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Brain Tumor Detection Using Deep Learning

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Abstract : Brain cancer is a very serious disease that causes the death of many individuals. Identifying a brain tumor in the early stages of life is a challenging task. In this review article, we focused on deep learning using brain tumor detection using normal brain images or abnormal using deep learning techniques. To detect a patient's brain tumor, we consider patient data such as MRI images of the patient's brain. The proposed network deals with over fitting problem by utilizing dropout regularize alongside batch normalization, whereas data imbalance problem is dealt with by using two phase training procedure. Here our problem is to identify whether the tumor is present in the patient's brain or not and classify the type of tumor and identify it's stage. There are three types of tumor Meningioma, Gliomas and pituitary. It is very important to detect tumors at the initial level for a healthy life for the patient. There is much literature on detecting these types of brain tumors and improving the accuracy of detection. In this paper, we estimate brain tumor severity using a convolutional neural network algorithm, which gives us accurate results. The proposed method is validated on BRATS 2013 dataset, where it achieves accuracy on 97.5%.

***IndexTerms* - Magnetic resonance imaging (MRI), Convolutional Neural Network, Gliomas, pituitary, Meningioma segmentation, Feature Extraction.**

1.INTRODUCTION

The brain is the most beautiful and diverse organ in the human body. It regulates our body mechanisms. Even every thought, feeling, and the plan is developed in our brains. Brain neurons capture every memory in our life. A brain tumor is difficult to identify axiomatically, mainly because of its great variability in shape and size. The origin of a brain tumor is unknown [2]. A tumor is categorized based on a molecular signature in the tumor cell with distinguishing characteristics. Some cells lose their ability to regulate their growth - they grow without any order, which is known as a tumor. Image segmentation is a very stimulating task due to the different shapes and grayscale similarity of neighboring organs and tumor tissues.

MRI images provide an unparalleled view of the human body. Manual brain tumor segmentation is relatively time-consuming and has an intra-rating variance. A semi-automatic technique is proposed for brain tumor segmentation; A two-way region growth method was used to segment the brain tumor. A convolutional neural network (CNN) is designed for classification because it needs both global context features and local features at the same time. The twoway CNN architecture helped to achieve a highperformance rate for image segmentation.[8] There can be many procedures and diagnostic imaging techniques it is done for early detection of any abnormal changes in tissues and organs such as computed tomography (CT)[7] scanning and magnetic resonance imaging (MRI). Although MRI appears to be effective in providing the location and size of tumors, is unable to classify tumor types, therefore biopsy application. A deep neural network is a stand-alone deep learning architecture for organizing a dataset into normal and abnormal brain images. The architecture is a feed forward network [9] that has an input layer containing a neuron for the input feature and is fed to an output layer containing a neuron for the output modules and a hidden layer is between the two layers. A deep learning network classifies high-level abstract features from the input and uses an ungrounded feature to regularize image patches. Keeping Big-Data Analytics will give us consent to interrogate the tumor in ways we couldn't do before.

2.LITERATURE SURVEY

The objective of this review section is to present the literature review of brain tumor detection and image segmentation methods. The main goal is to highlight the advantages and limitations of these methods. Key image. Processing techniques for brain MRI image segmentation are classified as k- means, SVM, other methods, etc.

Parveen, Amritpal Singh,"Detection of Brain Tumor in MRI Images, using Combination of Fuzzy CMeans and SVM" (2nd International Publisher: IEEE 2018) [1]. Purpose algorithm is a combination of SVM and fuzzy c-means, a hybrid technique for brain tumor prediction. Here the image is enhanced using contrast enhancement and mid-range stretching. [3] Double threshold and morphological operations are used for the skull streaking. Fuzzy means (FCM) [7] clustering is used for image segmentation. The gray level run length matrix (GRLLM) [9] is for feature extraction.

