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Brain Tumor Detection Using Image Segmentation

Harshit Jain[1] | Gaurav Maindola[1] | Dhruv Rustagi[1] | Bhanu Gakhar[1] | GunjanChugh[2]

[1]Department of Information Technology, Dr. Akhilesh Das Gupta Institute of Technology and Management, New Delhi, Delhi, India.

[2]Assistant Professor, Department of Information Technology, Dr. Akhilesh Das Gupta Institute of Technology and Management, New Delhi, Delhi, India.

Corresponding Author : harshitjain137@gmail.com

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ABSTRACT

A Brain Tumor is a mass or growth of abnormal cells in your brain. Many different types of brain tumor exist. Some brain tumors are noncancerous, and some brain tumors are cancerous. The goal of this research is to develop an automated brain tumor detection system using segmentation and classification of MRI images. Tumors in the brain can be of anyshape or size. This encourages us to use high-capacity deep neural networks. This article provides a summary of what we did and the methodology we used. We utilized the Kaggle dataset and tested the trained model. This dataset contains 5000 images for the segmentation task and 8000 images for the classification task. MRI scans are segmented using patch segmentation. This methodology shows an accuracy of about 95.6% on the test data set. We performed several experiments to determine the depth of our neural network and found the best architecture to be used. The exact location of the glioma was determined by a convolutional neural network. We useda combination of deep and convolutional neural networks to find the spectral localization of gliomas in lilac cells. This architecture can also be used to predict the future state for the long term.

KEYWORDS:Classification, Convolution Neural Network, Deep Neural Network, MRI, Segmentation, Tumour

1. INTRODUCTION

The growth of abnormal cells inside the skull is defined as a brain tumor. These abnormal growths cause problems because the inside of the skull is hard. Brain tumors can be divided into two main types. Noncancerous (benign) and cancerous (malignant) tumors. Additional cell growth in the brain can cause pressure inside the skull. This pressure can cause brain damage. And the damage can be life-threatening. There are two types of brain tumors: primary and secondary. Most primary brain tumors are benign. Metastatic brain tumors are another name for secondary brain tumors. These tumors do not necessarily start in the brain. They can spread from other organs, such as the chest or lungs.[1]. These tumors can be diagnosed using medical imaging. Imaging of body parts and tissues can be performed with medical imaging. It is used tomonitordiseases,treatdiseases,and diagnose diseases. Radiology is a field used in medical imaging. All physiological and anatomical details of the human body are represented in this medical image. This is done in high resolution to provide sharp images of body parts and tissues. Imaging techniques that can be used to diagnose disease include computed

tomography, x-rays, and magnetic resonance imaging (MRI). Every detail regarding the development of the human brain and the detection of abnormal cell growth in the brain can be detected by MRI. It can be used to obtain detailed anatomical information about tumors of the brain, ankle, and foot. It uses magnetic fields and radio waves for imaging. Therefore, it is the preferred imaging method over computed tomography and X-rays.[3].

In general, a brain tumor can be one of the causes of a stroke. If no brain tumor is found, a stroke is treated instead of a brain tumor. Therefore, tumor detection is an important step in the treatment of patients with brain tumors. Detecting tumors as early as possible can increase patient life expectancy. [4]. In general, low contrast is a problem with traditional medical imaging techniques. Therefore, MRI is the best method of diagnosing tumors that currently exist. Image segmentation is a very important step in brain tumor detection.

Segmentation helps to change the appearance of an image. Essentially, it alters the image to detect edges and splits the image into different regions to help find tumor areas. This area makes up the entire image [5].Therefore, it is necessary to develop an image segmentation system that provides accurate results and has properties such as fast calculation.

Image segmentation is a technique that divides an image into meaningful and meaningful regions based on properties such as texture, intensity variation, similarity, and heterogeneity. Edge detection is one of the methods used for image segmentation. The proposed method divides the image into different regions according to the edge and intensity changes between pixels. This method does not require any prior image information. This method is effective compared to other visualization methods due to features such as fast computation [6].

There are other segmentation methods based on intensity similarity between image pixels. Growing Zones, Uncontrolled Thresholds, and Thresholds are just a few of the methods that apply to this zone. The area growth technique is a simple technique that is more noise resistant compared to edge detection. This method divides the image into regions based on a predefined value that represents the similarity between pixels in the region.

