BRAIN TUMOR DETECTION USING CNN & ML TECHNIQUES

Mary Mathalin A#1, Karthiga T*2

[1,2]Department of Electronics Communication and Engineering,
Karpaga Vinayaga College of Engineering and Technology,
Chengalpattu-603308, India

Abstract

The human brain is the main controller of the humanoid system. Abnormal growth and division of brain cells causes brain tumor, and the proliferation of brain tumor causes a brain tumor. In the field of human health, computer vision plays an important role because it reduces human judgment and provides accurate results. CT scans, X-rays and MRIs are the most common imaging methods among the most reliable and safe magnetic resonance imaging (MRI) scans. MRI detects objects every minute. The purpose of our article is to focus on the use of different techniques to detect brain cancer through brain MRI. In this study, we performed preprocessing using a bilateral filter (BF) to remove noise from MRI images. This was followed by binary thresholding and convolutional neural network (CNN) segmentation techniques for reliable detection of tumor regions. Training, testing and validation datasets are used. With our machine, we predict whether the subject has a brain tumor or not. The results obtained are tested using various proven performance parameters including accuracy, sensitivity and specificity. It is assumed that the performance of the proposed work is better compared to similar ones.

Introduction

Medical image processing refers to a variety of possible technologies. It is used as a non-invasive method to examine the inside of the body. Medicine Imaging includes various imaging methods and processes Imaging the human body for treatment and diagnosis thus plays the most important and essential role in activities for the benefit of society. Improves people's health. Image segmentation is an essential and essential step of images. Processing that determines the success of a higher level image Processing .

The main purpose of image segmentation in medicine Image processing is mainly used to detect tumor and lesions and is effective. Perform image processing and obtain satisfactory results for further diagnosis. Increased sensitivity and specificity for tumor or lesions With the help of computers, this is becoming a central issue in medical imaging. Supported diagnostic systems (CAD). Besides them, there are also other cancers of the brain and nervous system. 10th cause of death and 5-year survival Brain tumor account for 3 % of men and 36% of women. In addition, the World Health Organization (WHO) states: 00,000 people worldwide have a brain tumor In recent years, 120,000 people have died. In addition, Anne Arviot has 86,970 new cases of primary malignant and non-malignant tumor in the brain and other central nervous system and# 0;CNSand# 1; tumor It is expected to be diagnosed in the United States in 2019. Brain tumor occur when abnormal cells form in the brain. There are mainly two types of tumor: malignant tumor and benign tumor. Malignant brain tumor start in the brain, grow rapidly, Actively penetrates the surrounding tissues. Can be contagious to others Part of the brain affects the central nervous system. Cancers can be classified as primary tumor that start from a tumor. Brain tumor or secondary tumor that have spread from elsewhere are So-called metastatic tumor of the brain. On the other hand, benign brain tumor are groups of cells that grow relatively slowly in the brain. Therefore, early detection of brain tumor can play an important role. A role in improving treatment options and maximizing benefits Survival options are within reach. However, manual segmentation Removing tumor and lesions is a time-consuming, complex and difficult task because many of his MRI images are generated as a medical routine. MRI, also called magnetic resonance imaging It is mainly used to detect brain tumor and lesions. brain tumor Segmentation of magnetic resonance imaging is one of the most important tasks in medicine Image processing (usually requiring a lot of effort) data.

In addition, the tumor may be poorly confined to the soft tissues. limit Therefore, obtaining accurate results is a very labor-intensive task Segmenting tumor from the human brain. In this article, we have suggested an effective and clever method. It helps segment and identify brain tumor based on both traditional classifications without human assistance. and convolutional neural networks.

Literature Survey

One of the most difficult and demanding tasks is the segmentation of the region of interest of the object, one of them is the segmentation of tumor from MRI brain images. ambitious Scientists around the world are investigating. Use this field for the most segmented ROI and different variations. A simulated approach from a specific perspective. recently Neural network-based segmentation gives excellent results The results and application process of this model are as follows. Growing every day.

