Ritu Agrawal*, Manisha Sharma and Bikesh Kumar Singh

Segmentation of Brain Tumour Based on Clustering Technique: Performance Analysis

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Abstract: Manual detection and analysis of brain tumours is an exhaustive and time-consuming process. Further, it is subject to intra-observer and inter-observer variabilities. Automated brain tumour segmentation and analysis has thus gained much attention in recent years. However, the existing segmentation techniques do not meet the requirements of real-time use due to limitations posed by poor image quality and image complexity. This article proposes a hybrid approach for image segmentation by combining biorthogonal wavelet transform, skull stripping, fuzzy c-means threshold clustering, Canny edge detection, and morphological operations. Biorthogonal wavelet transform and skull stripping are essential pre-processing steps for analysis of brain images. Initially, biorthogonal wavelet transform is used to remove impulsive noise and skull stripping is employed to eliminate non-cerebral tissue regions from the acquired images, followed by segmentation using fuzzy c-means threshold clustering, Canny edge detection, and morphological processing. The performance of the proposed automated system is tested on standard datasets using performance measures such as Jaccard index, Dice similarity coefficient, execution time, and entropy. The proposed method achieves a Jaccard index and Dice similarity coefficient of 0.886 and 0.935, respectively, which indicate better overlap between the automated segmentation method and manual segmentation method performed by an expert radiologist. The average execution time and average entropy values obtained are 1.001 s and 0.202, respectively. The results obtained are discussed in view of some reported studies in terms of execution time and tumour area. Further work is needed to evaluate the proposed method in routine clinical practice and its effect on radiologists' performances.

Keywords: Brain tumour segmentation, hybrid segmentation, fuzzy c-means threshold, k-means clustering, region growing.

1 Introduction

A tumour is an uncontrolled growth of cancer cells in any part of the body. Tumours are of different shapes and sizes, can have different characteristics, and thus need different treatment methods. Brain tumours are a group of abnormal cells that grow in or around the brain. They are generally classified as benign or malignant (cancerous) tumours. Benign brain tumours look relatively normal, grow slowly, and do not spread to other sites of the body. Benign tumours can still be serious and even life threatening if they are in the vital areas of the brain. Malignant tumours can be further divided into two categories: primary and secondary tumours. Primary tumours start within the brain, and secondary tumours spread from some other parts of the body to the brain.

According to the World Health Organization [17], brain tumours can be classified into grade I–IV. Generally, grades I and II are treated as low-grade tumours (benign), and grades III and IV as high-grade tumours (malignant). If a low-grade brain tumour is not treated properly, it is likely to develop into high-grade brain tumour, i.e. malignant tumour. There are different medical imaging modalities, such as magnetic resonance

*Corresponding author: Ritu Agrawal, Chhattisgarh Swami Vivekananda Technical University, Bhilai, India, e-mail: ritube_03@yahoo.co.in

Manisha Sharma: Department of Electronics and Telecommunications, Bhilai Institute of Technology, Durg, Chhattisgarh, India

Bikesh Kumar Singh: Department of Biomedical Engineering, National Institute of Technology, Raipur, Chhattisgarh, India

imaging (MRI), computed tomography (CT), etc., used to detect the presence of a brain tumour. Once the brain tumour is clinically suspected, radiologic assessment (manual operation) is required to decide the position, area, and extent of the tumour, as well as its relationship with the neighbouring structures. This information is very essential and crucial in the planning of treatment. However, due to excessive overload on radiologists/clinicians, manual annotation and segmentation of brain tumours become tiresome and time-consuming processes. Further, manual segmentation is subject to human errors and inter- and intra-observer variabilities. To address this issue, the so-called computer-aided detection has gained much attention in recent years. However, the performances of existing automated tumour detection systems do not meet the requirements of real-time application and clinical acceptance due to the following reasons:

- (a) Poor quality of available images.
- (b) Selecting the appropriate method for a specific image segmentation is a subjective issue.
- (c) There is no generally acknowledged technique for image segmentation.

