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Automated brain tumor detection of MRI image based on hybrid image processing techniques

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ABSTRACT

Primary challenges are the identification, segmentation, and extraction of the afflicted area from the scanning of magnetic resonance. However, it is a time-consuming and tiresome for clinical specialists. In this paper, an automated brain tumor system is proposed. The proposed system employs hybrid image processing techniques such as contrast correction, histogram normalization, thresholding techniques, arithmetic, and morphological operations to quarantine nearby organs and other tissue from the brain for improving the localization of the affected region. At first, the skull stripping process is proposed to segregate the non-designated regions to extract the designated brain regions. Those resultant brain region images are further subjected to discover the brain tumor. The planned scheme is studied on the magnetic resonance (MR) images with the use of T1, T2, T1c, and fluid-attenuated inversion recovery (FLAIR). The proposed hybrid method employed. The results reveal that the proposed method is quite efficient to extract the tumor region. The accuracy rate for segmentation and separation of area of interest in brain tumor reached to 95%. Finally, the significance of the proposed procedure is confirmed using the real image clinical dataset got from ten patients were diagnosed as begin, malignant, and metastatic brain tumors in Al-Yarmouk and Baghdad teaching hospital in Baghdad, Iraq.

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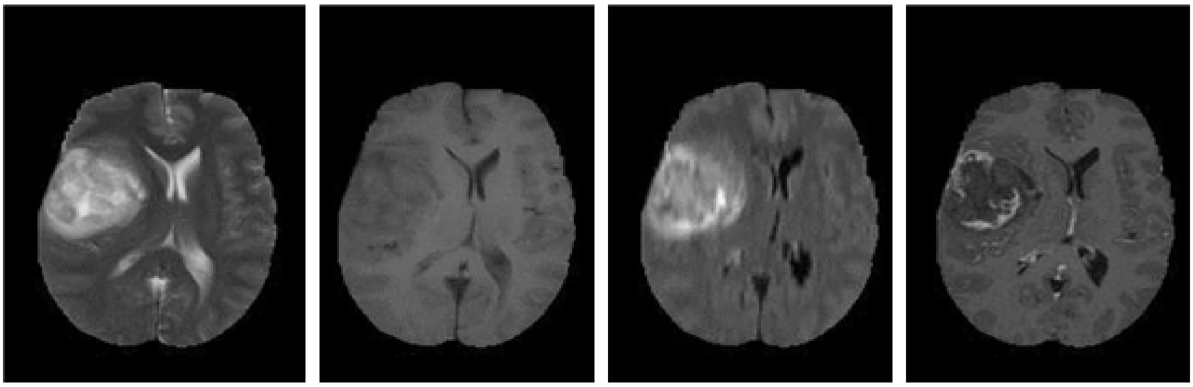
1. INTRODUCTION

The rising technology in medical image processing has piqued interest in brain tumors and their investigation. Conferring to a review prepared by the National Brain Tumor Foundation the realization of brain tumors among the public, as well as the death rate from brain tumors, is outpacing previous year’s numbers globally [1], [2]. In addition, various publications published in the last few decades have offered contexts or ways to focus the brain tumor area, which might or might not be surveyed by phases such as categorization, management planning, and prognosis of tumor. Segmentation of brain tumor medical pictures is crucial, yet it is often hampered by issues such as inadequate contrast, noise, and missing boundaries. Diagnostic procedures such as computation tomography scan, positron emission tomography and magnetic resonance imaging, are used to effectively control these parameters [3]. These imaging techniques aid in the detection of a variety of disorders. magnetic resonance imaging is popular in successfully identifying and treating brain cancers since they use innocuous magnetic fields and radio waves [4].

Malignancy progresses in the body when a cell’s growth and division become abandoned. It is called a brain tumor because of its location in the brain. A brain tumor is a mass of unneeded and aberrant cell development in the brain or an encephalon lesion takes up space inside the skull and causes a surge in intracranial pressure [5]. Because of differences in the size, site, and intensities, segmenting of brain tumors in magnetic resonance imaging is a challenging task [6], [7]. Segmentation of the image is a crucial stage in using magnetic resonance images of brain cancer research where the segmented part of the brain tumor might ignore perplexing features from another brain area, consenting for a more precise diagnosis of brain tumor subtypes and informing later diagnosis [8]. Brain tumor growth, shrinking, and relapse, may all be tracked using segmentation of linear magnetic resonance images (MRI) data. In modern clinical practice, manual delineation by operators is still employed for segmentation [9]. Manual the segmentation is a timewasting job that often includes segment-by-segment methods, and the results are highly reliant on the operators' skulls and knowledge. Furthermore, exact results are difficult to acquire even with the same operator. A multimodal and longitudinal clinical experimental causes a fully programmed, objective, and repetition of the segmentation method [10].

