



Feature Extraction from Brain MR Images for Detecting Brain Tumor using Deep Learning Techniques

Hanumanthappa¹, C D Guruprakash²

¹Research Scholar, Computer Science and Engineering, SSIT, Siddhartha Academy of Higher Education, Sri, Karnataka, Tumkur, India

²Professor, Computer Science and Engineering, Sri Siddhartha Institute of Technology, Karnataka, Tumkur, India

Email: hanukit@gmail.com

Article History

Received: 25 June 2023

Accepted: 22 July 2023

Published: 28 July 2023

Keywords:

Feature Extraction;
Segmentation;
ROI feature;
Brain Tumor Detection

Abstract

Detection of a brain tumor due to their intricacy, the irregularity of their tumor formations, and the variety of their tissue textures and forms, gliomas provide a difficult problem for medical image interpretation. Machine learning-based approaches to semantic segmentation have consistently surpassed earlier techniques in this difficult challenge. However some of the Machine learning techniques are unable to deliver the necessary local information associated to changes in tissue texture brought on by tumor development. In this study, we used Hybrid technique that combines supervised learning features and hand-crafted features. The texture features based on the grey level co-occurrence matrix (GLCM) are used to build the hand-crafted features. The recommended technique also lowers the intensity of nearby unimportant areas and only the region of interest (ROI) method is used, which precisely represents the input size of the entire tumor structure. ROI MRI scan pixels are divided into several tumor components using a decision tree (DT).

1. Introduction

The development of aberrant and uncontrolled cells inside the spinal cord or brain is referred to as a brain tumor. The Primary brain tumors can come in four different sub types tumors of the nerve sheath, pituitary adenomas, meningioma's, and gliomas. Brain tumor segmentation utilizing multi-modal magnetic resonance imaging (MRI) is crucial in biomedical analysis. Anywhere in the brain, gliomas can originate and manifest in different ways. Its complexity and wide variation in intensities and textures is astounding (Patel and Tse).

Consequently, the fundamental objective is to build a technique that produces exact segmentation and functions for a variety of tumour types and imaging technologies. Early tumor localiza-

tion and Detection might affect the patient's treatment strategy; this can affect how the patient's health turns out. Several methods for the identification and in the literature, there have been proposals for tumour segmentation in MRI modalities. Some people build models based on the features extracted from MR scans. Hand-crafted features were employed in several ways for segmenting brain tumors, which were then put into a decision tree (DT)-style classifier (Pinto et al.). The DT classifier outperformed other conventional classifiers in terms of outcomes (Menze et al.).

The drawback of systems based on manually created features is that they need a lot of characteristics to accurately depict the tissues of brain tumors. Because of this, they need data that is

huge in dimension, which takes more time to analyze computationally and necessitates several tests to optimize the classifier's parameters. Recently, various deep learning-based techniques that improve brain tumour segmentation accuracy were created to address these issues (Pereira et al. Dong et al.). To gain local characteristics, a 3D CNN model based on a modified version of the U-Net architecture was given (Ghafari, Sowmya, and Oliver). In order to improve performance, they used linked as a post-processing stage, component analysis is performed.

The research (Ranjbarzadeh et al.) employed a powerful CNN cascade model to extract global and local features using two distinct approaches and varying extraction patch sizes. An algorithm for the three hybrid CNN (Daimary et al.) is the high-accuracy automated segmentation of brain tumour detected via MRI are U-SegNet, Res-SegNet, and SegUNet. SegNet, U-Net, and ResNet, the three most popular CNN models for semantic segmentation, are the ancestors of the recommended models. However, for conducting an accurate brain tumour region segmentation, utilizing solely a deep learning-based approach is insufficient. The disadvantage of the SegNet-based method is that local characteristics associated to changes in tissue texture brought on by the factors affecting tumor growth are not thoroughly considered (Alqazzaz et al.). The pixel classes' regional Dependencies are also considered by certain manually created feature extraction techniques, such as texture features based on grey-level co-occurrence matrices (GLCM) (Lai et al.). According to one source, the GLCM is the most popular texture-based approach for MR Images (Holli et al.).