Due to the aforementioned reasons, the segmentation of brain lesions remains a challenging issue in medical image processing and computer vision [7]. This article proposes a hybrid segmentation technique combining biorthogonal wavelet transform, skull stripping, fuzzy c-means threshold clustering, Canny edge detection, and morphological operations for extraction of brain tumours. The various steps of the proposed technique are as follows:

- (a) Image pre-processing for reducing impulsive noise using biorthogonal wavelet transform.
- (b) Skull removal using the threshold method.
- (c) Fuzzy c-means threshold to segment the image into several components for further analysis.
- (d) Canny edge detection and morphological operations for detection of the brain tumour.
- (e) Performance evaluation and validation using several measures such as Jaccard index, Dice similarity index, execution time, and entropy.

The rest of the paper is organised as follows. Section 2 presents various studies reported in related areas. Section 3 describes materials and methods. Results and discussion are presented in Section 4, followed by the conclusion and future scope in Section 5.

2 Related Work

Brain tumour analysis is considered an important research area for the accurate and timely diagnosis of disease. Image segmentation, as defined by Bhandarkar et al. [4], is a process of partitioning an image into totally unrelated areas to such an extent that every area is spatially contiguous and the pixels inside the area are homogeneous as for a predefined area. The level of subdivision depends on the problem being solved, and segmentation stops once an object of interest in the application has been isolated [1]. Image segmentation techniques can be classified into four major categories: threshold based, region growing, pixel classification, and model-based technique. In this section, a brief overview of three techniques, namely threshold based, region based, and pixel classification (clustering methods based), are discussed. The threshold method is one of the canonical techniques and is helpful for image binarisation, which is a fundamental task in segmentation. It assumes that images are composed of regions with various grey level ranges. An intensity value called threshold is determined to isolate the desired object [26]. A combination of global thresholding and watershed segmentation methods for the extraction of brain tumour is proposed by Veer and Patil [27]. They evaluated their approach on a database of 75 brain MRI images. The suspicious tumour regions were segmented successfully and the tumour location, size, and shape were quantified.

Hojjatoleslami and Kittler [10] proposed a region-growing method for segmenting an image using the gradient property for characterising the boundaries of the region. Dubey et al. [8] proposed extraction of MRI brain tumours using the region-growing technique. Furthermore, the tumour area and volume were calculated, which are significant attributes in the treatment of tumours. Mohd Saad et al. [20] proposed

segmentation of brain tumours in diffusion-weighted MRI using the region splitting and merging method. The histogram thresholding technique was used to automate the seed selection process. The region was iteratively grown by comparing all unallocated neighbour pixels to the seeds. Hooda et al. [11] proposed a comparative analysis of brain tumour extraction using three known segmentation techniques, namely region growing, k-means, and fuzzy c-means clustering. The error percentage of tumour extraction was used as the performance criteria for comparative analysis. A database of 10 real MRI brain images was used along with the ground truth. Their results indicate that the fuzzy c-means segmentation method outperformed others in extracting the tumour in MRI brain images.

