**RESEARCH PAPER**

# Brain Tumor Detection Using Deep-Learning Framework

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**ABSTRACT**

Magnetic resonance imaging is a complex, tedious and lengthy procedure of achieving a cancer diagnosis by manual segmentation of brain tumors. Accuracy and the strength of segmentation of brain tumors are, therefore, one of the most important factors of the diagnosis, treatment planning, as well as treatment outcome examination. Most automated brain tumor segmentation techniques make use of manually formulated functions. Other classical methods of deep learning (such as convolutional neural networks) also require a large amount of annotated data to be trained on, which is usually difficult to acquire in the medical sector. Here we are introducing a brand new model of two-pathway-group CNN architecture of brain tumor segmentation which makes use of the local features alongside the global contextual features. The model employs the similarity between the bidirectional CNN model in order to reduce instability and overfit common parameter. Finally, we integrate the cascaded architecture to a two way multicast CNN in which the output of the simple CNN is used as an auxiliary source and summarised at the final level. The BRATS2013 and BRATS2015 data sets have been verified, and it can be concluded that the introduction of this group CNN to a pathway architecture would allow improving the overall performance compared to the performance currently published with an attractive complexity that is currently calculated.

**Keywords:** MRI,CNN ,Image Acquition , pre-processing,Classification.

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## 1.INTRODUCTION

Tumors will have a huge effect to the brain. Brain cells are destroyed in the area effect of tumor gets and can cause brain collapse. The outcome of the tumor is dependent on the size and area affected in the brain. The Brain connected every and each part of the body together to form it perfect sense. If something happens to the brain our whole system falls apart. Some neurons in brain do not have capability to regenerate and there some neurons which stops regeneration as a person age. If tumor is placed within any of that non-regenerative areas, a person even loosen one of his/her senses. Discovering the tumor at an early stage can save the life of a person. Artificial Intelligence is revolutionizing Healthcare in lot of way such as Disease Diagnosis with medical imaging, Surgical Robot Maximizing hospital efficiency. Deep learning has been proved to be better in detecting diseases through X-rays, MRI scans and CT scans which could bring a significant improvement in the speed and accuracy of diagnosis. Tumors are localized and diagnosed by a very acute medical procedure. One such process is the Magnetic Resonance Image (MRI). Our MRI model will be trained and validated. These images are sent into to model to make it learn about detecting and locating brain tumor.

Segmentation of brain tumors in multi-modal imaging data is a difficult problem given the unpredictable tumor shapes and sizes. Deep Neural Networks (DNNs) have already been used on segmentation problems, and have shown great improvements in performance over the previous methods [4]. We use Convolutional Neural Networks (CNNs) to carry out the brain tumor segmentation task on the large dataset of brain tumor MR scans provided by BRATS2015. CNNs are DNNs for which trainable filters and Local Neighborhood pooling operations are used alternately on raw input images so that it produces a hierarchy of more complex features. Specifically, we used multifield information from T1, T1c, T2 and Flair as inputs to different CNNs. The various intermediate layers perform convolution, pooling, normalization, etc. to learn the highly nonlinear functions that map the inputs to outputs. We take the output of the last hidden layer of each CNN as the representation of pixel in that modality and concatenate the representations of all the modalities as the features to train a random forest classifier.

Magnetic resonance imaging (MRI) is widely used medical technology for diagnosis of various tissue abnormalities, detection of tumors. The active development in the computerized medical image segmentation has played a vital role for the scientific research. This helps the doctors to take necessary treatment in an easy manner with fast decision making. Brain tumor segmentation is a hot point in research field of Information technology with Biomedical engineering.

The motivation behind the brain tumor segmentation is the assessment of the tumor growth, treatment response, computer-based surgery, treatment of radiation therapy and the development of tumor growth models. Therefore, computer-aided diagnostic system is meaningful in medical treatments to reducing the workload of doctors and give the accurate results. This chapter describes causes of brain tumor awareness of brain tumor segmentation and its classification, MRI scanning process and working, brain tumor classification and different segmentation methodologies.

## 2. LITRECTURE SURVEY

Magnetic resonance imaging (MRI) is a medical tool commonly used for tumour identification and for the diagnosis of various tissue abnormalities. The active development in the computerized medical image segmentation has played a vital role for the scientific research. This makes it easier for the doctors to make fast decisions and to administer the necessary medicine. Brain tumor segmentation is a hot point in research field of Information technology with Biomedical engineering.