This paper's inspiration came from the requirement for very accurate segmentation; it resulted in the creation of a hybrid technique. We propose a novel learning-based technique for automatic segmentation of brain tumour structures using ROI pictures generated from MRI scan data that combines manually constructed features with machine-learned features. The GLCM-based texture features are manually produced features, whereas the score maps, which are derived from the deep machine-learned features, are in the trained SegNet network's convolution layer.

On Kaggle's dataset, which is open to the public, the suggested approach was used and assessed.

2. Methodology

The five primary sections of the suggested segmentation approach are preprocessing, creating a ROI picture, Feature extraction and Selection, Feature fusion and Classification. First step in preprocessing is to clean up the MR images' artefacts and normalize their intensity ranges. The binary mask represents the ROI with exclusively tumor tissue is detected by a One, the SegNet model was trained using an MRI modality and to create ROI, all MRI modalities' images are given a mask. The artificial intelligence characteristics are retrieved for a second SegNet model that was ROI-trained is applied to each pixel. Images are computed, in addition the manually created texture characteristics. Founded on GLCM. As the last phase, the collected characteristics are passed to a DT classifier to link the pixels to the appropriate tissues. Figure 1 depicts the entire pipeline of the recommended approach.

2.1. Image Pre-processing

Our suggested technique starts with image preparation. There are a variety of factors might produce noise in a MR image, including electrical disruption, poor lighting, and channel noise, among others. The outcome is, there may be some blurring in particular portions of the image, which calls for image pre-processing. The image is initially converted to grey scale for noise reduction and enhancement.

2.2. Image Generation for ROI

An accurate tumor identification extent structure is the foundation for managing radiation dosage preparing and evaluating treatment outcomes. Furthermore, defining the tumour region, also known as the ROI, is critical for evaluating the progression of glioma grades and for subsequent tumour categorization by acquiring visual data from aberrant locations. (Niyazi et al.). This experiment made use of the SegNet semantic segmentation network. (Badrinarayanan, Kendall, and Cipolla) Was used to identify an initial ROI,

Every MRI technique was applied. Individually to train and alter a SegNet model that has already been trained for binary segmentation (normal and pathological tissues). The generation of ROI MRI images and the detection of ROI mask are the two primary processes in this method, view Figure 2.