Devkota et al. [7] Based general segmentation Processing based on mathematical morphological operations Spatial FCM algorithm to improve calculations We have time, but the proposed solution has not been tested yet. Evaluation phase and results: Detected cancer 92% Classifier accuracy is 86.6%. Yntao et al. [8. rank] This was similar to the histogram-based segmentation method. We consider the brain tumor segmentation task as three classes of tasks. (tumor including necrosis and tumor, edema and normal tumor Classification problem with two categories Flare and T1. Abnormal region was detected as follows. Region-based active contour model of FLAIR model. of Outlier, edema and tumor tissue regions were extracted based on contrast K- method and Dice coefficients for T1 modality are generated and Sensitivity was 73.6% and 90.3%.

Based on an edge detection approach, Badran et al. [9] A jointly developed intelligent edge detection model Adaptive thresholding method for ROI extraction is adopted. dataset It contained 102 images. The image was then processed first. The two sets of neural networks used Canny Edge detection from the first set, which was matched to the second set. A threshold calculation is carried out. The segmented image looks like this: Represented with layer number and functional properties Extracted using the Harris method. Then we have two neural networks that were originally used to detect healthy people and brains containing tumor, and the other is used to detect tumor. Presentation of results and comparison between the two Canny Edge detection methods showed a better performance model in accuracy results.

Pei et al. [10] Technology that uses tumor growth patterns as a new method Ability to improve tumor structure-based segmentation Longitudinal MRI. Marker maps are used for tumor search Modeling of proliferation and prediction of cell density after extraction Structure (such as fractals and mBm) and intensity features. The performance of the model is reflected in the average DSC. Tumor cell density - LOO: 0.819302 and 3 folders: 0.82122. Dina et al. We implemented a model based on [11]. Stochastic neural network models for vector quantization learning. The model was evaluated using 6 MRI images, using 18 MRI images as the test set and the rest as the training set. Gaussian filter The image is now smoother. The processing time was reduced by 79% with the modified PNN method. stochastic neural network, Othman et al. applied segmentation technique. Principal component analysis (PCA) was used for function. Unpack and reduce large dimensions as well.

Data [12]. MRI images are converted into matrices, where a probabilistic neural network is used for classification. Finally, a performance analysis is performed. data of training It contained 20 subjects and test data of its 15 subjects. Topic Based on the value of the spread, the accuracy is: 73% - 100%. A region-based fuzzy clustering and deformable model,

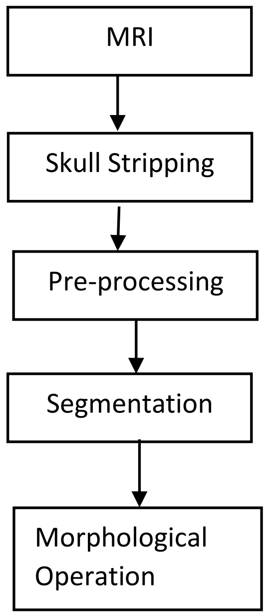
Rajendran et al. [13] achieved 95.3.1% of ASM and Jaccard index based on a stochastic fuzzy C-means model with multiple morphological elements.

Zahra et al. [1] Works with LinkNet network for tumor segmentation. Initially, a single link network was used, which was connected to the network and sent all 7 training datasets to this network segmentation. I did not consider the angle We present a method that can automatically process images and CNN segment the most common brain tumor where this occurs. No preprocessing steps are required. Achieve a dice score of 0.73 0.79 on a single network and 0.79 on multiple systems.

Proposed Methodology

Our proposed methodology has two different models For segmentation and detection of brain tumor. In first model Tumor were segmented according to FCM and classified according to conventional classification. and his second model tumor were detected using deep learning..

System Architecture



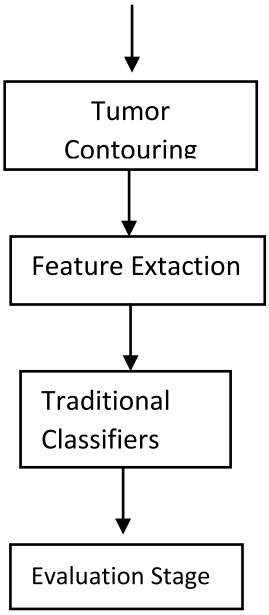


FIG: flow diagram for brain tumor detection

Skull Stripping: :Skull stripping is a very important step in medical image processing because of the background of the MRI image not containing any useful information, and it only increases the processing time. In our work, we removed the skull portion from the MRI images in two. These two steps are:

a) Otsu Thresholding: b) Connected Component Analysis.