The motivation behind the brain tumor segmentation is the assessment of the tumor growth, treatment response, computer-based surgery, treatment of radiation therapy and the development of tumor growth models. Therefore, computer-aided diagnostic system is meaningful in medical treatments to reducing the workload of doctors and give the accurate results. This chapter describes causes of brain tumor awareness of brain tumor segmentation and its classification, MRI scanning process and working, brain tumor classification and different segmentation methodologies.

Habib [1], used artificial convolutional neural network (ANN) to detect tumor using a similar brain tumor data sets used in this paper. He achieved 88.7 percent accuracy while testing. To improve his accuracy, he used a new neural network. The neural network contains two max pooling layers and one convolutional 2d (Convo2d) layer in the order.

Lin and Chang [2], used the K-means clustering algorithms with color based segmentation to track the objects of the brain tumor. K-means clustering groups the similar places together with the color. The interesting part in this paper is, they clustered color spaced image from greyscale using K-means algorithm.

The researchers in [4] use the MRI or second resonance images to detect the brain tumors. They classified MRI images which is complex due to variation in size and shapes of brain tumor. Decision Tree classifier, Multi-Layer perceptron are the two supervised classification learning techniques to detect brain tumor.

In this paper [7], the authors explained how misdiagnosis made by image processing or machine learning affect us and showed that they never always give accurate solution or result. There is other variable which need to be taken care while detecting brain tumor. In this paper, they have used an MRI augmentation technique. Which is sending images in model from various angles and different perspectives. This technique enables model to train on different new images and that got a good result and scores. They used CNN along with Link Net architecture.

Sharma and Komal [7] proposed a method which involves features detection of the brain tumor and classified based on the MRI data. They used different filters and image segmentation over images.

Sinthia and Malathi [8] proposed CNN which automated the process of brain tumor detection and segmentation. Neural network has been made using TensorFlow library. BRATS2015 dataset is used by them.

Guotai Wang [9], these researchers proposed an application of deep learning, in which it can interact with user. The application consists of different convolutional neural network 4 architectures that can create a model and can make segmentation of MRI images and can even highlight certain brain oragans. The user is able to adjust and force these organs to appear, and this is an interesting feature. They provided multiple architectures and made a comparison to get perfect result.

The authors of this research [10] suggested that the MRI pictures play an important role in the diagnosis of the illnesses. In order to make use of them in other articles, they even shared a few techniques of MRI image processing.

Google Net architecture codenamed Inception-v1 is the better utilization of computing resources inside the network [14]. The network with the inception architecture is faster than the network with non- inception architecture. The Google Net architecture including the inception module uses rectified linear activation function, average pooling layer and not fully connected layer and dropout after removal of fully connected layer.

Alex Net [15] architecture is more deep and much greater than Lent architecture. It consists of eight layers, five convolutional layers most of them are followed by max pooling and three fully connected layers. The output is the 1000 way soft max representing the classes. It is trained on the two parallel GTX 580 GPU 3GB which communicate only in certain layers. This scheme is shown to decrease the top-5 errors. Alex Net is improved with Zeit architecture which visualizes the Alex Net activities within the layers to debug problems and obtain better results. It makes it possible to observe the evolution of features during the training process and maps the activities back to the pixel space in intermediate layers.

**3.1 SYSTEM DESIGN**

To detected the Brain Tumor using Two-Pathway-Group Conventional Neural Networks. Use of traditional two-way cluster neural network for brain tumor detection System architecture

Brain tumor identification, it is really challenging task in early stages of life. But now it became advanced by deep-learning. Now a day issue of the identification of the tumor of the brain is of great interest. In Order to detect the brain tumor of a patient we consider the data of patients like MRI images of a patient's brain. Here our problem is to identify the presence or absence of tumor in brain of the patients. It is a very important to detect the tumors at starting level for a healthy life of a patient. There are many literatures on the detection of these kinds of brain tumors and enhancing the detection accuracies. In this paper, we estimate the severity of the brain tumor using Convolutional Neural Network algorithm which gives us accurate result.

**3.2EXISTING SYSTEM**

Existing systems describe the cell segmentation automation. The technique is employed to interactive multi label segmentation for N dimensional images. It segments the areas which are more difficult to be segmented. This is an iterative method and includes feedback to the user as the segment is calculated.