Thresholds are another simple technique. However, it is inefficient compared to other methods because it requires predefined information about the image. Unsupervised algorithms include means, fuzzy, self-organizing maps (SOM), and many others [7].Efficient and less error-sensitive. In this article, we developed a methodology inspired by deep neural networks and experimented with various CNN architectures. We have been working on this architecture using a small kernel at the convolutional level of the network for image processing. Smaller kernels can be stacked to achieve deeper architectures. We can have a large nucleus-like a receptive field. This architecture can apply more processing steps and eliminate data heterogeneity due to image acquisition [8,9].

2. LITERATURE SURVEY

Medical image processing is one of the main research topics. Many researchers have contributed their own algorithms and methods for augmenting medical images. Bandhyophyav and Paul [10] proposed a method using clustering for partitioning. During image processing, the image must be split into two parts to recognize the area with the brain tumor. One part of the brain is made up of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Another part of the brain is made up of tumor cells. This method combines multiple images. Good results have been obtained with this fusion method. However, this method has lost its strength. Anatomical information was also ignored in this method. This information includes the overlap of cells within brain regions and boundaries. Thereis another image segmentation method proposed by Mina and Raja [11] for positron emission tomography (PET) scans,which uses the Spatial Fuzzy CMeans clustering algorithm. This approach combines spatial neighboring data with FCM and then updates the objective function of each cluster. Based on the statistics provided by the objective function, the weight function is computed and then applied to the membership function. The Alzheimer's disease dataset is used to test this approach. This algorithm requires human participation. Quality assessment is not purpose-based. Therefore, no image quality is reported using this algorithm. Galvan and Holban [12] used convolutional neural networks in their proposed

system. Xray images are used in a segmentation process using CNNs as pixel classifiers. The classifier tries to divide the image into two groups: bones and not bones. The system analyzes each pixel in the image. This method gave the best results compared to other CNN configurations. This method takes more time to learn and won't work if you have some irregularities in your bones. Tathiraju and Mehta [13] used algorithms such as normalized cuts (NC) and expectation maximization (EM) for image segmentation. These two unsupervised algorithms were compared using the graph-based algorithm and the NC algorithm. In this algorithm, many clusters appear at individual locations in the image. Threshold and morphological operations are used in the technique proposed by M.A. Jaffar et al. [14]It is simple to comprehend and execute than the other techniques used for image segmentation.

3. METHODOLOGY

- **Input Images:** The steps to get an image start with getting a group of images from the database. Medical images are usually not displayed in standard formats (eg jpg, jpeg, png). Instead, they are in TIF (Tag Image File) format, and for convenience, they are stored in a panda datagram and loaded using the OpenCV framework.
- **ImagePre-processing:**In preprocessing, the MR image is corrected using displacement field distortion. Even in the same tissue, the intensity of MRI images is different. Intensity distributions of the same type of tissue may not certainly have similar intensities in MRI, which is considered the concept of many segmentation methods. The intensity distribution may be different even for images of the same infected person taken multiple times with the same scanner. Therefore, the proposed method can be used to enhance this normalization to change image properties such as contrast, color or brightness to obtain similarity with MR images. A frequency reference is obtained during training on the training set to perform the intensity normalization method. After training, we interpret the original intensities from the learned landmarks to achieve frequency normalization.
- **Image Segmentation:**Image segmentation is important because a large number of images are generated during a scan and the clinician is unlikely to isolate these images manually within a reasonable amount of time. Image segmentation refers to dividing a given image into multiple non-overlapping regions. Segmentation represents an image as a set of pixels that are more meaningful and easier to analyze. It is used to approximate the boundaries or objects of an image and the resulting segments together cover the entire image. The segmentation algorithm works with one of two main image intensity characteristics;similarity and discontinuity.
- **Feature Extraction:**Feature extraction is an important step in building pattern classification and aims to extract relevant information that characterizes each class. In this process, the relevant features are extracted from the object/alphabet to form a feature vector. These feature vectors are then used by the classifier to recognize input units as target output units. It becomes much easier for the classifier to classify different classes by looking at these features. Feature extraction is the process of extracting the most important data from raw data.
- **Classification:** Classification is used to classify each element in a data set into one set of predefined classes or groups. That is, classification is an important method widely used to differentiate images of a normal brain and a tumor brain. Classification in the data analysis task is to create a model or classifier for predicting category labels (properties of class labels). Classification is a data mining function that assigns target categories or classes to collection elements. The goal of classification is to accurately predict the target class for each item in the data.
- **Inference:** After training and evaluating the classification and segmentation model, we will proceed with building the pipeline. This involves taking an image as input, pre-processing it, and sending it as input to the classification model, which is only sent to the segmentation model for localization if there is a tumor in the image.