Furthermore, linear, quadratic, and a polynomial SVM technique is used to classify brain MRI images. A real dataset of 120 patient MRI brain images is used to detect "tumor" and "non-tumor" MRI images.[6] Then, the SVM classifier is trained using 96 brain

MRI images the remaining 24 brain MRI images were used for testing trained SVM. SVM classifier with linear, quadratic, and polynomial kernel functions gives 91.66%, 83.33%, and 87.50% accuracy and 100% specificity. [12]

Astina Minz, Chandrakant Mahobiya; Published 2017; IEEE 7th International Advance Computing Conference (IACC) 2007 [8] proposed an effective automatic classification method for brain MRI designed using the Adaboost machine learning algorithm.[14] The proposed system consists of three parts Preprocessing, feature extraction, and classification. Preprocessing removed noise in the raw data and transformed RGB image to grayscale, median filter, and threshold segmentation are used. [16] For feature extraction using the GLCM technique,[15]. 22 characters were extracted from an MRI. A boost technique (Adaboost) [11] was used for classification. It gives 89.90% accuracy and results in the normal brain in Malignant or benign types tumors In future work, we can work on quadratic and polynomial kernel functions. [18]

Husein, Eltahir Mohmmed; Mahmoud, Dalia Mahmoud Adam (Sudan University of Science and Technology, 2012) JETIR June 2012, Volume 6, Issue 6 (2012)[17] Brain tumor detection using artificial neural networks. Journal of Science and Technology. 13:31-39. Dalia Mahmoud et al. [17] presented a model using artificial neural networks for tumor detection in brain images.[19] They implemented a computerized recognition system for MR imaging using artificial neural networks.[20] It was observed that after using Elman's community during the recognition system, the period time and accuracy level were high compared to other ANN systems.[17] This neural community has a sigmoidal characteristic that increased the range of tumor segmentation accuracy.

Garima Singh, Dr. Ma Ansari, "Efficient detection of brain tumor from MRIs using k-means segmentation and normalized histogram", IEEE, Issue 2016 [10] proposed a new technique that includes histogram normalization and K-means Segmentation.[12] First, the input image is preprocessed to make it possible to remove unwanted signals or noise from it. Soundproofing filters such the as Median filter, Adaptive filter, Averaging filter, An un sharp masking filter and a Gaussian filter are used in MRI images.[4] The histogram of the preprocessed image is normalized and MRI classification is performed. Finally, the image is segmented using the K-means algorithm to capture and remove the tumor from the MRI. Efficient classification MRI is performed using NB Classifier and SVM [2] to provide accurate prediction and classification. Naive Bayes and SVM. The classifier provides an accuracy of 87.23% and 91.49%.[7] SVM provides better classification accuracy. For implementation, MATLAB is used.[17] The proposed method has some limitations that he could not ascertain the precise boundary tumor area. Images can be improved by using better morphological operations.

G Rajesh Chandra, Dr. Kolasani Ramchand h Rao "tumor detection in brain. using genetic algorithm" in 7thinternational conference on communication(2018) [12] proposed a method in which the MRI image of the brain is de-noised using DWT by thresholding the wavelet coefficient Genetic.[8] The current approach uses k-Means clustering methods for genetic algorithms for guiding the latter Evolutionary algorithm in search of the optimal or a suboptimal data partition. Achieved by this method segmentation accuracy from 82 percent to 97 percent detected tumor pixels based on ground truth. [9] The limitations of this work are that the wavelet transform requires large storage and its computational cost is high. [13]

Mukambika CM Vikram, K Umarani. 2013 International Conference on American Journal of Biomedical Science and Engineering 1 (5), 71-81, 2015 [3]. Methodology proposal in which image is processed through pre-processing's segmentation, Feature extraction Classification phase. In preprocessing, the Morphological technique [14] using double thresholding is used to remove the skull from the MRI brain images. One is based on the Level set method that uses non-parametric deformable models with active contour to segment a brain tumor from MRI brain images.[15] The other is the K-means algorithm.

K. Sudharani, Dr. T.C. Sarma, Dr. K. Satay Rasad Conference: 2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)At Kumara coil, India 2015[9] Suggested The methodology includes methods such as histogram, resampling, K-NN algorithm, distance matrix. First, the Histogram provides the total number of specified pixel values distributed in a specific image. Resampling and resizing the image to 629 x 839 for correct geometric representation. Classification of brain tumor identification using KNN, which is based on training k. The Manhattan metric was used in this work and calculated the classifier distance. The algorithm was implemented using Lab View. The algorithm has been tested on 48 frames. The identification score for all images is about 95%. Proposes an intellectual classification system recognizing normal and abnormal MRI brain images. Under these techniques, image preprocessing, image property extraction, and subsequent classification of brain cancer are successfully executed. In preprocessing RGB brain MRI images are converted to a grayscale image.