Pre-processing :For better segmentation, we need to maximize the MRI image quality with minimized noise as brain MRI images are more sensitive to noise than any other medical image. Gaussian blur filter was used in our work for Gaussian noise reduction existing in Brain MRI which prevailed the performance of the segmentation.

Segmentation using FCM: The Fuzzy C-Means clustering algorithm was employed for segmentation, enabling data to be assigned to multiple clusters. This resulted in the generation of a fuzzy clustered segmented image, thereby ensuring improved segmentation accuracy.

Morphological Operation: In order to isolate the tumor, it was necessary to separate the brain region from the skull region. To achieve this, morphological operations were applied to the images. Initially, erosion was performed to separate weakly connected regions within the MRI image. Subsequently, dilation was applied to further refine the segmentation.

Tumor Contouring: Tumor contouring was accomplished through an intensity-based approach known as thresholding. This method facilitated the extraction of the tumor cluster, resulting in an image where the tumor area is highlighted against a dark background.

Feature Extraction: For classification purposes, two types of features were extracted from the segmented MRI images. Texture-based features, including Dissimilarity, Homogeneity, Energy, Correlation, ASM, as well as statistical-based features such as Mean, Entropy, Centroid, Standard Deviation, Skewness, and Kurtosis, were utilized.

Traditional Classifiers: To evaluate the accuracy of tumor detection in our proposed model, we employed six traditional machine learning classifiers: K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine.

Evaluation Stage: In the evaluation stage, we compared our proposed segmentation technique with other region-based segmentation methods. Our model demonstrated superior accuracy in segmenting the region of interest (ROI) and effectively segregating the tumor portion.

Proposed Methodology Using CNN

The Convolutional Neural Network (CNN) is widely utilized in the field of Medical image processing. Numerous researchers have endeavoured to construct a model that can efficiently detect tumor. Our objective was to develop an exemplary model capable of accurately classifying tumor from 2D Brain MRI images. While a fully-connected neural network can detect tumor, we opted for CNN due to its parameter sharing and sparsity of connection.

For tumor detection, we have introduced and implemented a Five-Layer Convolutional Neural Network. This aggregated model, comprising seven stages including hidden layers, yields the most prominent results in apprehending tumor.

To begin, the convolutional layer is employed as the initial layer, generating an input shape for the MRI images of 64*64*3, thereby converting all the images into a homogeneous dimension. Subsequently, by consolidating all the images in the same aspect, a convolutional kernel is created and convoluted with the input layer. This convolutional kernel consists of 32 convolutional filters, each with a size of 3*3, supported by 3 channels tensors. The Rectified Linear Unit (ReLU) is utilized as the activation function to ensure compatibility with the output.

In this Convolutional Neural Network (ConvNet) architecture, the spatial size of the depiction is progressively reduced in order to decrease the number of parameters and computational time required by the network. When working with Brain MRI images, there is a risk of overfitting, which can be mitigated by using a Max Pooling layer. For spatial data that supports our input image, w horizontally e utilize the MaxPooling 2D layer in the model. This convolutional layer operates on a dimension of 31*31*32. Due to the division of the input images in both spatial dimensions, the pool size is set to (2, 2), indicating a down sampling by a factor of two vertically and .Following the pooling layer, a pooled feature map is obtained. Flattening is a crucial step after pooling, as it involves transforming the entire matrix representing the input images into a single column vector. This step is imperative for further processing. The flattened vector is then fed into the Neural Network for further processing.

Two fully connected layers were employed Dense-1 and Dense-2 represented the dense layer. The dense function is applied in Keras for the processing of the Neural Network, and the obtained vector is work as an input for this layer. There are 128 nodes in the hidden layer. Because the number of dimension or nodes proportional with the computing resources we need to fit our model we kept it as moderate as possible and for this perspective 128 nodes gives the most substantial result. ReLU is used as the activation function because of showing better convergence performance. After the first dense layer, the second fully connected layer was used as the final layer of the model. In this layer, we used sigmoid function as activation function where the total nu mber of the node is one because we need to lower the uses of computing resources so that a more significant amount assuages the execution time. Though there is a chance of hampering the learning in deep networks for using of the sigmoid as the activation function, we scale the sigmoid function, and the number of the nodes is much lesser and easy to handle for this deep network

Experimental Results

We used six classifiers algorithm and proposed model for detaction.To find performance evaluation we used following methods.