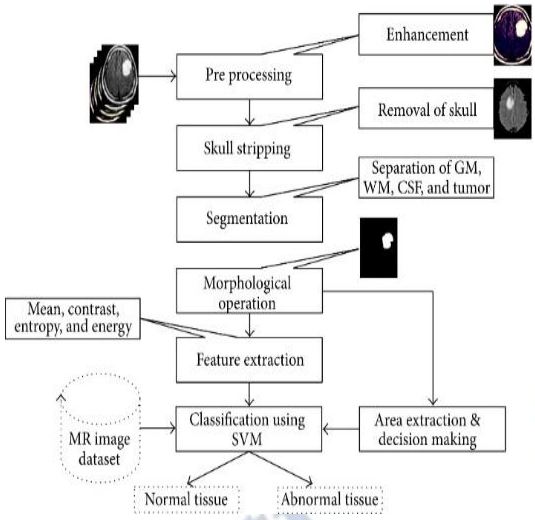

Figure 1: Methodology Flowchart [9]

4. IMPLEMENTATIONTION &RESULT ANALYSIS

Data augmentation is a technique for reducingoverfitting andgenerating more training data from the original data. In this article, we applied enhancement techniques such as flipping, adding noise and moving, and simple transformations. The figure shows examples of all transformations applied to the original image [15].

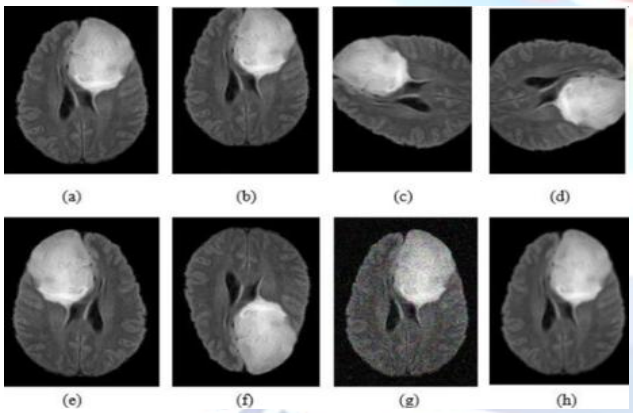

Figure 2 : Data Augmentation of Image

- **Classification:** The human brain is modelled using the design and implementation of neural networks. A layered layer consists of an input layer, a hidden layer, and an output layer. A closed loop feedback network is called a cyclic network. Neural networks are mainly used for vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification methods. Convolutional neural networks are used to automatically classify brain tumors. The brain imaging data set is from Image Network. The image network is one of the pre-trained models. To train on the initial layer, you need to train the entire layer (i.e.) as the final layer. So the time cost is very high. This will affect performance. To avoid this kind of problem, a pre-trained model-based brain dataset is used for the classification step [16]. In the proposed CNN, only the last layer of the Python implementation is trained. We don't want to train every layer. Therefore, the computation time of the proposed automatic brain tumor classification technique is short and the performance is high. The loss function is calculated using a gradient descent algorithm. Raw image pixels are mapped to class scores using a score function. The quality of a particular set of parameters is measured as a loss function. It is based on how well the derived scores match the true labels in the training data.

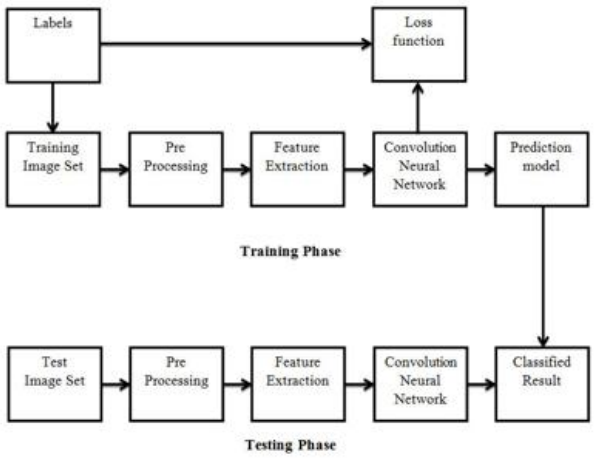

Figure3 :Block diagram of proposed brain tumor classification using CNN

The calculation of the loss function is very important to improveaccuracy. When the loss function is high then the accuracy is low. Similarly, the accuracy is high when the loss function is low. Gradient values are computed over the loss function to compute the gradient descent algorithm [17]. The slope of the loss function can be calculated by evaluatingtheslope values multiple times.