To offer the best ROI mask, the pre-trained Seg-

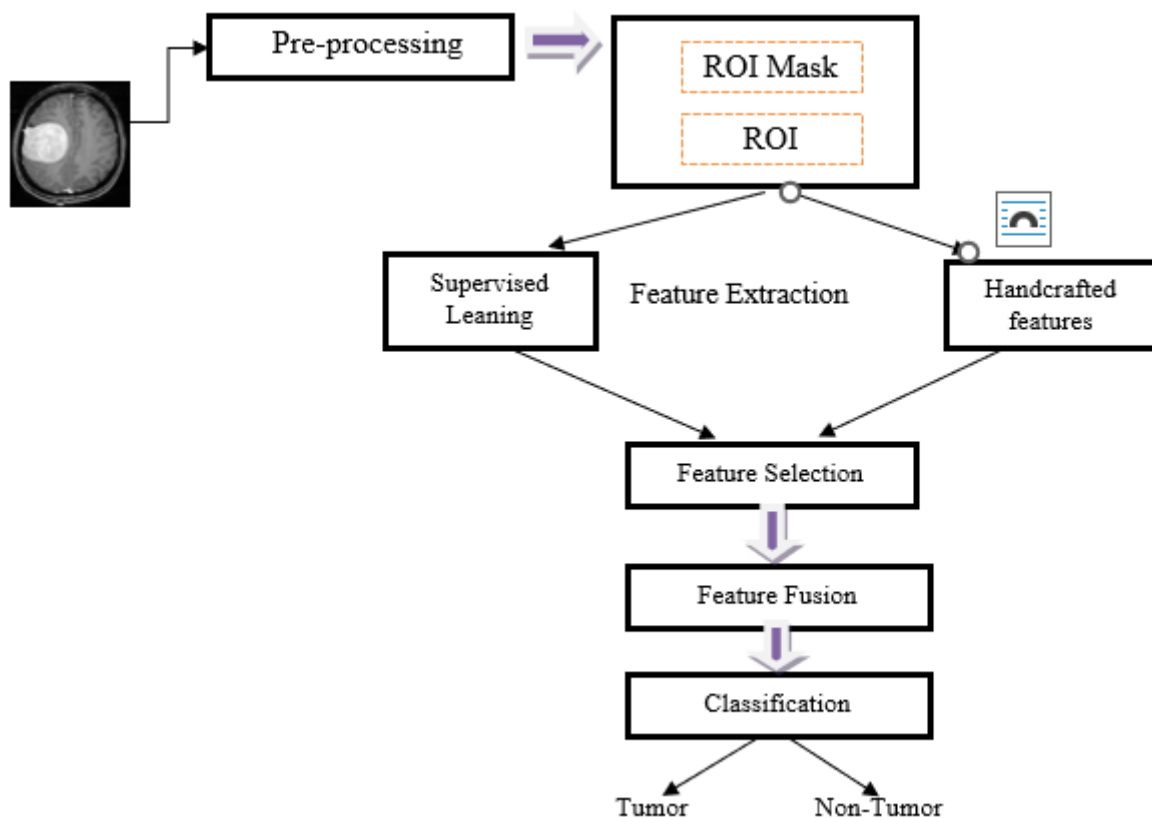


FIGURE 1. Proposed Hybrid Technique Architecture

Net network was modified independently for each MRI modality. The evaluation of the MRI modality testing datasets was performed. Segmentation of binary images using trained SegNet models. The algorithm used to calculate the Region of Interest in MRI. The successful model best in the subsequent phase in terms of F measure accuracy was image. Data from various MRI techniques can be used to differentiate between places inside the cancer. In order to segment the T1 and T2 MRI images, they were combined. The resulting ROI mask images were then used to construct the ROI images obtained from the combined MRI modalities, where all of the combined MRI modalities' pixels that the zero values that correlate to the ROI masks are set to zero, while the others are left alone.. The subsequent stage of our suggested strategy to segment sub tumor structures employed the obtained ROI pictures as inputs. View Figure 3.

2.3. Feature Extraction and Selection

In image processing, the most crucial phase is feature extraction. By assessing certain traits, the original dataset is reduced. A GLCM, or grey level

co-occurrence matrix was utilized, the differences between a tumor and a non-tumor the watershed segmentation area is segregated, and the recovered MRI images are saved separately in a text file. Characteristics can reveal the presence of tumors. Because different types of tissue have distinct

textures in MRI pictures, Features of GLCM-based textures may be used to define a variety of areas. The texture descriptors will be as a result able to discriminate between the different region types (Bahadure, Ray, and Thethi). Incorporating more potent describing features into the final segmentation can assist to get over the SegNet network's limitations and boost the effectiveness of segmenting brain tumors by combining SegNet features with GLCM-based texture features. Since only the ROI regions require segmentation, we retrieved SegNet features and GLCM-based texture features by analyzing the ROI areas of MR images. The GLCM technique may provide Grey tone spatial interrelationships that can be exploited to improve brain tumour segmentation.