Multi-modal brain tumor segmentation using deep convolutional neural networks. In: Proceedings of BRATS-MICCAI (2014) [15] the median of the filter is used to remove noise from the MRI image. Then Skull Masking is used to remove no brain tissue from an MRI brain image. Achieved by this method segmentation accuracy from 82 percent to 97 percent detected tumor pixels based on ground truth.[9] When different machine learning techniques: Support Vector Machine (SVM), KNearest Neighbor (KNN), and Hybrid A classifier (SVM-KNN) is used to classify 50 images the results showed that the SVM-KNN hybrid classifier demonstrated the highest classification accuracy rate of 98% among others.

Sources	Technique	Advantage	Disadvantage
L. Szilagyi,Automatic brain tumour segmentation using a fuzzy k-means ,algorithm, In 2015 12th international conference on fuzzy systems and knowledge discovery (FSKD),	Comparison of Gabor and statistical features using **svn, knn, k-means**	1) Single contrast mechanism with high precision and low calculation complexity. 2) No prior anatomical knowledge required. 3) Smaller dimensionality.	1) Statistical characteristic are more accurate than characteristic of Gabor wavlet.

Natarajan P, Krishnan N, , "Tumour Detection using threshold operation in MRI Brain Images", IEEE International Conference on 2013	Sobel edge detection algorithm, close counter algorithm, thersold	1)No need of initial assumptions. 2)Segmented images are better compared to tumors removed by normal edge detection	1) Increase the region area and decrease borderline line thickness of regions 2) Room for improvement for close counter algorithms.
Gupta, Gaurav and Vinay Singh. "Brain Tumor segmentation using Fem and support vector machine." (2017).	Segmentation texture feature, Support Vector Machine (SVM), Ensemble base classifier.	1)Accuracy more than 99% 2) Extract tumor region from brain Mr images.	1) Measuring the thickness, 2) Measuring tumour area of extracted region.
Chellamuthu Chinna Gounder, Advanced Brain Tumour Segmentation from MRI Images, 2018.	Super pixel, Extremely Randomized Tree (ERT), SVM, Gabor Texton Feature	1)Improve accuracy of feature extraction 2) Reduces computation time.	1) Super pixel based ERT in flair but not implemented in work.

Table 2.1 Literature Survey

3. System Architecture:

3.1 Block Diagram

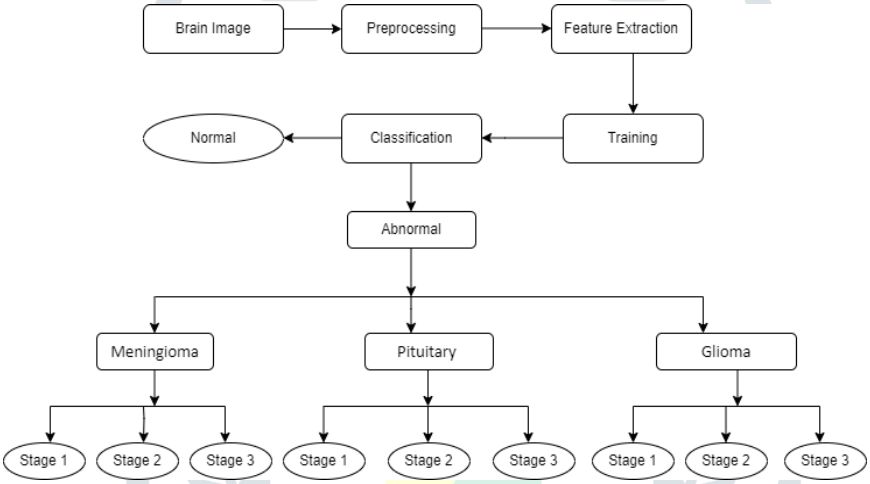


Fig 3.1 Block Diagram

In our system the image will be taken as an input from the user then it will be passed for the pre-processing part. After pre-processing the various types of feature will be extracted like smoothness, entropy, variance, kutosis, skewness, idm, correlation, homogeneity, mean and standard deviation.[7] After feature extraction the data will be classified into 3 parts. The 3 parts are training, testing and validation. The training part contains the 70% of the data, testing part contains 15% of the data and the validation part contain remaining 15% of the data.[11] After these the result part will be done and the results are classified like normal and the abnormal. The abnormal image is having the tumour. The tumour is further classified into various parts Gliomas, Pituitary and Meningioma.[13] After the cancer type it will also predict the level of the cancer os the stage of the cancer. So people may get to know how sever is the cancer. After all prediction it shows the approx. cost to cure the cancer, medicines and precautions.

