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# Detecting Brain Tumors from Magnetic Resonance Image (MRI) Segmentation Using Deep Learning

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## ABSTRACT

**Brain tumors are major contributing factor for mortality and morbidity in the world. The diagnosis of brain tumors is a challenging task, requiring specialized expertise and advanced imaging techniques. This paper describes the proposed approach for the segmentation of Magnetic Resonance Image (MRI) scans of the brain and the detection of brain tumors. In general, tumors have a higher water content and more hydrogen atoms than healthy tissue, this creates noticeable variations in MRI image intensity between tumor regions and normal tissue. In this methodology, Convolutional Neural Network (CNN) was used as main deep learning algorithm to analyze the brain's MRI scans. The performance of different deep learning models was compared to determine the optimal approach for brain tumor detection and classification. The developed system provides a user-friendly interface for the visualization and interpretation of brain MRI scans. Deep learning can help provide more accurate and efficient diagnoses, improving outcomes for patients affected by this debilitating condition.**

**Keywords: Convolutional Neural Network, Brain Tumor Detection, Healthcare technology, Machine Learning,Image Classification,Segmentation**

## INTRODUCTION

The brain is one of the most intricately designed organs in the human body and has a staggering number of cells. A brain tumor is an abnormal growth of cells in the brain and it is One of the main reasons for the rise in mortality among people. These tumors can be either malignant (cancerous) or benign (non-cancerous). Tumors can form and stay in one place, or they can invade and expand into nearby tissues.[20] Most of the brain tumors are primary tumors which means they are created within the brain and do not spread from other regions. Gliomas, Meningiomas, Pituitary adenomas, Medulloblastomas, and Schwannomas are the most occurring types of brain tumors among patients.

The causes of brain tumors are not fully understood, but some risk factors have been identified, such as exposure to radiation, certain genetic disorders, and a weakened immune system. Symptoms of brain tumors can vary depending on their location and size, but they may include headaches, seizures, changes in vision or hearing, weakness or numbness in the limbs, and difficulty with speech or coordination.

Diagnosis of brain tumors typically involves a combination of imaging tests, such as MRI which is a medical imaging technique that uses radio waves and a strong magnetic field to generate detailed images of the body's internal structures or CT scans, and a biopsy includes slicing off a tiny sample of tumor tissue for analysis. It is also important to note that brain tumors can be difficult to diagnose, as their symptoms can be similar to those of other conditions. Treatment options for brain tumors depend on factors such as the type, size, and location of the tumor, as well as the patient's overall health. Treatment may include radiation therapy, chemotherapy, surgery, or a combination of these approaches.
Estimates from the International Agency for Research on Cancer (IARC) suggest that there were approximately 280,000 new cases of brain and nervous system tumors worldwide in 2020. According to the American Brain Tumor

Association, it is estimated that in the United States in 2022, approximately 91,470 new cases of primary brain tumors were diagnosed, including both benign and malignant tumors.

The detection of brain tumors is difficult because of the complex structure of the Brain. Most of the currently present methods to detect brain tumors are semi-automatic and dependent on human perception of a choice made during an MRI scan, which increases the possibility of a mistaken diagnosis and the identification of brain tumors, among other risks. Detection is also difficult for many of the machines because of the noise present in the MRI images. [1]. The previously proposed automated systems and models based on machine learning are not that effective because they were handled on limited data.

The method discussed in this paper is fully automatic. This method uses the fundamental property of Magnetic Resonance Images which is 'Intensity Difference.' The CNN algorithm, which is one of the Machine Learning classification algorithms uses this property to classify MRI images. This automatic system has mainly 3 phases.

i) Image Pre-Processing: Noise Reduction from MRI images
ii) Image segmentation - To detect which part of the brain has a tumor
iii) Image Post-processing: Extraction of brain Tumor

The CNN approach which is used in the proposed system of the paper is one of the most effective algorithms for image segmentation and it is good at detecting patterns and features in images with no need for manual feature extraction.
The structure of this paper is organized as follows: Section II is a literature survey, Section III is Methodology and different algorithms & techniques used for various Methods.

