


Fig -2.5: CNN Model

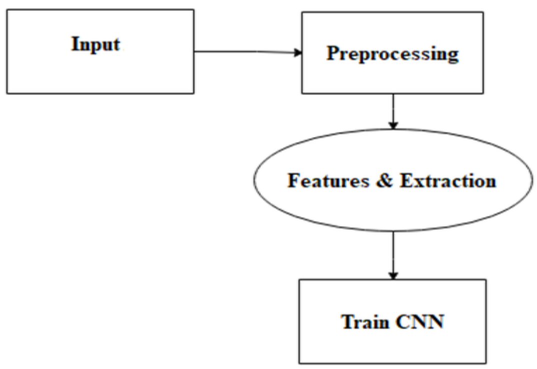


Fig -2.6: Training of CNN Model

We trained the model for 5 epochs with input size as 150 X 150 X 1 and the initial learning rate is 0.0001.No.of. iterations used per epoch is 22. Finally, CNN is employed for automatic brain tumor classification. Results of Multimodal fusion is taken as input and classification is performed.

CNN helps to detect presence of tumor and indicates no tumor if the brain is healthy. If tumor is detected, then the type of tumor is identified. We designed to classify both Benign (Meningiomas & Pituitary adenomas) and Malignant (Gliomas). Gliomas are tumors that arise from brain tissues other than nerve cells and blood vessels. On the other hand, meningiomas arise from the membranes that cover the brain and surround the central nervous system, whereas pituitary tumors are lumps that sit inside the skull. Because of the information mentioned above, the precise differentiation between these three types of tumors represents a very important step of the clinical diagnostic process and later effective assessment of patients.

CNN is considered as the best technique for image classification due to high accuracy. It is used over feed forward neural networks as it can be trained better in case of complex images to have higher accuracies. It can automatically learn to perform any task just by going through the training data.

2.5 Segmentation of tumor region

As tumor leads to low survival rates, accurate segmentation of the tumor region plays an important role for image interpretation, analysis and measurement. For Segmentation, we used fused image as input. Input image is converted into grayscale and then processed using Anisotropic Diffusion process to sharpen edges. This aims at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for interpretation of the image. Texture filter is applied to determine the texture image. Then smoothening filter is used to filter the texture image. We computed morphological opening using the structuring element and subtract the result from original image. Then contrast of the image is improved and threshold value to perform segmentation is determined.

Otsu thresholding based Segmentation is used to represent the tumor region from Non-tumor region. Otsu method is one of the most successful methods for image thresholding because of its simple calculation. Otsu is an automatic threshold selection method. It segments the image into two classes: 0 if less than the level.1 is given if greater than or equal to the level. The tumor region is separated from healthy tissue after performing Morphological erosion. Then we outlined the tumor region. Finally detected tumor region is displayed for treatment purpose.

3. IMPLEMENTATION

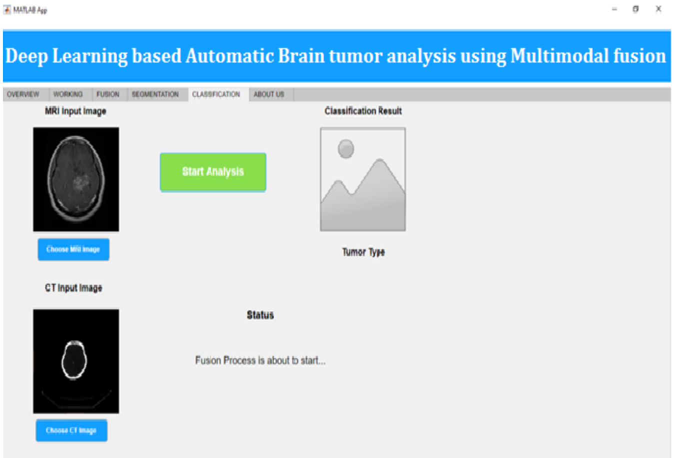
The whole tumor analysis process is implemented using App designer in MATLAB software .We used MATLAB 2020b version on Intel Core(TM) i5-8265U CPU at 1.60GHz and 8GB memory. In MATLAB, we developed app interactively using App designer. It is self contained in MATLAB which provides simple and click interface to code. We used interactive controls like menus, buttons and sliders.

4. RESULT AND DISCUSSION:

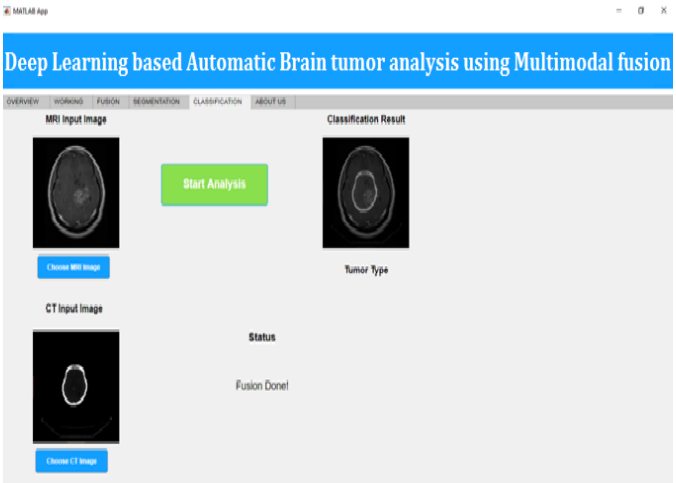
This section provides the experimental results of the proposed work.