4. Proposed Methodology

The proposed methodology contains three main stages corresponding to pre-processing followed by a CNN and a post-processing step, as shown in Fig.1 the different stages of the proposed methodology are discussed in detail in subsequent sections.

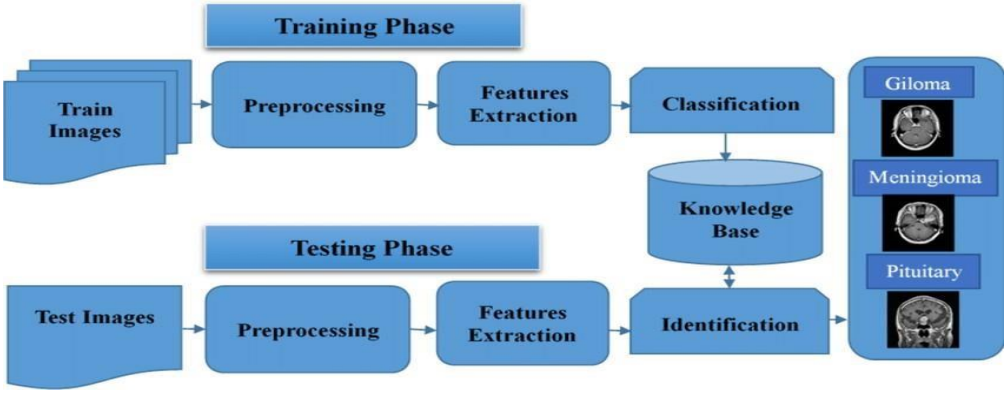


Fig 4. Sequence Diagram

4.1 Pre-processing

MR images can acquire artifacts, such as bias field distortion and motion heterogeneity, because of the movements made by the subject during acquisition or the limitations of the MRI machine. The induction of false intensity levels it is caused by the artifacts [4] leading to false positives in the segmented image. To deal with such artifacts, the bias field correction technique N4ITK is used, which is an improved version of the nonparametric, no uniform intensity normalization (N3).[8] Due to varying resolutions in the third dimension of the BRATS dataset, 3D MR images are converted into 2D slices.[9] Therefore, axial slices are used in the proposed methodology having consistent dimensions. The intensity values in these slices vary, making it difficult for CNN to adapt to the features of a particular class label.[17] The intensity variation is dealt with by using the intensity normalization process, which brings the intensity values in the dataset into a coherent range such that the mean intensity value approaches zero and the standard deviation approaches one. The input slice i is normalized in terms of mean μ and standard deviation σ to get output io as

$$io = \frac{i - \mu}{\sigma} . \quad (1)$$

After normalizing the slices, the patches of size N × N used for the training and testing purposes are