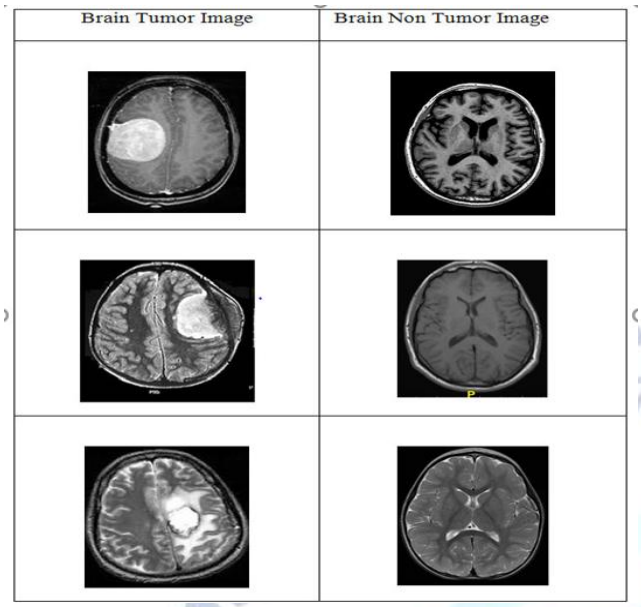

Figure 4 :CNN Based on classified results

We calculate the training accuracy, validation accuracy, and validation loss to determine the performance of the proposed brain tumor classification scheme. Current method utilize the Support Vector Machine (SVM)-based classification to detect brain tumors. This requires a feature extraction output. Generate classification results based on feature values and calculate accuracy. Detection of tumors and non-tumor tumors based on SVM has a long computation time and low accuracy.

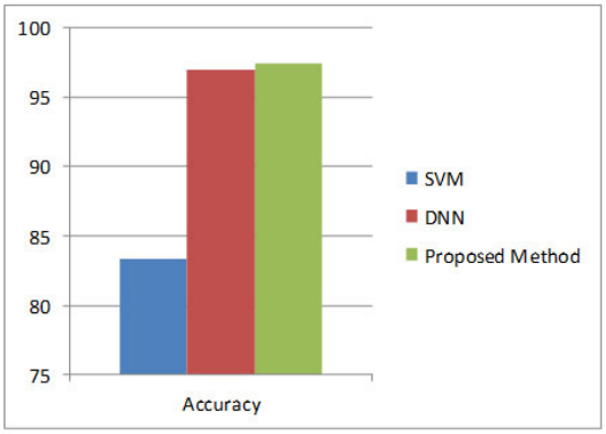

Figure 5 :Accuracy of Brain Tumor classification

The proposed CNN-based classification does not require a separate feature extraction step. The feature values are taken from the CNN itself. Figure 5 shows the results of classifying images of brains with and without tumors. Therefore, the complexity and computation time is low, and the accuracy is high. The results of the classification accuracy of brain tumors are shown in Figure 5. Finally, the classification results as Tumor brain or nontumor brain based on the probability score value. The normal brain image has the lowest probability score. The tumor brain has the highest probability score value when compared to the normal and tumor brain.

- **Segmentation:** We need to continue to segment the tumor before classifying the image and discovering that there is a tumor in the output prediction. Most approaches to tumor segmentation rely on fundamental truths involving substantive expert intervention. This problem is time-consuming and does not guarantee 100% accurate results. Our method solves these problems of labelled images and requires no expert intervention based on features extracted from CNN models [18].
- After extracting the features from the gradient of the last convolutional layer, we find the mean and global maxima and combine them into two vectors of size 32 instead of a matrix of shape (32,32,32) to get: Neuron importance weighting, minimizing function size and saving time.

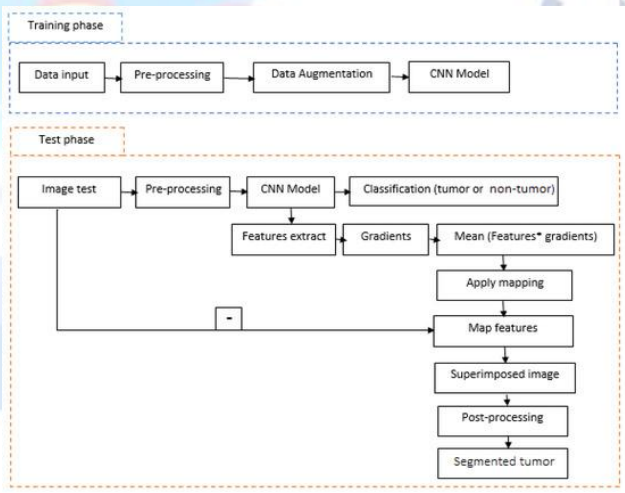

Figure 6 :Segmentation Pipeline Architecture

After that, we multiplied each feature map with corresponding pooled gradients stocked in the two vectors previously calculated, to extract more pertinent and detailed spatial information and specify the pixels that have a very high intensity which would be the tumor to segment. Then we obtained 32 significant images; since we needed just one, we calculated the mean image and threshold it with a specific threshold to

obtain our mask which precisely contained the tumor's pixels. This mask was represented in grayscale intensities as it would be hard to measure small changes; then we applied a color map.