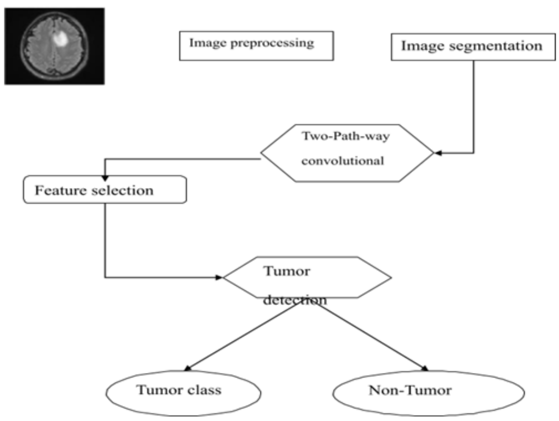
**3.3 PROPOSED SYSTEM**

We take a second dimension to propose a new strategy of MRI of the patient's brain. Here preprocessing is done with Gaussian which can be line filter. Then, identifying the area of the tumor GLCM functions, function extraction is carried out from the image. CNN architecture of bidirectional clusters for brain tumor segmentation, At the same time, it has its own functions and international information dissemination functions. This model provides the equivalence in the

two-channel CNN model to minimize backward jitter and eliminate the parameter sharing. Finally, we integrated the cascaded architecture in the dual-channel CNN pool, in which the basic CNN pins will be processed as other sources, and finally, combined the CNN into a two-way architecture, which also improved the overall performance. As compared with the now disclosed by

progressive method, this method is improved, and the complexity of the process is still quite pleasant.

**Architecture Diagram:**




**3.4 PROPOSED METHOD OF IMPLEMENTATION**

**3.4.1 Convolutional Neural Network**

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the 2D image.

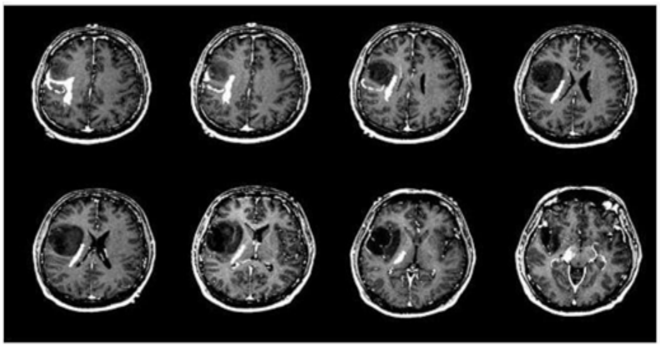


image and be able to distinguish one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are handengineered, with enough trainings, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is similar to that of the connectivity pattern of Neurons in the Human Brain, and was inspired by the organization of the Visual Cortex.

Individual neurons only respond to stimulus in a limited area of the visual field called the Receptive Field. A collection of such fields overlaps to cd over the whole area of vision. The objective of Convolution Operation is to extract the high level features such as edges, from the input image. Over the entire visual area a cluster of these fields overlap to form CD. Conventionally, it is the first Cavalier that is responsible for the LowLevel features, like edges, color, gradient orientation etc. With added levels, the architecture adapts to High-Level features as well giving us a network, which has the wholesome understanding of images in the dataset, similar to how we would.

### 3.4.2 Magnetic Resonance Imaging (MRI)

The MRI is a diagnostic tool that is used for analyzing and studying the human anatomy. The medical images obtained in different bands of the electromagnetic spectrum. The wide variety of the sensors used for acquisition of images and the physics behind them, make each modality suitable for a specific purpose. In MRI, the images are generated by using magnetic field which is about 10,000 times more than the earth's magnetic field. The MRI yields more detailed images than other techniques, such as CT or ultrasound. The MRI also gives maps of anatomical structures which have a high soft tissue contrast. Basically, is the magnetic resonance of hydrogen (1H) nuclei of water and lipid is measured by an mri scanner. As the signal values are 12 bit coded, 4096 shades can be represented by a pixel [11]. The MRI scanners require magnetic field and it is available at 1.5 or 3 T. In comparison with the earth's magnetic field (100 ft. or so) the magnetic field of a 3 T MRI scanner is about 60,000 times the earth field. The patient is placed in a strong magnetic field and it causes the protons in the water molecules of the body to align in either parallel or anti-parallel with the magnetic field. A radiofrequency pulse is introduced and the spinning protons are made to move out of the alignment. When the pulse is stopped the protons realign and give of radio frequency energy signal that is localized by the magnetic fields and are spatially varied and rapidly turned on and off. A radio antenna inside the scanner picks up the signal and develops the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution.