Clustering techniques have been widely investigated in medical image segmentation. However, three of the most popular clustering methods, namely k-means, fuzzy c-means, and mean shift, are discussed in this paper. Bandhyopadhyay and Paul [2] proposed a hybrid technique for MRI brain tumour extraction. Their method comprised three stages: k-means segmentation, nearby standard deviation-guided matrix-based coarse grain localisation, and nearby standard deviation-guided matrix-based fine grain localisation. Before tumour extraction, the processed brain image is segmented into two sections, one of which included the normal brain tissue while the other section contained abnormal tumour cells. Islam and Ahmed [13] proposed a comparative analysis of clustering algorithms using k-means, k-medoids, and hierarchical clustering on natural images. Their results suggested that the k-means clustering method outperformed other techniques and is easy to implement. Kabade and Gaikwad [15] proposed an automatic segmentation technique of MRI brain images using k-means and fuzzy c-means algorithm. Their method comprised four steps: pre-processing (to remove noise), segmentation using k-means and fuzzy c-means clustering, feature extraction using thresholding, and quantifying the tumour area by using a binarisation method. Bangare et al. [3] proposed extraction and quantification of the brain tumour in MRI medical images using k-means and fuzzy c-means methods. Initially, the median filter was used to remove noise. Feature extraction was then carried out by using the thresholding method followed by segmentation using k-means and fuzzy c-means. Finally, tumour area and stage detection (critical or initial) was determined using a binarisation method. Bhoi and Gupta [5] proposed a comparison of two clustering segmentation methods, namely k-means and fuzzy c-means, in terms of execution time and tumour area calculation. Their results indicated that the k-means segmentation method performed better than fuzzy c-means, as its execution time is less and it can extract the tumour region more precisely when compared to fuzzy c-means. Padole and Chaudhari [22] proposed detection and tumour area calculation of brain MRI images using conventional algorithms based on mean shift and normalised cut. MRI brain images were pre-processed by using the mean shift algorithm to generate multiple-region and one-region nodes. These region nodes are represented as a weighted undirected graph and were used for constructing the weight matrix, whereas the normalised cut method was used for region nodes clustering.

Having reviewed the related studies, the following research gaps are identified: (i) the performance of the segmentation method is highly dependent on the visual quality of the medical images; the majority of the reported works adopted noise removal techniques that blur and sharpen the edges of medical images. Hence, the biorthogonal wavelet transform noise removal method has been used in this study to avoid loss of edges and sharp details. (ii) Only two of the reported works discussed about execution time, which is an important parameter for making decisions regarding the adoption of the segmentation algorithm. (iii) None of the reported works considered standard online datasets for validating their segmentation algorithm. From related works, it is found that the clustering technique is the most frequently used method for segmentation of brain tumours. Thus, we compared the performance of the proposed approach with some of the reported studies based on clustering and region-growing techniques.

2.1 Contributions and Outline of the Paper

The contributions of this paper are summarised as follows:

- We present a hybrid approach for brain lesion segmentation by integrating biorthogonal wavelet transform, skull stripping, fuzzy c-means thresholding, Canny edge detection, and morphological operations.

- We evaluate the proposed approach on different publically available datasets and on brain images acquired from different imaging modalities.
- We evaluate the proposed approach by highlighting its advantages and drawbacks in comparison to some recently reported studies.

3 Materials and Methods

This section presents the source of brain tumour image datasets, the algorithm used to perform brain tumour extraction, and a validation stage for comparing the proposed method with ground truth. Figure 1 provides a flow diagram of the proposed algorithm.

3.1 Brain Tumour Image Datasets

The brain image used in the study was obtained from standard online datasets, BrainWeb [6], BRATS [19], and Internet brain segmentation repository (IBSR) [12]. The BrainWeb and BRATS datasets were acquired using a 1.5-T Siemens Magnetom Spectral MR machine and a (1.5- to 3-T) Siemens Magnetom Spectral MR machine, respectively. For the IBSR datasets, CT scan images were acquired using Siemens Samatom DR3 (64 slices) and positron emission tomography (PET) scan images were acquired using Siemens Medical Solutions. The characteristics of the BRATS dataset are shown in Table 1.

Figure 1: Framework of Tumour Extraction.

Table 1: Characteristics of MRI Brain Image BRATS Dataset.

Dataset property	Value/type
Total number of tumour cases	65
Type	True colour
Bit depth	24
Resolution	96 dpi

3.2 Pre-processing

The objective of the pre-processing stage is to enhance the quality of brain images and make them suitable for further processing. This stage consists of two substages, i.e. noise removal and skull stripping.