## LITERATURE SURVEY

Sunil et al. [1] discuss the methodologies and findings of 20 research papers published between 2000 and 2020 on the detection and segmentation of brain tumors using MRI images. The use of CNN classification techniques is found to be effective for accurately detecting brain tumors with a low error rate. The review suggests that future work should focus on improving accuracy and reducing errors using different classifier techniques. Overall, this literature survey highlights the potential of automated techniques for improving the detection and treatment of brain tumors.

Gobhinath et al. [2] propose a new method for brain tumor recognition involving three stages: 1) image pre-processing, 2) image segmentation, and 3) image morphological function. The proposed method uses wavelet transform and PCA to acquire the image features of a tumor and KSVM (kernel support vector machine) to classify the tumor. The proposed method was tested on 240 MRI scan human brain images, including seven general brain diseases, and achieved a classification accuracy of 98.17% using the GTB kernel. The results of this study indicate that the proposed PCA+DWT+KSVM method with the GTB kernel provides accurate classification and feature extraction output.

Mahnoor et al. [3] focus on using deep learning algorithms to accurately segment brain tumors from medical images. The paper proposes an ensemble of two segmentation networks, 1) 3D CNN and 2) U-Net. The system proposed in this paper is trained on the BRATS-19 challenge dataset. The outputs of these networks are combined in a technique that results in better and more accurate predictions for tumor tissue type. The proposed ensemble achieved good dice scores on the validation set, outperforming state-of-the-art techniques. The paper also analyzed different ensemble techniques to determine which is the most accurate. The results showed that the proposed ensembling scheme is better than simple average.

Vaishnavee et al. [4] proposed HFS-SOM for segmentation and PSVM for the classification of brain MRI images. GLCM-PCA is employed for feature extraction and selection. The system achieves high accuracy and less error rates for normal and abnormal brain classification. The study highlights the importance of accurate medical image processing for disease diagnosis, particularly brain tumor detection.

Yang et al. [5] propose an improved U-net model for the automatic segmentation of brain tumor MRI images. To solve the unbalanced data distribution problem the method uses a patches-based input and introduces a feature recombination layer to shorten training time and reduce training parameters. The study evaluates the proposed algorithm is using the HGG dataset of the Brats 2015 training set using a five-fold cross-validation method, demonstrating strong competitiveness compared to other convolutional network models. However, the evaluation is limited to the HGG dataset, and traditional data augmentation methods are not used, indicating the need for further research to validate the proposed method's performance on other datasets and address the unbalanced data distribution problem.

Navpreet et al. [11] discuss a self-adaptive K-means clustering algorithm to accurately detect brain tumors with minimal execution time, without requiring user input for the number of clusters. The segmented part is processed into a binary image for size and location estimation, and To extract textural and color-based features for growth analysis the gray version is used. The final segmented part undergoes size estimation using area and perimeter metrics. The algorithm detects brain tumor growth in each slice of the MRI image, and the graphical profile of the area and perimeter are consistent. The algorithm could potentially be used to compute tumor growth in the blood oxygen area during fMRI for the state of brain analysis.

Kabir et al. [12] propose a brain tumor detection algorithm that uses a support vector machine (SVM) and artificial neural network(ANN). The algorithm includes steps like image enhancement, segmentation, feature extraction, and classification, and has achieved 97.7% accuracy on the BRATS dataset. The neural network uses a fully connected backpropagation model with 40 neurons in the hidden layer and a tanh activation function. The proposed algorithm provides better accuracy than existing methods and can be further improved by incorporating convolutional neural networks for larger datasets.

Vidya et al. [13] discuss the use of diagnostic imaging for medical analysis and the detection of brain tumors. The authors propose a new system for brain tumor detection using a combination of k-means partitioning and object labeling algorithms for tumor area detection. The proposed technique involves preprocessing using a median filter and morphological operation to remove noise and the skull part of the brain. The paper provides a detailed explanation of each stage of the proposed system, including algorithms used and results obtained.