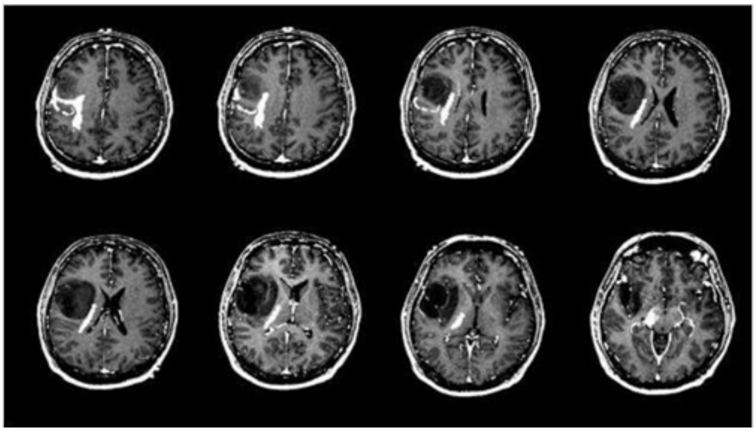


**Figure 4.6 MRI of Human Brain**

The most common method makes use of a technique known as blood oxygen level dependent contrast. This is an example of endogenous contrast, exploiting the natural differences in the content of oxygenation, i.e., the intrinsic signal differences in blood oxygenation. In the normal resting state, a high concentration of deoxyhemoglobin attenuates the MRI signal because it is paramagnetic. However, the neuronal activity, in response to some task or stimulus, results in a local demand for the oxygen supply, which results in an increase in fraction of oxy hemoglobin, resulting in a signal increase on T2 or T2*-weighted images. In a typical experiment, a series of rest and task intervals are imposed on the patient and the MRI images are obtained repeatedly. A radio antenna located in the scanner picks up the signal and forms the image. Functional MRI is a method to investigate the brain activation, which, unlike PET, is non-invasive and has relatively high spatial resolution. The signal changes during the course of time are then examined on a pixelby pixel basis to test for how well they correlate with the known stimulus pattern. The pixels showing statistically significant correlation are highlighted in color and superimposed on a grayscale image from the MRI machine to produce an activation map of the brain. The location and the extent of activation is related to the form of stimulus. Thus a simple movement task involving thumb fingers will generate activation in the primary motor cortex.

### 4.1 MODULES

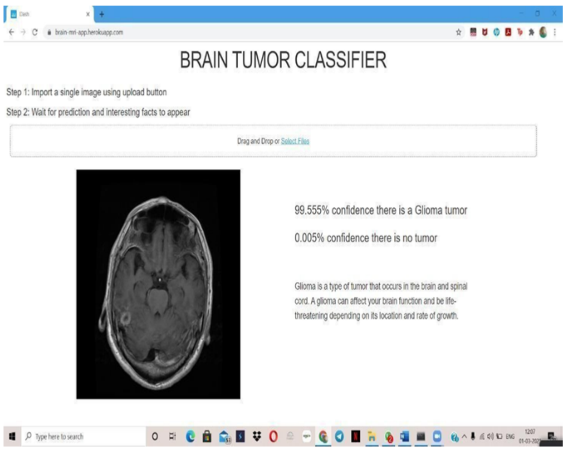
- Image acquisition
- Image preprocessing
- Image segmentation
- Convolutional neural network
- Tumor detection

#### 4.1.1 Image Acquisition

The Primary Phase is the acquisition of images. After the Images collection, the images obtained have to be prepared with a wide range of vision. First get the input images from available source

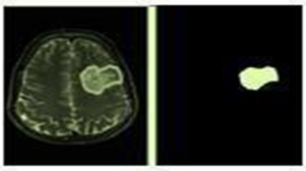
#### 4.1.2 Pre-Processing

The images which are collected are subjected to pre-processing. In Pre- processing stage basic steps are being image resizing and applying of Gaussian filters for perfect input clear image for easy identification of an image. Pre-processed images will be divided digitally into different pixels. We do this segmentation for an image is to modify its representation to have more clarity to analyze the images.