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

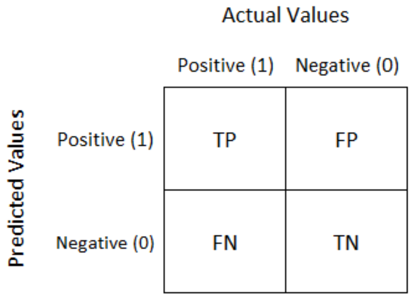


Fig: Confusion-matrix

After using the algorithms we've got accuracies with special fashions:

Classifiers	Accuracy (%)
K-Nearest Neighbor	89.39
Logistic Regression	87.88
Multilayer Perception	89.39
Naïve Bayes	78.79
Random Forest	89.39
PROPOSED	92.42

We achieved an accuracy of 92.42%, which is quite remarkable when considering the utilization of a five-layer CNN.

Conclusion

We proposed a computerized method for the segmentation and identification of a brain tumor using the Convolution Neural Network. The input MR images are read from the local device using the file path and converted into grayscale images. These images are pre-processe for the elimination of noises that are present inside the original image. and Convolution Neural Network segmentation is applied, which helps in figuring out the tumor region in the MR images. The proposed model had obtained an accuracy of 92.47% and yields promising results without any errors and much less computational time.

REFERENCES

[1] Kasban, Hany & El-bendary, Mohsen & Salama, Dina. (2015). "A Comparative Study of Medical Imaging Techniques". International Journal of Information Science and Intelligent System. 4. 37-58.J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2] D. Surya Prabha and J. Satheesh Kumar, "Performance Evaluation of Image Segmentation using Objective Methods", Indian Journal of Science and Technology, Vol 9(8), February 2016.

[3] Brain Tumor: Statistics, Cancer.Net Editorial Board, 11/2017 (Accessed on 17th January 2019)

[4] Kavitha Angamuthu Rajasekaran and Chellamuthu Chinna Gounder, Advanced Brain Tumour Segmentation from MRI Images, 2018

[5] General Information About Adult Brain Tumor". NCI. 14 April 2014. Archived from the original on 5 July 2014. Retrieved 8 June 2014. (Accessed on 11th January 2019)

[6] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[7] B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A. K. Singh, A. Elchouemi, "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction," 6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India.

[8] Song, Yantao & Ji, Zexuan & Sun, Quansen & Yuhui, Zheng. (2016). "A Novel Brain Tumor Segmentation from Multi-Modality MRI via A Level-Set-Based Model". Journal of Signal Processing Systems. 87. 10.1007/s11265-016-1188-4.

[9] Ehab F. Badran, Esraa Galal Mahmoud, Nadder Hamdy, "An Algorithm for Detecting Brain Tumor in MRI Images", 7th International Conference on Cloud Computing, Data Science & Engineering - Confluence, 2017.

[10] Pei L, Reza SMS, Li W, Davatzikos C, Iftekharuddin KM. "Improved brain tumor segmentation by utilizing tumor growth model in longitudinal brain MRI". Proc SPIE Int Soc Opt Eng. 2017.

[11] Dina Aboul Dahab, Samy S. A. Ghoniemy, Gamal M. Selim, "Automated Brain Tumor Detection and Identification using Image Processing and Probabilistic Neural Network Techniques", IJIPVC, Vol. 1, No. 2, pp. 1-8, 2012.

[12] Mohd Fauzi Othman, Mohd Ariffanan and Mohd Basri, "Probabilistic Neural Network for Brain Tumor Classification", 2nd International Conference on Intelligent Systems, Modelling and Simulation, 2011.

[13] A. Rajendran, R. Dhanasekaran, "Fuzzy Clustering and Deformable Model for Tumor Segmentation on MRI Brain Image: A Combined Approach," International Conference on Communication Technology and System Design 2011.

[14] Sobhaninia, Zahra & Rezaei, Safiyeh & Noroozi, Alireza & Ahmadi, Mehdi & Zarrabi, Hamidreza & Karimi, Nader & Emami, Ali & Samavi, Shadrokh. (2018). "Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images".