Saroj et al. [14] present a new fractional mask design for detecting benign brain tumors, which addresses the limitations of existing techniques. The proposed method is tested on a numerical head phantom, and a comparative study is conducted with popular boundary-based methods like Sobel, Prewitt, Canny, and Laplacian of Gaussian (LoG). The results show that the fractional order mask is superior to existing methods and is able to detect small intensity variations in the image. Quantitative analysis is also performed to evaluate the performance of the proposed method, which demonstrates its effectiveness in detecting benign brain tumors.

Amruta et al. [15] propose a system to detect and classify brain tumors into benign and malignant. The proposed methodology involves pre-processing the MR image, segmenting the tumor using morphological operations, extracting tumor features using Discrete Wavelet Transform (DWT), and classifying the tumor using Support Vector Machine (SVM). The image is first pre-processed by resizing and converting to grayscale, followed by morphological operations. The DWT is used to extract features from the image, which are then used as input to the SVM classifiers to classify the tumor as benign or malignant.

Acharya et al. [19] discuss the problem of automatic segmentation of brain tumors in MRI images using deep learning models. The current state-of-the-art model uses a CNN with small convolution kernels, which has shown significant improvement in accuracy, specificity, and sensitivity while reducing processing time. To address these limitations, the authors propose a DNN model that includes modifications in the segmentation and feature-extraction stages. They used only 10 MRI images to train the model and to check its performance which is too less. Validation of the model with a larger dataset is recommended also there may be a decrease in response time & decline in the performance of the model when trained on a larger dataset.

Hayder et al. [20] In this paper used Hidden Markov Random Fields (HMRF) model. These models have been widely proposed for segmenting homogeneous and noisy regions in MR images. In this context, the EM algorithm is widely used to estimate the parameters of relevant probabilistic models. The proposed method achieved good results for segmenting glioma tumors. The hybrid methods that combine HMRF and thresholding techniques have also shown promising results in brain tumor detection.

## METHODOLOGY

This research for brain tumor detection are focused on achieving accurate and efficient analysis of medical images. The proposed approach consists of several stages, including image pre-processing, segmentation, post-processing, feature extraction, and classification. The image pre-processing stage aims to enhance the quality of the medical images and prepare them for further analysis. Segmentation is used to isolate the tumor region from the rest of the brain tissues, while post-processing employs morphological operations to further refine the segmented region. Feature extraction is performed using CNN with windowing techniques, which enable the extraction of relevant features from the medical images. Finally, classification is used to classify the medical images as either containing a tumor or not.

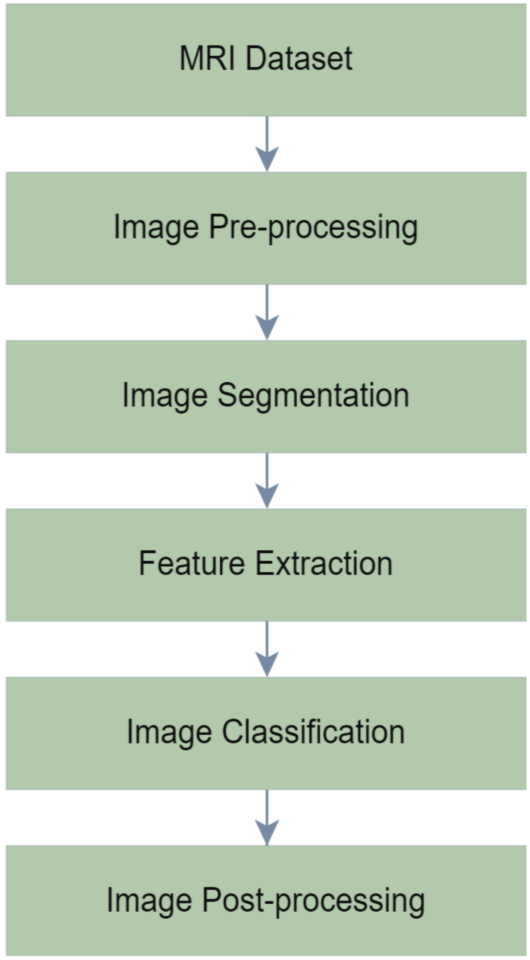


Figure1.Process flow of the system

**Image pre-processing**

The first step is image enhancement, which aims to improve the quality of the medical images to enhance the visibility of the brain tumor. We can use a variety of image enhancement techniques to preprocess the MRI images such as Gaussian filtering, Contrast stretching, and Histogram equalization.