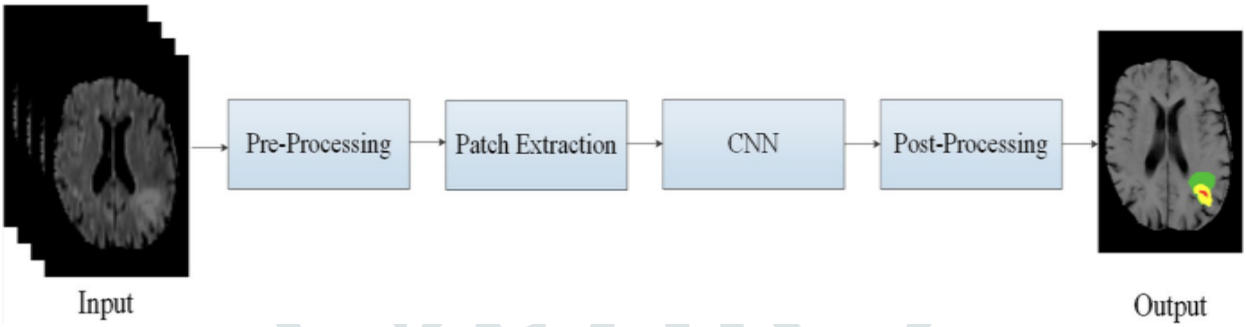


Fig. 4.1 Block diagram of the proposed methodology

4.2 Convolutional Neural Networks

Pattern recognition is an innate feature of CNNs, which have performed remarkably well in detecting patterns in images of varying types. A typical CNN consists of input, convolution, max pooling, fully connected (FC) and output layers stacked hierarchically.[16] The convolution layer is the fundamental block of a CNN and contains kernels that are convolved over input images to detect features and patterns in them. A CNN kernel is a filter of different shapes such as 3 × 3, 7 × 7, and 13 × 13, which is convolved over the input in a sliding window manner to generate a feature map. [12] A feature map is a group of the features arranged in a topologically ordered manner, where each point in a map is connected to the previous layer. The weights on connections are trained using back-propagation which updates weights after each mini-batch of data passes through the network during the training phase.[11] Since a kernel is responsible for a complete map, convolution layers usually have fewer weights compared to FC layers, making them fast.[15] The individual features in a feature map are called neurons, and the neighboring pixels of a neuron is responsible for its value.[16]

The area of the number of pixels that can influence the activation of a neuron is called its receptive field. The receptive field of a neuron increases as the convolution layers above it increases in the hierarchy. A convolution neural network is built using Tensor Flow in python. Tensor Flow is an open source library based on python. It helps us with numerical calculations during the creation of the CNN classification model. [5] He can train and run deep neural networks for classification models for neural networks. Tensor Flow can support the production prediction scale with the same models used for training. [9] It provides activation functions and uses outage regularization. Inception-v3 is a pre-trained model on Tensor Flow and is the most commonly used image recognition model. [7]

Kernel dimensions in a convolution layer, as kernel size, define the neighborhood of a pixel. By increasing the kernel size, the neighborhood area increases, and more contextual information is added to the feature map in the form of neuronal activations. The feature map Faj is computed as

$$Faj = b_a + \sum K_{aj} *, I_j$$

Where ba, Kaj, and I are the bias term, convolution kernel, and input plane, respectively, whereas ∗ represents the convolution operation. Following the convolution layer, a nonlinear activation

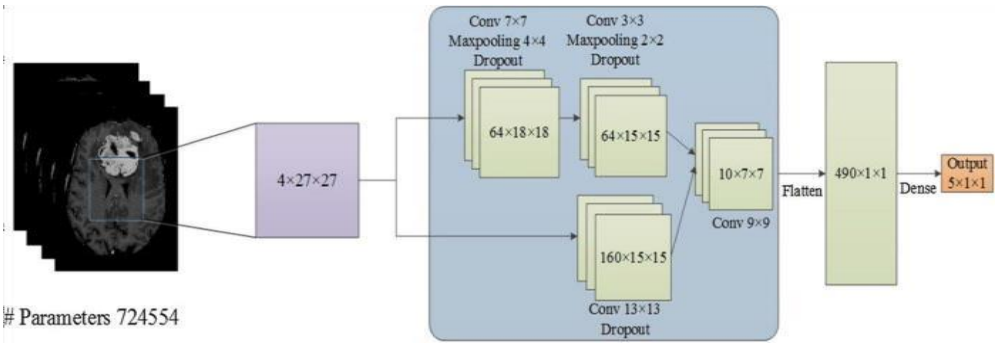


Fig. 2 Convolution layers of CNN model

The function is applied to get nonlinear feature maps. The simplest nonlinearity rectified linear unit (ReLU) is adopted in the proposed architecture and has proven to be particularly useful for the tumor segmentation task. and the input Ix; therefore, the nonlinear activation map f (x) is computed as

$$f(x) = \max(0, Ix). \quad (3)$$

A CNN produces translation-invariant feature maps via the use of the max pooling layer.[9] The pooling layer deals with local translations by selecting the maximum value out of a specified window of size pl × pl.[11] The pooling layer shrinks the size of the input feature map by a factor of pool size and pool stride.[16] CNNs learn complex features directly from the input images in contrast to the statistical classifiers that require handmade features as input.

4.2.1 Two-Path CNN

The two-path CNN is constructed by passing the input through two streams in the network as shown in Fig. 2. [8] The first stream has small to get local information from the image, whereas the second stream has kernels with a large the receptive field, convolution layers, while two pooling layers are used in the first stream succeeding the convolution layers. The final convolution layer combines the feature maps generated by individual streams, and the following FC layer converts the combined results into a 1D feature vector.[10] ReLU activation is employed to get sparse feature representation which is reduced further via the max pooling layer. This model is comparatively faster than the three path model, as it requires less processing due to fewer streams. [13] To deal with the over-fitting problem, a dropout of 0.5 is applied in the initial layers of the model, which decreases as the network grows deeper. The FC layer contains 490 features, which correspond to five output classes.