3.2.1 Noise Removal

The brain image contains impulsive noise and is to be reduced before segmentation to improve its quality. Most of the impulse noise-diminishing filters blur the image boundaries. Thus, an appropriate filter that reduces the impulsive noise and at the same time preserves edges and sharp details of the image should be selected. Therefore, we employed a biorthogonal wavelet-based denoising filter that preserves the edges of an image and reduces the impulsive noise effectively [24]. Image denoising using wavelet transform comprises three stages: (i) image decomposition, (ii) hard thresholding of wavelet coefficients, and (iii) image reconstruction. The acquired brain images were decomposed into four sub-bands, LL, LH, HL, and HH, by applying discrete wavelet transform (DWT) using biorthogonal bior 1.3 mother wavelet. In wavelet domain, the noise is consistently spread throughout in all coefficients, while most of the image information is concentrated in the couple of higher coefficients. The most vital way of recognising data from noise in the wavelet domain comprises thresholding the wavelet coefficients. Thresholding is mainly divided into two categories: hard and soft. In this study, we employed bior 1.3 wavelet with hard thresholding transform to remove the noise from medical images and then used inverse DWT to reconstruct the denoised image. The functional block diagram of the denoising method is illustrated in Figure 2.

3.2.2 Skull Stripping

Skull stripping is an important preliminary step in brain imaging where non-cerebral tissues like the skull, scalp, vein, and meninges are to be removed [25]. This is due to the fact that non-cerebral tissue does not usually contain any useful information but increases the execution time of detection. Therefore, to remove the skull from brain images, a threshold-based method is adopted in this study. It involves three steps. In the first step, the original medical image is processed and converted into grey scale equivalent as shown in Figure 3A, and then into a binary equivalent image as illustrated in Figure 3B. In the second step, the

Figure 2: Functional Block Diagram of Denoising Method.

Figure 3: Brain Skull Stripping.

(A) Real grey brain image, (B) binary image, and (C) skull-stripped image.

threshold value is set and the input binary image is processed by retaining the fixed threshold level and discarding other pixel values. This value is called mask. Finally, in the third stage, the skull-stripped image is obtained by multiplying the mask value with the input image, as shown in Figure 3C. The output of the third stage is a noise-free image that contains only the human brain.

3.3 Fuzzy c-Means Threshold Clustering

The fuzzy c-means thresholding algorithm is an unsupervised clustering technique and is used to produce a soft partition for a given dataset. To perform the soft partition, the objective function Q is to be expanded in two ways, one by incorporating the fuzzy membership degrees in the cluster and then introducing a weight exponent used in fuzzy membership [14]. The aim of the fuzzy c-means thresholding method is to locate an optimal fuzzy c-partition by updating the membership function of Eq. (1). To achieve the objective function Q , Eq. (2) is to be minimised by iteratively updating the cluster centre of Eq. (3) and the membership function. The flowchart for the fuzzy c-means thresholding method is shown in Figure 4.

$$U_{ij} = \frac{1}{\left[\sum_{k=1}^c \left(\frac{\|v_i - u_j\|}{\|v_i - u_k\|} \right)^{\frac{2}{m-1}} \right]}, \quad (1)$$

$$Q = \sum_{i=1}^c \sum_{j=1}^N (U_{ij})^m \|Z_j - v_i\|^2 \quad (2)$$

where $Z_j \in Z$ and $Z = \{z_1, z_2, z_3, \dots, z_N\}$ and $v_i \in V$, where $V = \{v_1, v_2, v_3, \dots, v_c\}$. Here, N is the number of pixels in the image and c is the number of clusters [18].

$$v_i = \frac{\sum_{j=1}^N (U_{ij})^m}{Z_j \sum_{j=1}^N (U_{ij})^m} \quad (3)$$

3.4 Canny Edge Detection

Canny edge detection is used to obtain a high-contrast binary mask of segmented image. Canny edge detection works on the principle of calculating a gradient value of contrast between the segmented image and the background image.

3.5 Morphological Operations

Morphology is a well-known image processing technique based on the idea of probing an image with a small shape known as structural element (SE). It is feasible to utilise SE of various shapes to perform a particular task. Dilation and erosion are the basic morphological operations widely used in image analysis [21]. The basic idea of dilation is to enlarge the areas of foreground pixels (usually white pixels), whereas erosion operation removes the boundaries of the foreground pixels on the binary image (usually white pixels). The tumour area is then calculated in terms of the number of white pixels in the segmented brain image.