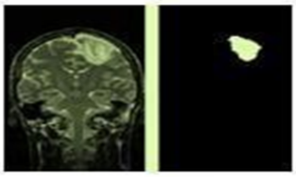



#### 4.1.3 image segmentation

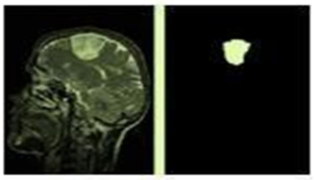
In the first stage, the magnetic resonance image of the pre-processed brain will be converted to a binary image with threshold of 128 as the cut off. Pixel values greater than the values specified are mapped as white, with other areas of the region marked as black: the two of these allow different regions to be created around the disease. In the second stage, an erosion process of morphology is used to extract white pixels. Eventually, the eroded area and the original image are divided into two equal areas, and the area with black pixels of the eroding is counted as a mask of brain Magnetic Resonance image. In this paper, wavelet transformation is applied to perform the efficient segmentation of the brain Magnetic Resonance image. The fully automatic heterogeneous segmentation is shown in figure 3. Figure 3(a) shows the axial image and its segmentation figure 3(b) Coronal image and its segmentation figure 3 (c) Sagittal images and its segmentation



3(a)



3(b)



3(c)

**4.1.4 Extraction Feature**

The efficient texture operator that labels the pixels of the image can be used during the feature extraction procedure. Here, we extract the image traits and characteristics to make the brain tumor identification simple.

**4.1.5 Classification**

Convolutional neural networks are applied to the clustering of brain pictures. It is producing the best outcomes with the image.

**4.1.6 Tumor Detection**

Lastly, look at the image by filters and Convolutional neural networks algorithm, to find out the tumor or Non-tumor.

**5. RESULT**

In our dataset, we have tumor and non-tumor MRI images, which have been found on different sources on the internet. Detect using convolution neural network. It is modeled using Python language. Determine the accuracy and compare with all other contemporary methods.

Training accuracy, verification accuracy and verification loss must be calculated to tell how the brain proposed works. The system of tumour classification. The technology that is currently available in the detection of brain tumors involves the use of SVM (Support Vector Machine) classification. Output Required in the process of feature extraction. According to the value of the feature, output of classification is obtained and the accuracy is determined. Support vector machine based tumor and non-tumor detection are lengthy and lack of accuracy in calculation. The CNN-based classification proposed does not take advantage of an independent feature extraction step. The value of this functionality is based upon CNN itself. In the picture. The result of tumor and non-tumor brain imaging is classified is presented. Hence, it is not complex and has low calculation time and accuracy. The figure reports the results from the correctness of classification of brain tumors. Lastly, based upon the worth of the probability score, it is categorised into brain tumor or non- tumor brain. This is hardly likely to be typical brain imaging. The value of the score in comparison with normal and neoplastic brains.