Here are the steps involved in Image pre-processing:

1. Load the MRI image and convert it into grayscale
2. Apply noise reduction techniques such as median filtering to reduce noise and enhance the image's contrast
3. Apply the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm for enhancing the image.

CLAHE is the best algorithm for image enhancement as it adapts the contrast to local regions of the image, which enhances the contrast of the brain tumor region while preserving the contrast of the surrounding healthy tissues [12].

**Algorithm for CLAHE:**

1. Divide the image into small regions called tiles
2. Apply the Histogram Equalization algorithm to each tile to enhance the contrast
3. Limit the contrast amplification of each tile to prevent noise amplification and improve the overall contrast

**Image segmentation**

The simple and widely used technique for image segmentation is “Global Thresholding”, which assumes that the foreground and background pixel intensities can be separated by a threshold value. The threshold value is calculated based on the histogram of the image, which represents the distribution of the pixel intensities. The global threshold is

chosen in such a way that all the pixels with intensity values below the threshold are assigned to the background, and all the pixels with intensity values above the threshold are assigned to the foreground [18].
Here are the steps involved in global threshold segmentation:

1. Firstly, Convert the input image into grayscale.
2. Calculate the histogram of the grayscale image.
3. Calculate the cumulative distribution function (CDF) of the histogram.
4. Normalize the CDF values between 0 and 1.
5. Choose a threshold value based on a desired criterion such as maximizing inter-class variance or minimizing intra-class variance.
6. Threshold the image by setting the intensity values below the threshold to 0 (background) and the intensity values above the threshold to 1 (foreground).

**Feature Extraction**

Feature extraction is an essential step in identifying and extracting relevant features from an image that can be used for further analysis and classification. In the case of brain tumor detection, CNN can be used for feature extraction using the windowing technique. This technique involves dividing the image into smaller sub-images or windows and then applying the CNN to each window to extract relevant features.

Windowing techniques are used to adjust the contrast and brightness of the image by mapping the pixel values to a new range of values. This is achieved by selecting a window of pixel values that are within a certain range and scaling these values to the full range of intensity values. This helps to highlight the important features in the image and make them more visible to the human eye.

Let I(x,y) be the input image, and I_w(x,y) be the output image after applying windowing. Then, the windowing function can be defined as:

$$I\_w(x,y) = (I(x,y) - L) * (H - L) / (H - L)$$

where L is the lower limit of the window, and H is the upper limit of the window. This function scales the pixel values within the window to the full range of intensity values.

**Image classification**

Image classification is the process of assigning a label or category to an image based on its features. In the case of brain tumor detection, the features extracted using the CNN can be used to classify the image as either containing a tumor or not. Different algorithms and techniques such as SVM, Random Forests, and KNN classifiers can be used for image classification. The brain tumor detection system performance can depend heavily on the choice of these techniques and their specific parameters. Therefore, it is important to carefully evaluate and compare different methods in order to determine the best approach for your specific application. CNNs have been widely used in image classification tasks due to their ability to learn complex features from the images. CNNs can be trained on large datasets and can achieve high accuracy in image classification tasks.

**Convolutional Neural Network(CNN)**

Convolutional Neural Network (CNN) is a type of deep learning algorithm commonly used in image processing tasks such as image recognition, segmentation, and classification. It consists of several layers of interconnected nodes that perform convolutions on the input image data to extract features and patterns that can be used for classification.

In the context of detecting brain tumors from magnetic resonance image segmentation, CNNs can be trained to analyze MRI images and identify regions that indicate the presence of a tumor. The CNN would take MRI images as input, and after several convolutional layers, it would output a probability map indicating the likelihood of a tumor in each region of the image. This can then be used to segment the tumor and make a diagnosis.