- **Result Analysis:**The classification model was tested on 800 images with 69% accuracy. Since there is no predefined test concept in the segmentation model/framework, wedefined a custom loss based on the intersection (IOU loss) for the join.

Classification Model Loss: 65%
Segmentation Model Accuracy: 95%

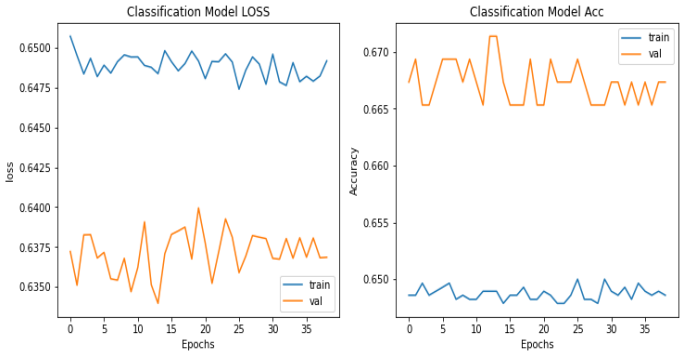

Figure 7 :Loss and Accuracy of Classification Model

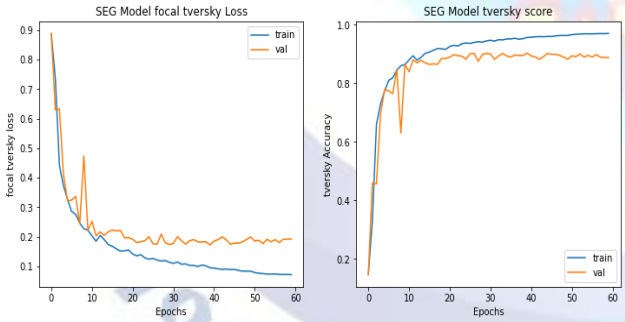

Figure 8 : Loss and Accuracy of Segmentation Model

5. FUTURE SCOPE

Kernel-based CNNs combined with Multiclass Support Vector Machine(MSVM) represent an efficient method for tumor enhancement and automatic segmentation. This method consists of a pre-processing step, a feature extraction method, and tumor segmentation. Improve MRI quality and extract features based on brain shape, size, and location using Gaussian Laplace filtering (LOG) and adaptive contrast-limited histogram equalization. Core-based CNN methods useMRI and MSVM to classify segmented tumors using core-based CNNs. Use a fixed wavelet transform (SWT) together with a growing convolutional neural network to better segment tumor regions. SWT improves the level of accuracy of GCNN for segmentation.

6. CONCLUSION

In this paper, we have automated the diagnosis procedure for brain tumor detection by the use of image processing. All the steps for detecting brain tumors have been discussed, starting from MRI image acquisition and pre-processing steps to successfully classify the tumor using segmentation and classification techniques. Pre-processing involves operations like wavelet-based methods. Quality enhancement and filtering are important because edge sharpening, artificial enhancement, noise removal, and undesirable background removal improve the image quality as well as the detection procedure. Among the different filtering techniques, the Gaussian filter suppresses the noise without blurring the edges and it is a better outlier without reducing the sharpness of the images. It reduces the noise, enhances the image quality, and is computationally more efficient than other filtering methodologies. After the image quality improvement and noise reduction discussed here, the segmentation methodology for a brain tumor from an MRI of the brain image is being used. Classification-based segmentation segments tumors accurately and manufactures sensible results for a big information set, however, undesirable behaviours can occur in case wherever a category is unrepresented in training data. This classification method can first determine whether a tumor is present and, if so, whether the tumor is benign or malignant.Clustered-based segmentation yields segmentation masks quickly and directly, except for noisy pictures, which leads to serious inaccuracy within the segmentation masks. Neural network-based segmentation performs better in noisy fields and does not require assumptions about the underlying data distribution, but the learning process is one of its major drawbacks. Apart from several existing brain tumor segmentation and detection methodologies present for MRI of brain images, our research has proved to provide an overall accuracy of up to 95%.Despite some challenges, atomizing brain tumor segmentation using a combination of threshold analysis and classification with SVM and SOM overcomes the problem and

provides efficient and accurate results for brain tumor detection.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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