Figure 4: Flowchart of Fuzzy c-Means Threshold Clustering Technique.

3.6 Performance Evaluation

This section explains the different performance measures used for evaluation of the proposed approach. Three different brain imaging modalities, MRI, CT scan, and PET scan, were used in the experiments. MRI

Table 2: Abbreviations, Definition, and Equations.

Abbreviation	Definition	Equation
DSC [23]	Dice similarity coefficient	$DSC(A,G)=2\frac{ A\cap G }{ A + G }$
Jl [23]	Jaccard index	$Jl=\frac{ A\cap G }{ A\cup G }$
Execution time [16]	Execution time	Time required for the system to reach the stabilised condition
E [23]	Entropy (measure of randomness)	$E=-\sum_{i=1}^k e_i \log e_i$
ANOVA	Analysis of variance	$F=\frac{MSC}{MSE}$

A represents segmented results, G represents the ground truth, e represents pixels frequency, i represents pixel intensity value, MSC is mean square between columns, and MSE is mean square within columns.

Figure 5: Datasets of Different Modalities.
From left to right: (A, B) MRI brain, (C) CT scan brain, and (D) PET scan brain.

Table 3: Results of Various Steps of the Proposed Framework Applied on Three Different Datasets.

DS	Original image	Biorthogonal wavelet transform	Skull stripping	Fuzzy c-means threshold	Canny edge detection	Morphological operations
DS1 (BrainWeb)			Already skull removed			
DS2 BRATS			Already skull removed			
DS3 (IBSR)						
DS4 (IBSR)						

brain images from BrainWeb [6] and BRATS [19] studies are publically available along with their ground truth. However, the CT scan and PET scan datasets employed were obtained from IBSR [12] for which no ground truth is available. Therefore, the ground truth of CT scan and PET scan images were obtained by an expert radiologist from Shree Shyam Hospital, Nagpur, India. The performance of the proposed algorithm for three different datasets was evaluated by employing four different metrics, namely, DSC, JI, execution time, and entropy. The abbreviations used in this study are shown in Table 2 along with their definitions and equations. The results of performance evaluation is explained in Section 4.

4 Results and Discussion

In this section, the results and comparative evaluation of the proposed segmentation method are presented and discussed. The proposed segmentation method was evaluated for datasets of three different modalities, i.e. MRI, CT scan, and PET scan, as shown in Figure 5. The images were obtained from the publically available standard benchmark datasets BrainWeb and BRATS consisting of real brain MRI images with known

Figure 6: Extraction of Tumour for Real CT Scan Brain Medical Image Using MATLAB.

Figure 7: Ground Truth Datasets of Different Modalities.

From left to right: BrainWeb MRI, BRATS MRI, CT scan brain, and PET scan brain.

Table 4: Comparison of Ground Truth and Tumour Area Segmented by the Proposed Segmentation Method for the Brain Tumour Datasets.

Datasets	DSC	JI	Execution time (s)	Entropy
BrainWeb [6]	0.815	0.687	1.005	0.231
BRATS [19]	0.995	0.990	0.994	0.187
IBSR (CT scan) [12]	0.976	0.953	1.002	0.194
IBSR (PET scan) [12]	0.956	0.915	1.004	0.198

Table 6: Percentage Average Error and Standard Error on 10 Images.