Radiation management for brain tumors relies on proper (MRI) segmentation, which necessitates the precise pixel labeling of MRI scans as healthy tissue or tumor [11]. However, Figure 1(a) T2-w (T2-weighted), Figure 1(b) T1-w (T1-weighted), Figure 1(c) fluid-attenuated inversion recovery (FLAIR), and Figure 1(d) T1c-w (T1-weighted) magnetic resonance images modalities are employed in brain tumor splitting up and abstraction. This is because of T1c-w is counterbalance-enhanced, and FLAIR is a fluid-attenuated reversal, as shown in Figure 1. Glial cell tumor, for example, has fuzzy boundaries that make it difficult to differentiate between it and other normal tissue [12].



(a) (b) (c) (d)

Figure 1. Samples of four pathological MRI slices: (a) T2-w, (b) T1-w, (c) FLAIR, and (d) T1c-w [11]

2. RELATED WORK

Brain tumor segmentation for diagnosis is a hard process. Segmentation refers to the partition of an image into different relevant segments. The availability of publicly available datasets has recently given a common venue for academics to create and objectively evaluate their methods using existing techniques.

Mehena and Adhikary [13] demonstrated an upgrade to the watershed transform for segmentation and morphological operator-based brain tumor retrieval from magnetic resonance (MR) images in 2015. When contrast enhancement is used, this technique can extract brain tumors from MR images in a variety of age groups. The proposed technique provides more information about brain tumors and aids physicians in diagnosing them. Unfortunately, a significant disadvantage of this strategy is excessive segmentation and poor detection of signals with a low signal-to- noise ratio.

Dhanve and Kumar [14] proposed an efficient picture segmentation strategy based on the technique named K-means clustering, which is combined with the s algorithm of fuzzy C-mean in 2015. As a consequence, to ensure the brain tumors detection is successfully achieved, stages of thresholding and level set segmentation were carried out. The suggested technique capitalizes on the advantages of K-means clustering for picture segmentation to compute time. It can benefit from the accuracy advantages of fuzzy C-mean s. The K-mean approach is faster than fuzzy C-mean s in detecting brain tumors; yet, fuzzy C-mean s is more accurate at predicting tumor cells; however, this method is not suited for non-convex shape data segmentation.

In 2015, Pan *et al.* [15] applied an enhanced convolutional neural network and non-quantifiable local surface feature with a structure of deep learning conventional approach for brain tumor detection. In which three-layer conventional neural network and multiple phase magnetic resonance imaging level was used to improve the performance rate. The experimental result shows improvement in sensitivity, specificity and performance of about 18% over the bassline one but, the disadvantage of this method is it is complex and may not apply in the simple conventional approach and the date which used for low grade is relatively small.

In 2016, Bhima and Jagan [16] proposed Watershed techniques for brain MRI images. Their technique was involving on region detection and mathematical morphology, which made this technique useful for grayscale image segmentation. Their work investigates the existing techniques for segmentation of brain image, such as the using both of K-means and fuzzy C-mean s, multi-region and multi-reference frameworks and fuzzy knowledge-based seeded region growing (FKSRG).

In 2017, Bahadure *et al.* [17] presented strategies of berkeley wavelet transformation (BWT) imaging for identification of brain tumor and using magnetic resonance imaging. By using skull stripping, 95% segmentation was achieved. this was carried out by omitting all non-brain tissues for identification reasons. However, this technique requires a lengthy training period for huge datasets.

Chen *et al.* [18] published a method for segmenting MRI images in 2017 that incorporates fuzzy clustering and markov random fields (MRF). MAP-MRF is used to merge the coarse scale image and the membership of fuzzy clustering extracted from the original image into potential functions of the single-site clique. To model the neighborhood constraint with MRF, defined potential functions and distance weights are introduced. The proposed method has an average similarity index of 36.8%, 33.7%, and 2.75% higher than fuzzy C-mean (FCM), fast generalized fuzzy C-mean (FGFCM), an fuzzy local information C-means clustering algorithm (FLICM), respectively, showing that the MRI segmentation method is a robust and precise method. However, the certainty of the probability of some value is one method' drawbacks.

In 2018, Devkota *et al.* [19] proposed using mathematical morphological reconstruction (MMR) to develop a computer-aided detection method for the early stages of brain tumors diagnosing. Their method involved in preprocessing the image to eliminate artifacts and noise before the image is being segmented in order to identify regions with possible tumor. The results show a high level of accuracy and significantly lowering time of calculation. Their work shows that their technique may be successfully used in diagnosing of brain tumors in patients. However, the computational complexity acts as a barrier to this strategy.

In 2018, Shree and Kumar [20] demonstrated how to extract seven characteristics from GLCM pictures using region-based segmentation. MRI Images with a resolution of 256×256, 512×512 pixels are included in the dataset. The dataset was compiled from the website www.diacom.com. 95% of testing datasets are accurate. One disadvantage is that a seed point with a different value may produce a different value.

In 2019, Mascarenhas *et al.* [21] introduced a histogram normalization, contrast correction and binarization strategy for decoupling nearby structures from the brain. Besides, they enhancing the region of interest of brain tumors. The results were compared to manual segmentations performed by two radiologists to ascertain out the algorithms' efficacy. The poor results showed that the suggested system could autonomously locate and delineating the tumor location without user intervention, based on two novel strategies for detecting brain extreme sites on magnetic resonance imaging.