4.2.2 Three-Path CNN

The three-path network contains three layers in parallel, which are combined using a convolution layer as shown in Fig. 3. The parallel paths use different convolution kernels to detect a multitude of features.[18] The deeper networks tend to have more parameters on layers; therefore, a small number of convolution layer kernels is utilized.[15] The network uses five convolution layers in total alongside one pooling layer used in the third stream of the network.[14] This model is comparatively more accurate, as it has a vast receptive field compared to two path model. A dropout of 0.5 is utilized in this model to deal with the over-fitting problem, while ReLU[7] activation is used on the kernel maps generated from convolution layers. The final convolution layer combines the output of three streams, while flatten layer is used to convert 2D feature maps into a 1D feature vector. [5]

4.2.3 Hybrid CNN

The concatenating ability of the convolution layers is exploited to form a hybrid model, which combines the output of two- and three-path CNNs as shown in Fig. 4. The hybrid CNN combines the receptive fields of two CNNs, enabling it to learn a variety of features while adding contextual and local information. The network successfully models local dependencies between output labels, which is a major drawback of the two- and three-path networks, as they do not take labels. Surrounding the predicted label into account. By adding a convolution before the output layer of the hybrid model, the output of two- and three-path networks is concatenated and convolved using 1 × 1 kernels to compute the final feature maps. As the final maps are constructed using the output nine convolution layers, but it is still efficient as most of the processing is done in parallel.

4.3 Post-processing

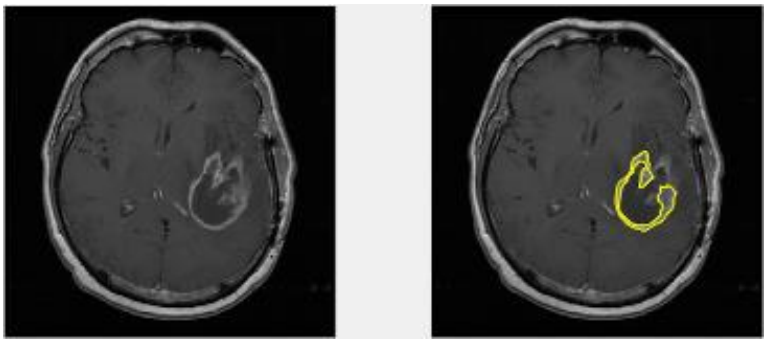
Small false positives appear around the skull portion of the output segmentation, due to high intensity in that region.[8] In the final step of the proposed methodology, morphological operations are utilized to improve the segmentation results by removing small false positives around the edges of the predicted output.[1] The simple operation of erosion is used to remove false positives, and then a dilation operation is performed to enlarge the output to its original size.[2] Erosion followed by dilation is called opening operation and is used in the post processing step.

5. Conclusion

We proposed a computerized method for the segmentation and identification of a brain tumor using the Convolution Neural Network.[8] The input MR images are read from the local device using the file path and converted into grayscale images.[9] These images are pre-processed using an adaptive bilateral filtering technique for the elimination of noises that are present inside the original image. The binary thresholding [6] is applied to the demised image, and Convolution Neural Network segmentation is applied, which helps in figuring out the tumor region in the MR images.[5] The proposed model obtained an accuracy of 84% and yields promising results without any errors and much less computational time.[15] It is observed on vast training set for better accurate results; in the field of data is a tedious job, and, in a few cases, the datasets might not be available.[17] One limitation is that the proposed solution was not tested until the evaluation phase to compare with the current one the best solution. Since the other methods after segmentation are the same for the remaining stages (feature extraction, feature reduction, and classification), the proposed method can be expected to provide better classification accuracy. [13]

6. Result

Original Image: Output Image:



However, this still needs to be implemented. This is one direction in which research should continue pp. In all such cases, the proposed algorithm must be robust enough for accurate recognition of tumor regions from MR Images. The proposed approach can be further improvised through cooperating weakly trained algorithms that can identify the abnormalities with minimum training data and also self-learning algorithms would aid in enhancing the accuracy of the algorithm and reduce the computational time.

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