Sr. no	Method	% Average error	Standard deviation
1	Fuzzy c-means	0.090	± 0.022
2	k-Means	0.165	± 0.039
3	Region growing	0.164	± 0.031
4	Proposed	0.052	± 0.016

ground truth. The BrainWeb dataset consists of 152 T1-weighted MRI images with slice thickness (1 mm, 3% noise and 20% intensity non-uniformity) and were acquired with a field strength of 1.5 T. The BRATS dataset consists of 65 multi-contrast MR scans from glioma patients along with expert annotations for “oedema” and “active tumour.” MRI sequencing was performed with different field strengths (1.5 and 3 T). The other set of datasets used were 10 real CT scan brain images and 10 real PET scan images from IBSR. However, ground truth was not available for these datasets. Thus, in order to evaluate the segmentation performance of the proposed algorithm, the ground truth of CT scan and PET scan was obtained from an expert radiologist of Shree Shyam Hospital, Nagpur, India. Further, the performance of the proposed segmentation algorithm was compared with some state-of-the-art segmentation approaches: region-growing, k-means, fuzzy c-means, and mean shift clustering methods. The proposed work was implemented on MATLAB R 2010a 64-bit version platform, and experiments were conducted on DELL Inspiron System Intel Core i3-5005u CPU @ 2.00 GHz processor and 4 GB RAM with Windows 8.1, 64-bit operating system and X 64-based processor. Table 3 illustrates the primary stages of the proposed segmentation method on different datasets for brain tumour extraction. The proposed segmentation method consists of following steps: (i) a biorthogonal wavelet transform filter is initially applied to remove impulsive noise from acquired brain images; (ii) skull stripping is performed to remove non-cerebral tissue followed by segmentation of tumour area using the fuzzy c-means threshold method. In order to improve the operating speed of the fuzzy c-means threshold technique, the fuzzy weighted index parameter $m=2$ is considered and the number of iterations is fixed to 3. The Canny edge detection method is then applied to obtain the high-contrast binary mask of the segmented image. The tumour region is finally extracted by using morphological operations (dilation and erosion). Figure 6 shows a snapshot of the tumour area calculation for a real brain CT scan image.

After performing segmentation, qualitative comparison was carried out using various performance measures such as similarity measure, execution time, and entropy. The similarity measures used were DSC and JI [23], as defined in Table 2. The values of DSC and JI lie between 0 and 1, where 1 indicates perfect segmentation and 0 indicates improper segmentation. Execution time [16] and entropy [23] are other performance metrics utilised for the evaluation of the proposed approach. Figure 7 shows the ground truth of brain images shown in Table 3 (second column). Table 4 shows the results of quantitative comparison between ground truth and the results of the proposed segmentation in terms of DSC, JI, execution time, and entropy. It was found that the maximum similarity value achieved in terms of DSC and JI was 0.995 and 0.990, respectively, for the BRATS MRI brain image. However, the minimum similarity value achieved in terms of DSC and JI was 0.815 and 0.687, respectively, for the BrainWeb MRI brain image. It was observed that the highest entropy (E) of 0.231 was obtained for the BrainWeb MRI brain image and the lowest entropy (E) of 0.187 was obtained for

Table 7: ANOVA Calculation for the Error % Using Three Segmentation Methods and the Proposed Method.

Source of validation	Sum of squares	Degree of freedom	Mean squares	F-value
Between columns (treatment)	SSC = 0.0946	$4 - 1 = 3$	MSC = $0.0946/3 = 0.03153$	$F = \text{MSC}/\text{MSE} = 3.8687$
Within columns (error)	SSE = 0.29365	$40 - 4 = 36$	MSE = $0.29365/36 = 0.0815$	
Total	SST	$40 - 1 = 39$		

SSC, Sum of squares between columns; SSE, sum of squares within samples; SST, total sum of squares; MSC, mean square between columns; MSE, mean square within columns.

Figure 8: MRI Brain Tumour Medical Images for Comparison.

First column: original image for tumours 01–05. Second column: tumour extracted by reported segmentation methods proposed in Refs. [27], [2], [15], [3], and [5], respectively. Third column: tumour extraction by the proposed method.

Table 8: Comparison of the Proposed Method with Some Recently Reported Methods in Terms of Execution Time and Tumour Area.