The convolutional layers of a CNN in the context of detecting brain tumors from MRI segmentation involve applying a series of filters to the input MRI image to extract relevant features. These filters or kernels are typically small in size (e.g., 3x3 or 5x5) and are slid over the image to compute the dot product between the filter weights and the image pixels in a local region. This process is repeated multiple times to create a feature map that highlights important patterns and structures in the image.

The feature maps are then processed through additional layers, such as pooling layers or more convolutional layers, to further downsample or extract higher-level features. Finally, the output of the CNN is fed into a fully connected layer or softmax layer to generate the final prediction.

In the specific case of detecting brain tumors, the convolutional layers of the CNN would learn to identify features such as changes in tissue texture, shape, or intensity that may indicate the presence of a tumor. By training on a large dataset of MRI images with and without tumors, the CNN can learn to recognize these patterns and generalize to new images.

It is important to note that the architecture and hyperparameters of the CNN, such as the number of layers, filter size, and learning rate, can greatly impact its performance on this task. Therefore, careful design and tuning of the network are necessary to achieve optimal results.

**Image post-processing**

Morphological operations are used in image post-processing to clearly locate the tumor part in the brain. Morphological operations, such as erosion and dilation, are used to remove noise and fill gaps in the image. Erosion is used to reduce the size of the objects in the image, while dilation is used to increase the size of the objects. These operations are applied using a structuring element that defines the shape and size of the neighborhood to be considered.[18]

Let A and B be two sets, where A is the image and B is the structuring element. The dilation of A by B is defined as:

$$(A \oplus B)(x,y) = \max \{A(x-i,y-j) + B(i,j)\}$$

Similarly, the erosion of A by B is defined as:

$$(A \ominus B)(x,y) = \min \{A(x+i,y+j) - B(i,j)\}$$

where (x,y) is the center of the structuring element, and (i,j) are the coordinates of the structuring element.

**Dataset Size and Diversity:**

The dataset comprises of MRI scans. The dataset contains almost 3000 MRI scans out of which 1500 scans are Tumor affected and 1500 scans are of normal brain i.e., without brain tumor. The dataset of MRI scans contains MRI scans collected from various sources on internet. From the dataset 80% of the data is used for training the model and 20% of the data is used for testing the model.

Total no. of images used -> 3000
Images with Tumor [Yes] -> 1500
Images without Tumor [No] -> 1500
80-20 Training-Testing is used i.e. 80% of the data is used for model training and 20% of the data is used for testing the model.

**Proposed System:**

The proposed system for brain tumor detection and classification involves a pipeline of image processing techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE) for image pre-processing, global threshold segmentation for tumor segmentation, morphological operations and windowing techniques for image classification, and a Convolutional Neural Network (CNN) algorithm for tumor type classification. Additionally, a user interface has been developed using React.js and Flask, allowing users to upload MRI images and receive predictive output for brain tumor detection and classification. This system aims to provide accurate and reliable results for medical professionals in a timely and user-friendly manner.