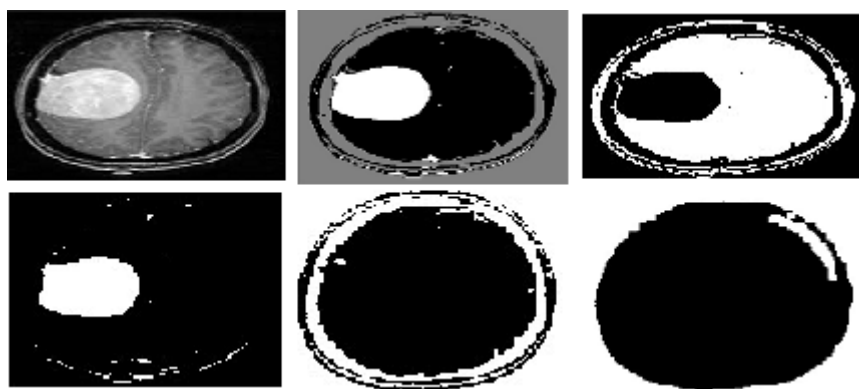


FIGURE 2. T1 Weighted Modality

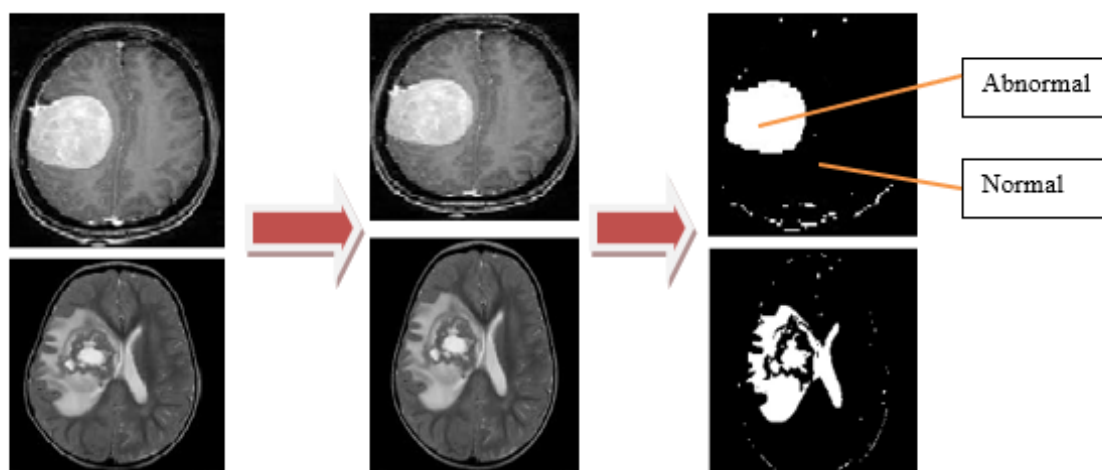


FIGURE 3. (a) Combined MRI Modalities (b) Images of ROI Mask (c) ROI MR Images

2.4. Decision Tree

Each pixel is classified by the DT or decision tree into normal or malignant brain tissues using a tree structure resembling a flowchart. The leaf nodes of the tree indicate class labels, while every non-leaf node is a test for an attribute. A pixel will eventually reach a leaf node in the tree that corresponds to its class, such as healthy or a specific sort of tumor tissue. The method is implemented utilising the pixel’s feature representation. The tree develops into a certain tree depth called D_{tree} throughout the training stage. The use of DT as a classifier, in this investigation was justified since DT has previously been shown to function with excellent precision in the segmentation of brain tumours We just account for every pixel in the tumor, target region using ROI images as our input. The DT classifier is trained employing a feature vector, where each pixel is given access to 7 different features. On the Kaggle dataset, several depths (D_{tree}) were evaluated in order to choose the DT classifier’s ideal parame-

ters.

3. Results and Discussion

TABLE 1. Results for the Kaggle dataset’s binary segmentation of brain tumours

Techniques	F-measure	CTS
ROI_T1_SegNet.	0.75	
ROI_T2_SegNet.	0.81	

Creating the necessary dataset is the initial step in evaluating the SVM’s effectiveness, DT, and CNN algorithms. In this study, a collection of 100 MR brain tumor and non-tumor images was employed and downloaded from kaggle.com. The data is utilized for both training and testing, as well as for categorization of target classes, high accuracy and performance of the algorithm depend on the quality of the data preparation. To distinguish the normal and Abnormal MR images in our situation, a sizable

TABLE 2. Using the Kaggle dataset. In order to compare the results of our experiment for the overall tumor (WT), the tumor core (TC), and the enhanced tumor (ET), we examined the F-measure (mean and standard deviation).