Images	Author and year	Hardware configuration	Performance metrics	
			Execution time (s)	Tumour area (pixels)
Tumour 01	Bandhyopadhyay and Paul [2]	DELL Inspiron system Intel Core i3 CPU @ 2.13 GHz processor and 4.00 GB RAM with Windows 7 Home Basic 64-bit operating system. The support analysis software used was MATLAB R2010a 64-bit version	12.360	37,492
	Proposed	^a	1.0067	31,580
Tumour 02	Kabade and Gaikwad [15]	Not provided	–	2789
	Proposed	^a	1.0078	2549
Tumour 03	Veer and Patil [27]	Not provided	–	1077
	Proposed	^a	1.0017	1092
Tumour 04	Bangare et al. [3]	Not provided	–	5463
	Proposed	^a	0.9953	5782
Tumour 05	Bhoi and Gupta [5]	Not provided	1.7090	3122
	Proposed	^a	1.0012	2485

^aThe hardware configuration of the proposed method is described in Section 4.

the BRATS MRI brain image. The results thus indicate that the proposed method can successfully segment the tumour area with an acceptable accuracy when compared to manual delineations. Moreover, the execution time required for tumour extraction is minimum for the BRATS MRI brain image and maximum execution time was required for the BrainWeb MRI brain image dataset. We found that the proposed segmentation algorithm provides the best accuracy, as the similarity measures is high, entropy value is low, and the execution time is minimum.

We then compared the performance of the proposed approach with one of the recent studies reported in this field on 10 real MRI brain images [11]. These images have different tumour sizes, shapes, and locations. The comparison of region growing, k-means clustering, and fuzzy c-means clustering in terms of error percentage is reported in Ref. [11]. Error percentage is defined as the ratio of error value to ground truth. A low value of error percentage is desired, as it indicates that the automated segmentation results are matching with the ground truth. The error percentage is calculated by taking the difference between the ground truth values and area of lesion obtained by the automated segmentation method. Table 5 shows the results of the comparative evaluation of different segmentation techniques. Further, Table 6 shows the average performance of the same. It was observed that the proposed approach achieved a minimum error percentage of 0.052 with a standard deviation of ± 0.016 . On the other hand, the k-means clustering-based segmentation technique achieved the highest percentage average error of 0.165 ± 0.039 , thus demonstrating poorest performance. It was also found that the proposed method demonstrated lower variability due to the smaller value of standard deviation achieved. The analysis of variance (ANOVA) test was also performed between the three different segmentation methods of Hooda et al. [11], and the results are shown in Table 7. It was observed that the F value of the proposed algorithm was 3.868, which is higher than the critical value obtained from the F table at 95% confidence level, i.e. 2.84. Hence, the null hypothesis is rejected and the alternative hypothesis is accepted. Thus, there is enough evidence to believe that there is a significant difference between the three different segmentation methods while considering the error percentage in the analysis.

We now discuss and compare the performance of the proposed method in view of some recent studies in terms of execution time and tumour area. The sample images used for comparison are shown in Figure 8 along with the segmentation results of some reported studies [2, 3, 5, 15, 27]. The brain tumour images (01–05) were obtained from Refs. [27], [2], [15], [3], and [5], respectively. Table 8 shows the execution time and tumour area (pixels) of the proposed method and other reported segmentation algorithms along with the

Table 9: Comparison Between the Proposed Method and Reported Scheme for Brain Tumour Extraction.