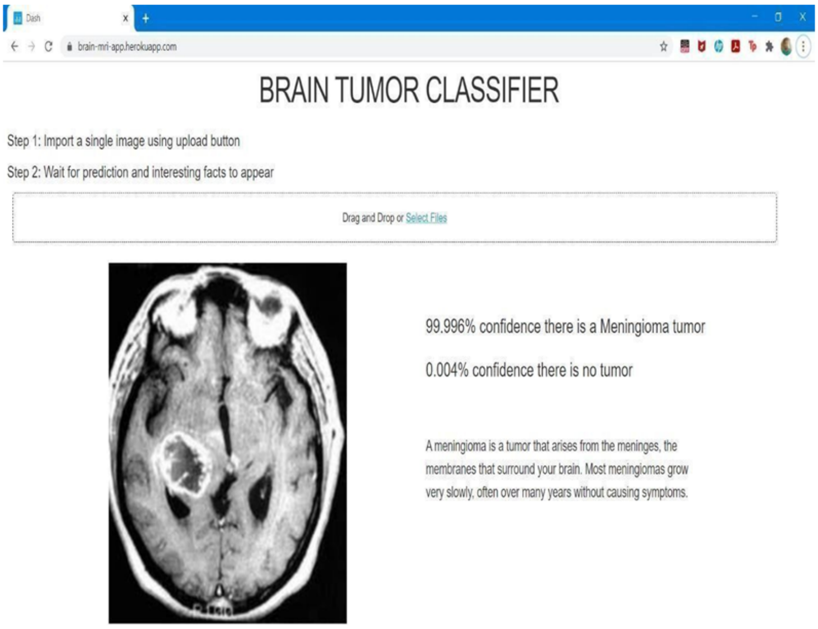



**Figure : E.1 Meningioma Tumor classifier**

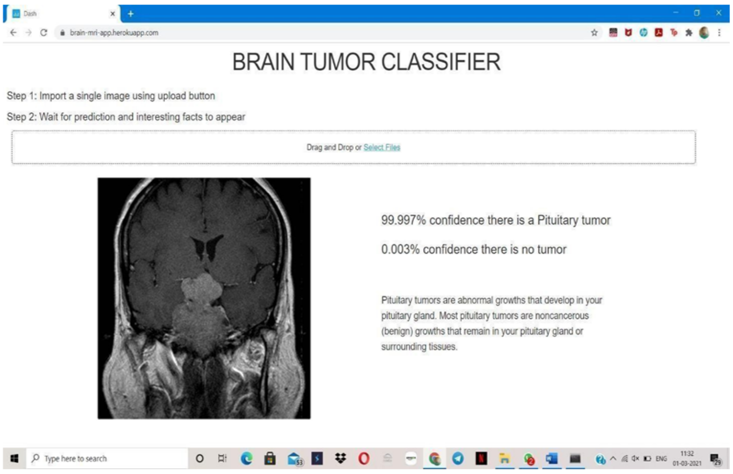



**Figure: E.2 Glioma Tumor Classifier**

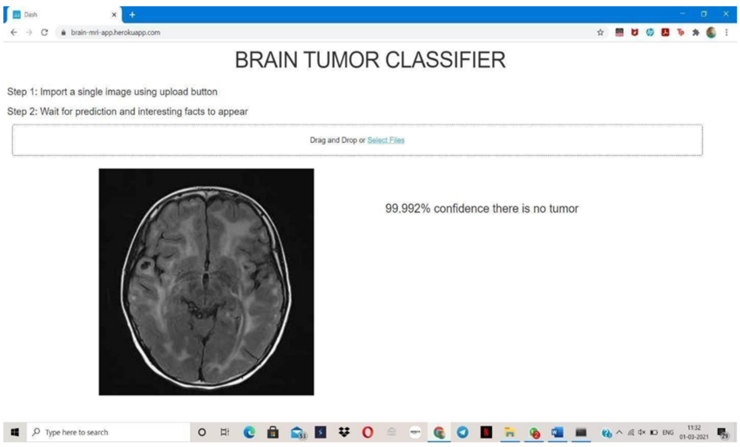



**Figure: E3 No Tumor Classifier**

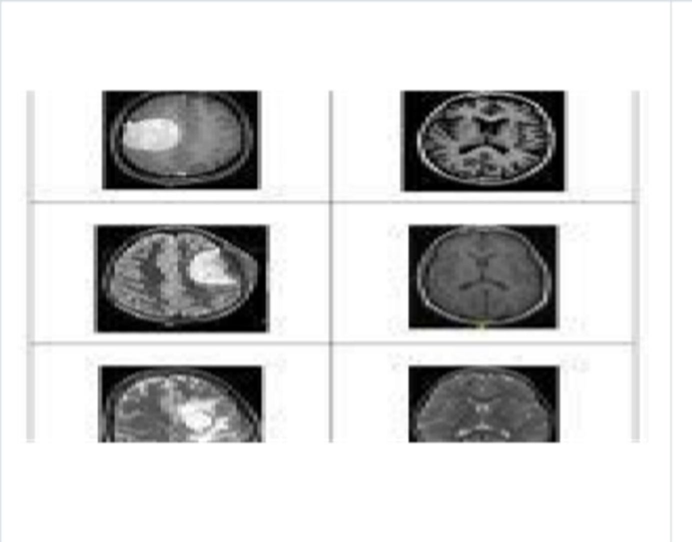


**Figure: E4 Pituitary Tumor Classifier**

**CONCLUSION**

The kind of data we possess is the tumor MRI images and non-tumor images which can be found on different online sources. There are actual cases of patients which are found in radiation podia. The test data of Radio podia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 is a set of tumor images. The identification is made with the help of convolutional network. Python language is used to model. Determine the precision and compare it to all the other contemporary techniques. Training accuracy, verification accuracy and verification loss, have to be computed in order to ascertain the effectiveness of the proposed brain.

Scheme of classification of tumors. The current brain tumor detection technology uses the classification of SVM (Support Vector Machine). Output is needed in feature extraction. The classification output is generated and the accuracy is calculated depending upon the value of the feature. Non-tumor and tumor detections by using support vectors machines are time consuming and lack calculation accuracy. The CNN-based classification that is proposed does not need the use of a separate feature extraction step. CNN has taken the value of this functionality. In the picture. The analysis outcomes of tumor and non-tumor brain scans presented. Thus, it is poor in complexity and time of calculation and correct. The figure indicates the outcome of accuracy of classifying brain tumor. Lastly, as per the value of the probability score, gets classified as brain tumor or non-tumor brain. This is hardly likely to be typical brain imaging. The value of the score against the normal and neoplasm brains.

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