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## RESULTS AND DISCUSSION

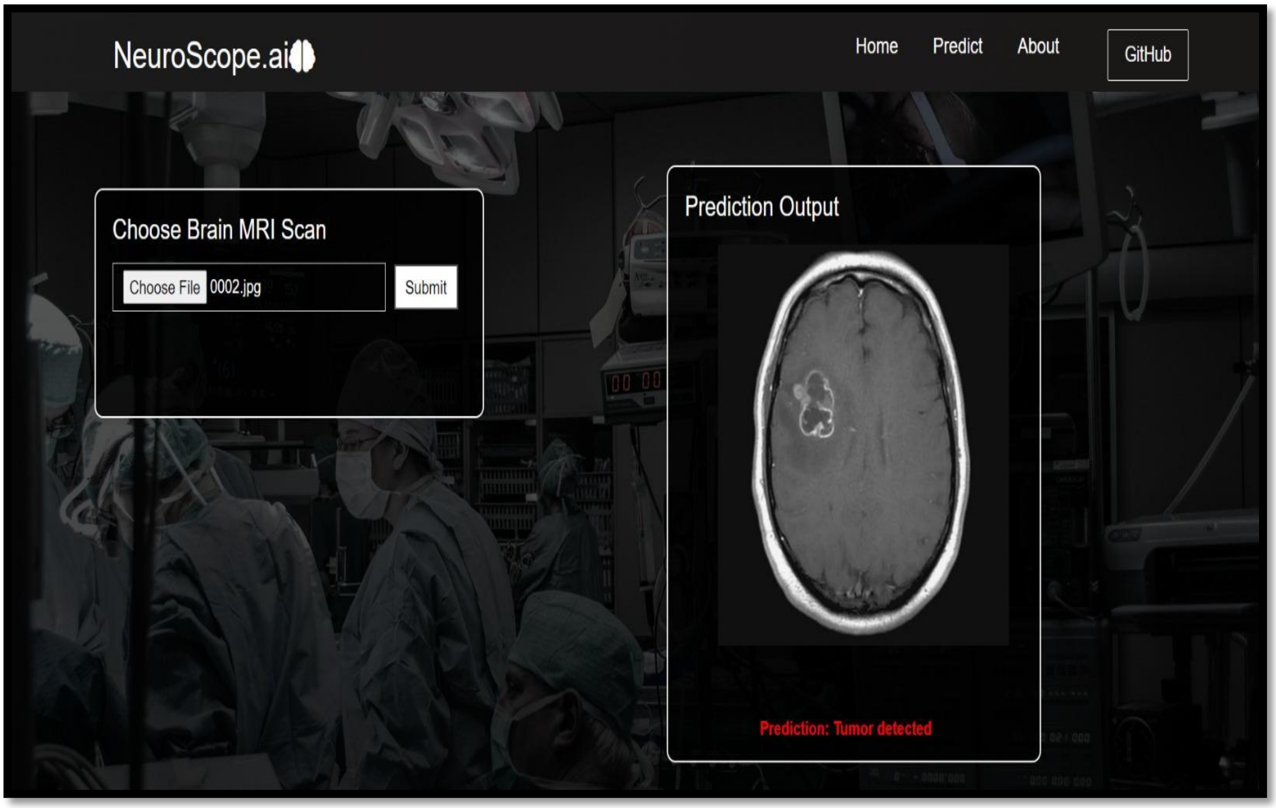


**Figure2. User Interface after uploading and submitting the image on the portal.**

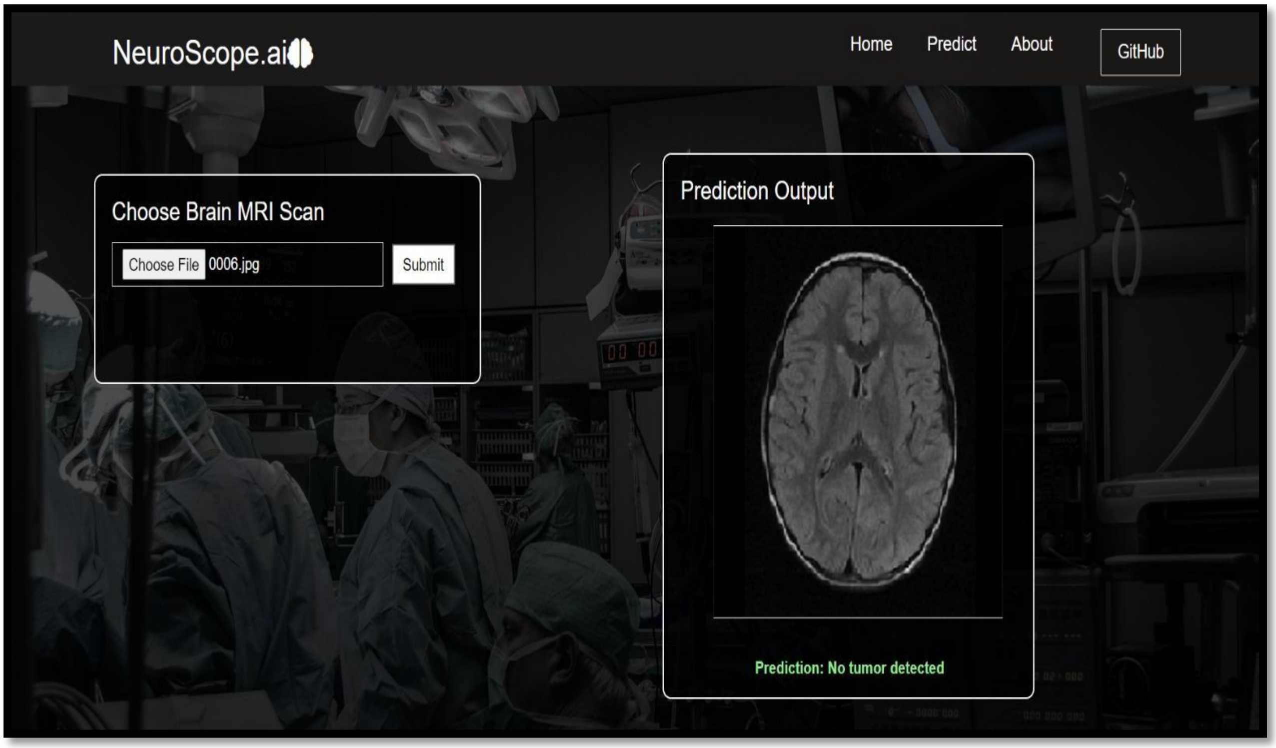


**Figure3. Output Screen of the portal**

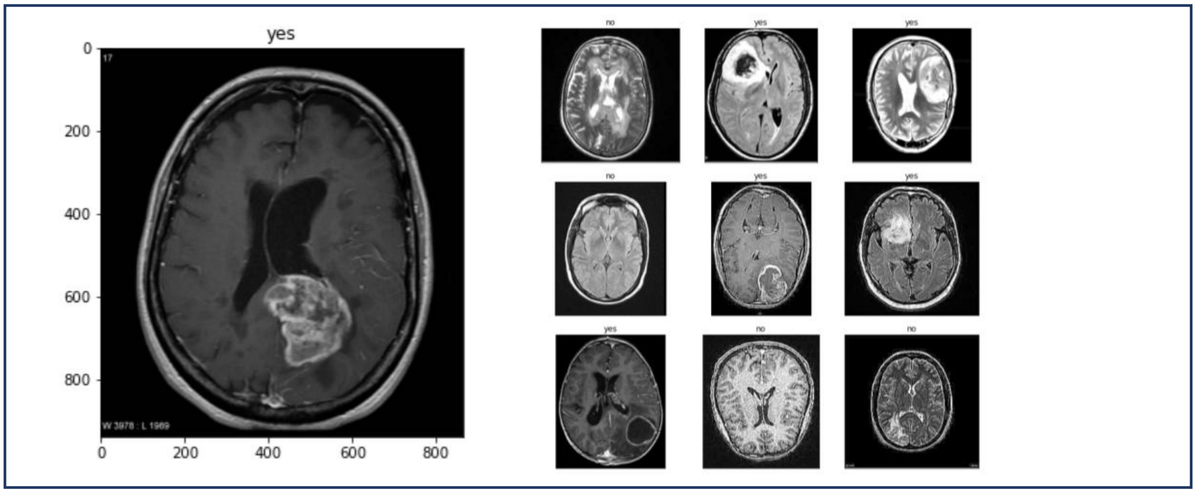


**Figure4. Output of Visualization**

**Performance Evaluation**

- **ACCURACY**: 0.98

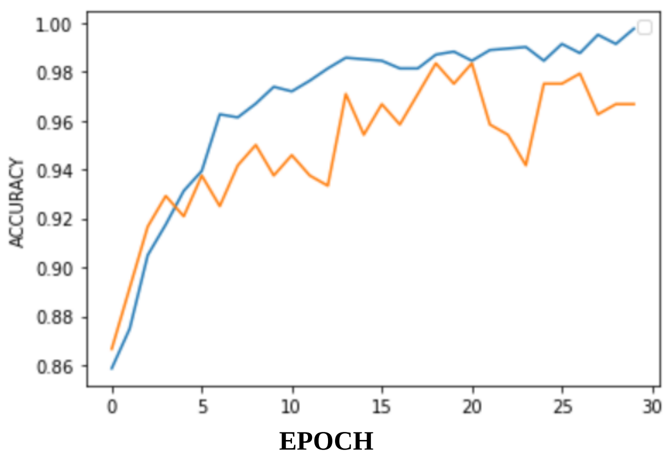


**Figure5. Graph of performance evaluation (Accuracy vs. Epoch)**

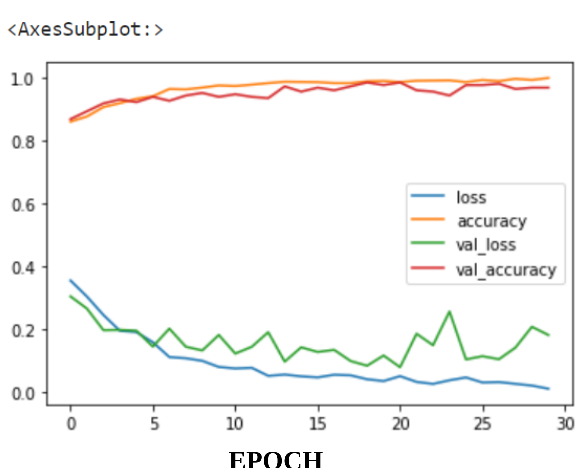


**Figure6. Graph of performance evaluation**

**Comparison with existing models**

**Table1.Comparison with existing model**

| **Existing Model** | **Accuracy** |
|---|---|
| "An Superior Achievement of Brain Tumor Detection Using Segmentation Based on F-Transform" [17] | 96% |
| "Computer Aided System for Brain Tumor Detection and Segmentation"[18] | 97% |
| "Early Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique"[12] | 97.7% |
| Model Proposed In this paper (vast dataset of 3000 MRI images) | 98% |

**Future Directions**

There are several future directions that can be explored based on the proposed features for the website's user interface. Future research can focus on integrating more comprehensive information on brain tumor types, including a wider range of precautions and treatment options for each type.