		WC	TC	EC
Techniques F Measure				
Seg_Net.	Mean	0.87	0.65	0.7
	Standard	0.03	0.34	0.36
	Deviation			
GLCM_SegNet._SVM	Mean	0.92	0.77	0.70
	Standard	0.02	0.33	0.34
	Deviation			
GLCM_SegNet._DT	Mean	0.94	0.80	0.75
	Standard	0.01	0.32	0.37
	Deviation			

manual effort was required. For this study, 100 MR images yielded 81 samples of recovered MR image data that were evaluated.

4. Conclusion

A novel technique for segmenting brain tumours using MR images was presented. We suggested first creating ROI pictures that only include tumour tissues before segmenting the ROI into sub-tumor regions. to save calculation time and increase segmentation precision. We integrated the hand-crafted GLCM features with the supervised learning features from a SegNet model because Supervised learning features alone MR scans are unable to accurately depict the cancer tissues. The collected attributes were then utilized to categorize each pixel into a sub-tumor zone using a DT. According to experimental findings, the most effective MRI modality for ROI is T2. Additionally, testing demonstrated that the suggested GLCM_SegNet_DT and GLCM_SegNet_SVM approaches are outperformed. Specifically, our algorithm segmented the whole tumour on the Kaggle dataset with an F-measure of 0.92 and 0.94. Although our approach can segment complete tumours with extremely high accuracy, it is still possible to increase the accuracy when segmenting cancer cores and augmented tumours.

References

Alqazzaz, Salma, et al. "Automated brain tumor segmentation on multi-modal MR image using Seg-

Net". *Computational Visual Media* 5.2 (2019): 209–219.

Badrinarayanan, Vijay, Alex Kendall, and Roberto A Cipolla. "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". *IEEE Transactions on Pattern Analysis and Machine Intelligence* 39.12 (2017): 2481–2495.

Bahadure, Nilesh Bhaskarrao, Arun Kumar Ray, and Har Pal Thethi. "Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM". *International Journal of Biomedical Imaging* 2017 (2017): 1–12.

Daimary, Dinthisrang, et al. "Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks". *Procedia Computer Science* 167 (2020): 2419–2428.

Dong, Hao, et al. "Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks". *Communications in Computer and Information Science*. Springer International Publishing, 2017. 506–517.

Ghafari, M, A Sowmya, and R Oliver. "Automated brain tumour segmentation using cascaded 3d densely-connected u-net". *International MICCAI Brainlesion Workshop*. Springer, 2020. 481–491.

Holli, Kirsi K, et al. "Texture analysis of MR images of patients with Mild Traumatic Brain Injury". *BMC Medical Imaging* 10.1 (2010): 8–8.

Lai, Y, et al. “A texture-based classifier to discriminate anaplastic from non- anaplastic medulloblastoma”. *IEEE 37th Annual Northeast Bioengineering Conference (NEBEC)* (2011): 1–2.

Menze, Bjoern H, et al. “The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)”. *IEEE Transactions on Medical Imaging* 34.10 (2015): 1993–2024.

Niyazi, Maximilian, et al. “ESTRO-ACROP guideline “target delineation of glioblastomas””. *Radiotherapy and Oncology* 118.1 (2016): 35–42.

Patel, Mahesh R and Victor Tse. “Diagnosis and staging of brain tumors”. *Seminars in Roentgenology* 39.3 (2004): 347–360.

Pereira, Sergio, et al. “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images”. *IEEE Transactions on Medical Imaging* 35.5 (2016): 1240–1251.

Pinto, Adriano, et al. “Brain Tumour Segmentation based on Extremely Randomized Forest with high-level features”. *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (2015): 3037–3040.

Ranjbarzadeh, Ramin, et al. “Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images”. *Scientific Reports* 11.1 (2021): 1–17.



© Hanumanthappa et al. 2023 Open Access.

This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

Embargo period: The article has no embargo period.

To cite this Article: , Hanumanthappa, and C D Guruprakash. “Feature Extraction from Brain MR Images for Detecting Brain Tumor using Deep Learning Techniques.” *International Research Journal on Advanced Science Hub* 05.07 July (2023): 242–247. <http://dx.doi.org/10.47392/irjash.2023.049>