4.1 Multimodal Fusion Results

Fig-4.1 illustrates the results obtained for Multimodal fusion. (4a) shows the input given to Multimodal fusion process and (4b) shows the multimodal fusion result which is combination of MRI and CT scan images obtained through Principal component analysis.



(4a)



(4b)

Fig -4.1 Results for Multimodal Fusion
(4a) Input image (4b) Output Image

4.2 Classification Result for No tumor

Fig-4.2 shows classification result for no tumor image. This confirms that the patient is healthy and not affected by tumor.

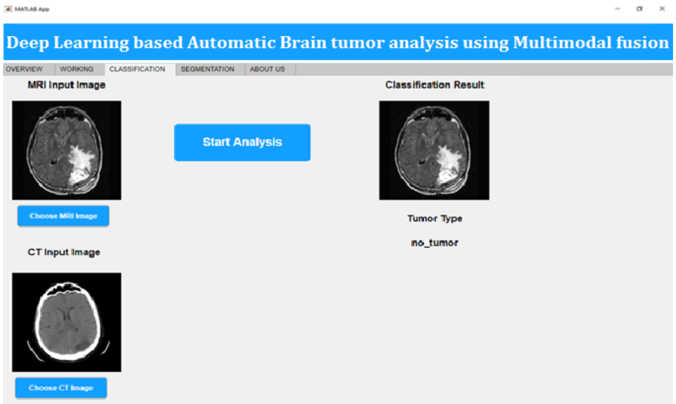


Fig -4.2: Classification result showing No tumor

4.3 Classification Result for Glioma tumor

Fig-4.3 shows classification result for Glioma tumor which has varying degrees of vascularity and blood brain barrier disruption.

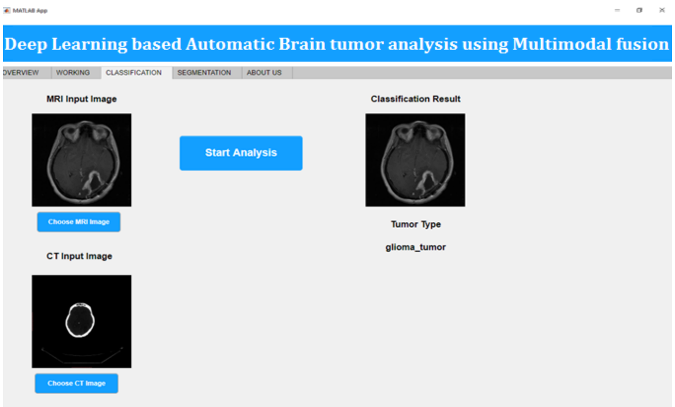


Fig -4.3: Classification of Glioma tumor

4.4 Classification Result for Pituitary tumor

Fig-4.4 present classification result for Pituitary tumor which forms in pituitary gland near the brain and it does not spread beyond the skull.

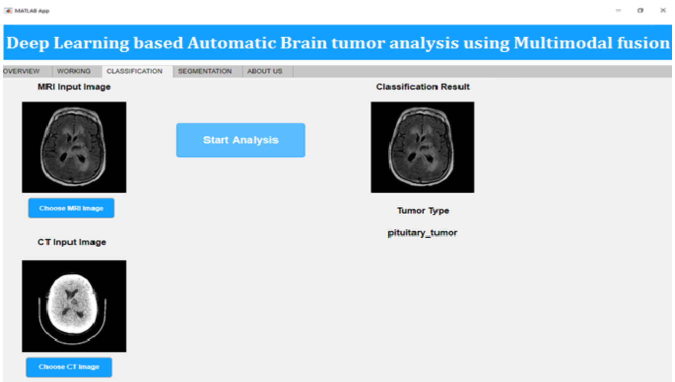


Fig -4.5: Classification of Pituitary tumor

4.5 Classification Result for Meningioma tumor

Classification result for Meningioma is shown in Fig-4.5 which is highly vascular without a blood-brain tumor.

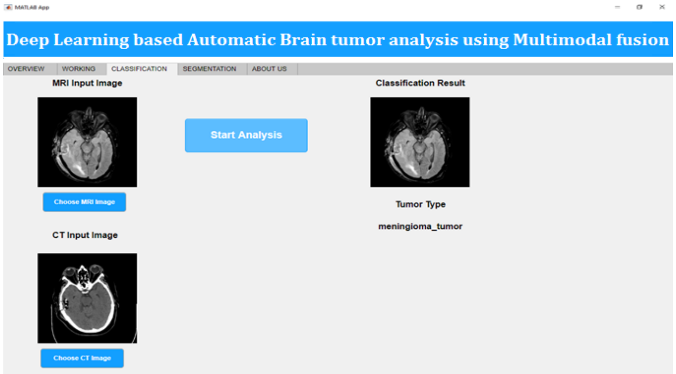


Fig -4.5: Classification of Meningioma tumor

4.6 Segmentation Result

Fig-4.6 explains steps carried out in Segmentation process. Finally detected tumor region is displayed.