In terms of suggesting the best treatment center for brain tumor patients, future research can explore the use of machine learning algorithms to personalize recommendations based on individual patient needs, such as proximity to their location and treatment preferences. This can also involve leveraging patient data to better understand the effectiveness of different treatments and the factors that contribute to positive outcomes.

Finally, in terms of keeping patient records, future research can focus on developing secure and effective data management systems that allow doctors to easily access and update patient information. This can involve integrating patient data from multiple sources and leveraging analytics tools to track patient progress and treatment effectiveness. Overall, these future directions can lead to more accurate diagnosis, personalized treatment options, and improved patient outcomes for those with brain tumors.

## CONCLUSION

The use of deep learning techniques for brain tumor detection from magnetic resonance image (MRI) segmentation has shown promising results. With advancements in deep learning algorithms, MRI segmentation has become an effective tool for accurately identifying and localizing brain tumors, which can aid in diagnosis and treatment planning.

The research paper has highlighted the importance of using deep learning-based approaches for brain tumor detection, as they can achieve high accuracy and efficiency compared to traditional methods. The use of convolutional neural networks (CNNs) and other deep learning architectures have shown great potential in segmenting brain tumors from MRI scans, with the ability to handle complex patterns and variances in tumor shapes and sizes.

However, there are still challenges that need to be addressed in this field. Research and development are needed to refine and validate these deep learning methods, and to translate them into practical clinical tools for routine brain tumor detection in clinical practice.

In conclusion, the integration of deep learning-based MRI segmentation methods into clinical practice has the potential to improve the accuracy and efficiency of brain tumor detection significantly, leading to better patient outcomes. Continued research and collaboration between medical and machine learning will pave the way for further advancements in this field and ultimately benefit patients as well as doctors.

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