Author/year	Technique	Performance measure	Number of cases studied	Ground truth validation	Advantages	Disadvantages
Padole and Chaudhari [22]	Mean shift + normalised cut	Tumour area, centroid, eccentricity, boundary box	3	No	Reduces the execution time for segmentation	Study limited to small number of cases
Mohd Saad et al. [20]	Region growing	Area overlap, false-positive rate, false-negative rate, misclassified area, mean absolute percentage error	43	Yes	Simple and easy implementation	Proper selection of seed and similarity criteria is crucial
Bandhyopadhyay and Paul [2]	k-Means	Segmentation accuracy execution time, tumour area	100	Yes	Computationally efficient, simple and easy implementation	Sensitive to outliers
Kabade and Gaikwad [15]	k-Means + fuzzy c-means	Tumour area	–	No	Combination improves segmentation accuracy	Sensitive to outliers, no information about number of cases studied
Veer and Patil [27]	Global thresholding + watershed segmentation	Tumour area	75	No	Simple and easy implementation, usually results in closed and connected image regions	May fail when the background illumination is highly non-uniform. Watershed segmentation method may result in oversegmentation [9]
Bangare et al. [3]	k-Means + fuzzy c-means	Tumour area	–	No	–	No information about number of cases studied
Proposed method	Hybrid	DCC, JI, execution time, entropy, error %, average error % and standard deviation, tumour area	218 MRI brain images + 10 CT scan images + 10 PET scan images	Yes	Simple and fast, evaluated on multi-modal data, low error percentage	Low numbers of CT and PET cases used

hardware specification used. It was found that the execution time of the proposed segmentation method was 1.0067, which is less than that reported by Bandhyopadhyay and Paul (12.360) [2] and Bhoi and Gupta (1.7090) [5]. However, other studies, i.e. Veer and Patil [27], Kabade and Gaikwad [15], and Bangare et al. [3], have not reported the execution time of tumour extraction. It was observed that for tumour 01, the tumour area obtained by the proposed approach was 31,580 pixels, which is lower than that reported by Bandhyopadhyay and Paul [2] (37,492). This is evident from first row of Figure 8 in which the proposed method segments the tumour area more accurately. Similar results were obtained for tumours 02 and 05, respectively, as reported by Kabade and Gaikwad [15] and Bhoi and Gupta [5]. However, for tumours 03 and 04, the results of tumour area extracted by the proposed approach was almost similar to that reported by Veer and Patil [27] and Bangare et al. [3], respectively. We concluded that the proposed method offers better tumour extraction than the other five explored techniques. Furthermore, only Bandhyopadhyay and Paul [2] described the hardware configuration and the other reported studies [3, 5, 15, 27] did not provide any information about hardware details. Moreover, no ground truth data were provided by authors of Refs. [3, 5, 15, 27] to validate their algorithms, except in Ref. [2].

A benchmarking table giving the overview of different segmentation techniques reported in last few years is shown in Table 9. It was observed that the clustering method is the most commonly used technique for segmentation. Further, some hybrid approaches by combining k-means and fuzzy c-means clustering are also reported. The advantages and disadvantages of different techniques are also summarised in Table 9 (last two columns). It was also observed that none of the reported studies used standard datasets to validate their segmentation results unlike the proposed study. Furthermore, only Bandhyopadhyay and Paul [2] examined execution time for tumour extraction, which is one of the important parameters for choosing the segmentation algorithm. Unlike the reported studies, the proposed approach is evaluated on brain images of three different modalities, namely MRI, CT scan, and PET scan.

5 Conclusion

This article proposed an automated technique for the accurate detection of brain tumours in MRI, CT scan, and PET scan. The proposed approach comprised the following steps: (i) noise removal using biorthogonal wavelet transform; (ii) removal of non-cerebral tissue, i.e. skull stripping using the threshold technique; (iii) fuzzy c-means threshold clustering technique for segmentation; and, finally, (iv) brain tumour extraction using Canny edge detection and morphological operations. Exhaustive experiments were conducted for evaluation of the proposed approach on publically available standard databases. The performance measures used to validate the accuracy of the segmentation algorithm were DSC, JI, execution time, and entropy. From the experimental results, it was found that the proposed approach of brain tumour detection can successfully segment the lesions in brain images of different modalities. Further, the performance of the proposed approach was also compared with that of some recently reported studies using performance measures such as tumour area (in pixels) and execution time. It was found that the proposed approach outperformed other techniques in terms of most of the performance measures. Future work is needed to evaluate the performance of the proposed method in clinical practice and its effect on radiologists' performance. Inter-observer and intra-observer variability analysis can also be explored in the future.

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