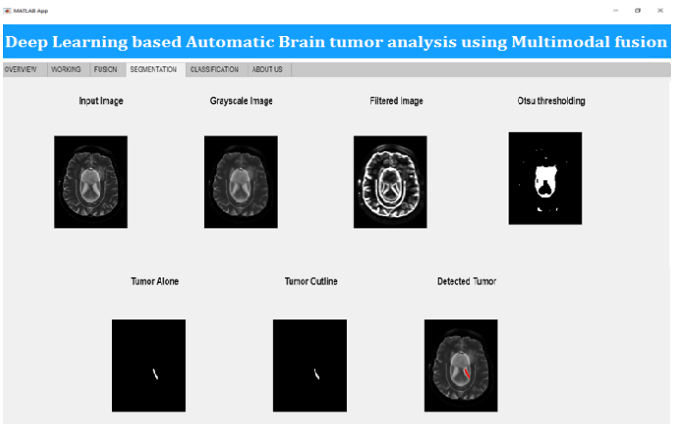


Fig -4.6: Segmentation of Tumor

4.7 App designer

In Fig-4.7 ,the outlook of the proposed work is displayed.

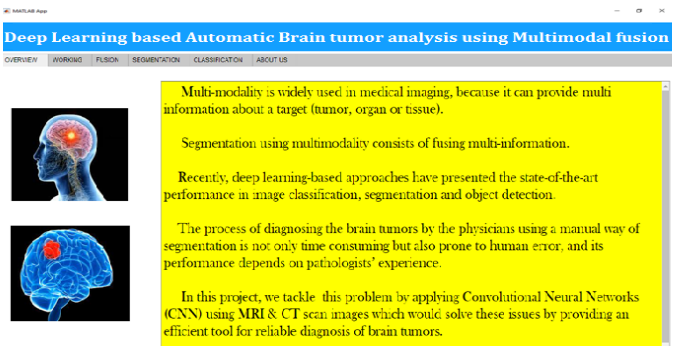


Fig -4.7: Implementation in App designer

4.8 Accuracy and loss obtained in Training Process

Fig-4.8 provides result obtained in Training Process. We got an accuracy of 97 % and loss which is less than 0.2.

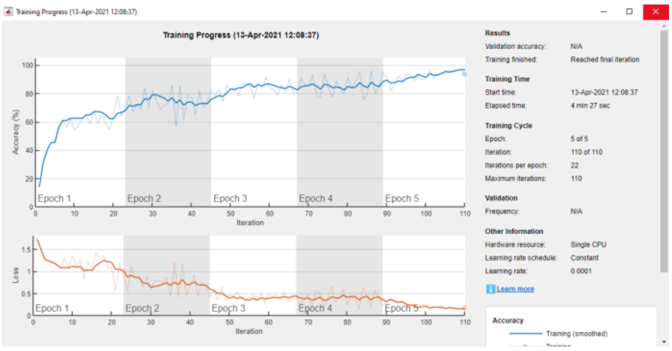


Fig -4.8: Accuracy and Loss

Table -1: Comparison analysis of Brain tumor analysis methods

Performance Evaluation			
S.NO	AUTHOR	METHOD USED	ACCURACY
1	P.S. Mukambika and K Uma Rani [5]	Level set method , k-Means Segmentation and SVM classifier	94.12% & 82.35%
2	A. Minz and C. Mahobiya [6]	Adaboost & Neural Algorithms	89.90% & 74.00%
3	G.S Chandra and K.R. H Rao [7]	DWT Filtering and Genetic Algorithm	90.00%
4	G. Singh and M.A. Ansari [8]	k-Means Segmentation and SVM & Naive Bayes classification	91.49 & 87.23%
5	Parveen and A.Singh [9]	FCM Segmentation and SVM classification	91.66%
6	Our Proposed Work	PCA Multimodal fusion, CNN Classification and Otsu thresholding for Segmentation	>97% (Both Benign and Malignant Tumor)

5. CONCLUSIONS

We empirically demonstrate several findings. Firstly, Modality combination results show that the results obtained through Multi-Modality fusion in our proposed work are better than Single-Modality used in various Existing System. Results acquired through PCA Multimodal fusion are quick and it takes only 20 sec to complete over all Fusion Process.

Among the existing data analysis methods, deep learning is undoubtedly the most effective one. We trained more than 2800 images and we provided better accuracy with faster iterative cycles using CNN. As the tumor diagnosis is a complicated and sensitive task, accuracy and reliability are always assigned much importance. We got accuracy rate greater than 97%.The loss is very minimum and it's less than 0.2.This is very good alternative to existing system which are time-consuming. It greatly aid in Clinical management by identifying type of Tumor.

Finally, segmentation results are useful to provide treatment quickly as it locates tumor from non-tumor region. The computational time is also low. Accurate results and automatic detection minimize the workload of pathologist and reduce error rate. Our proposed work can save numerous lives through its effective and reliable Brain Tumor Analysis.

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