In 2019, Kumar and Kumar [22] reported segmentation and feature extraction using the FCM clustering algorithm and gray-level cooccurrence matrix (GLCM) and Gabor are nine features. Preprocessing is accomplished using a median filter. The precision is 91.17%.

Jeong *et al.* [23] suggested in 2020 to use a reconstructing convolutional neural network 3D mask region-based convolutional neural network (R-CNN) approach. However, their method detects and segments a high and low grade of the brain cancers automatically for dynamic susceptibility contrast MRI images. This study enrolled 22 high and low-grade patients with 50 to 70 of perfusion time point volumes. The proposed technique achieved an overall 895 of dice similarity, 90% of precision, 87% of recall, and 1.270.67% of center of a mass distance. This precision is a result of a lack of specificity.

In 2021, Sumir *et al.* [24] proposed a fully automatic brain tumor segmentation approach with updated morphological and thresholding operations. This approach was used for segmenting uncontrolled growth of mass-containing tissues from brain tumor MRI images. Moreover, this approach achieved more accuracy results, and it reduced computational time. Additionally, and based on the quantity of area, this approach aids in determining the stage of tumor efficiently. By using the approach of discrete wavelet transform (DWT) for the MRI image, most of the mean, correlation, contrast, skewness, energy and homogeneity are determined.

In 2021, Anantharajan and Gunasekaran [25] used a weighted fuzzy factor approach based on kernel metrics. To improve prediction accuracy, a deep autoencoder (DAE) combined with a weighted fuzzy clustering algorithm was applied in order to provide a segmentation for the lesion area from the remaining parts of MRI image. The planned procedure affords better performance with accurateness related to the further current procedures.

3. PROPOSED METHOD

With the aid of non-specialists, this study proposed approach for understanding of the diagnostic and decide whether the tumor is existed or not in the area of interest. To build and verify a suite of computational algorithms for automatic tumor segmentation on magnetic resonance imaging of the brain. Pre-processing, skull stripping, and tumor segmentation are the three phases that make up the approach. The suggested system steps are depicted in Figure 2.

3.1. Pre-processing

Pre-processing includes techniques for removing artifacts from photographs, enhancing their quality. And for more segmentation precision and comprehensive visualization, highlighting an area of interest is included as well. To highlight the tumor location, this stage involved picture contrast enhancement. In all photos, the intensities of grey-level pixel were uniform between zero and one. Equality of histograms unlike other imaging techniques, MRI does not have a contract value for the pixel intensity concerning the tissue image, i.e., the varied intensities might exist in the same tissue, which make it easy to use the properties of intensities as a useful information during segmenting pictures. The non-standardized intensities problems can be reduced by using the method of normalizing. Histogram equalization is used to make the anticipated portions of the image brighter than the surrounding area, making extraction easier.

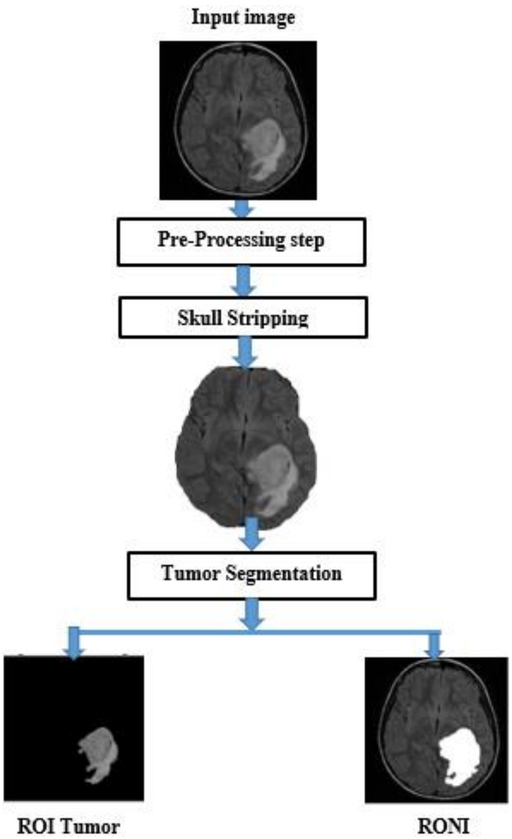


Figure 2. The proposed system of brain tumor detection of MRI

3.2. Skull stripping

This step is suggested to automatically externally eliminate the areas which are not useful, such as the meninges, the skull bone, and subcutaneous fat, by used gamma correction, thresholding, arithmetic operation, and morphological operations. The skull stripping procedure is a necessary pre-processing step that separates non-specified brain regions to extract the designated brain regions. The resulting brain region images are then analyzed to determine a brain tumor. Algorithm 1 illustrates the stages involved in skull stripping, whereas Figure 3 illustrates the steps involved in skull stripping. Figure 3(a) original image, Figure 3(b) correct gamma, Figure 3(c) binarization, Figure 3(d) image complement, Figure 3(e) great mask, Figure 3(f) image multiplications, and Figure 3(g) skull stripping.

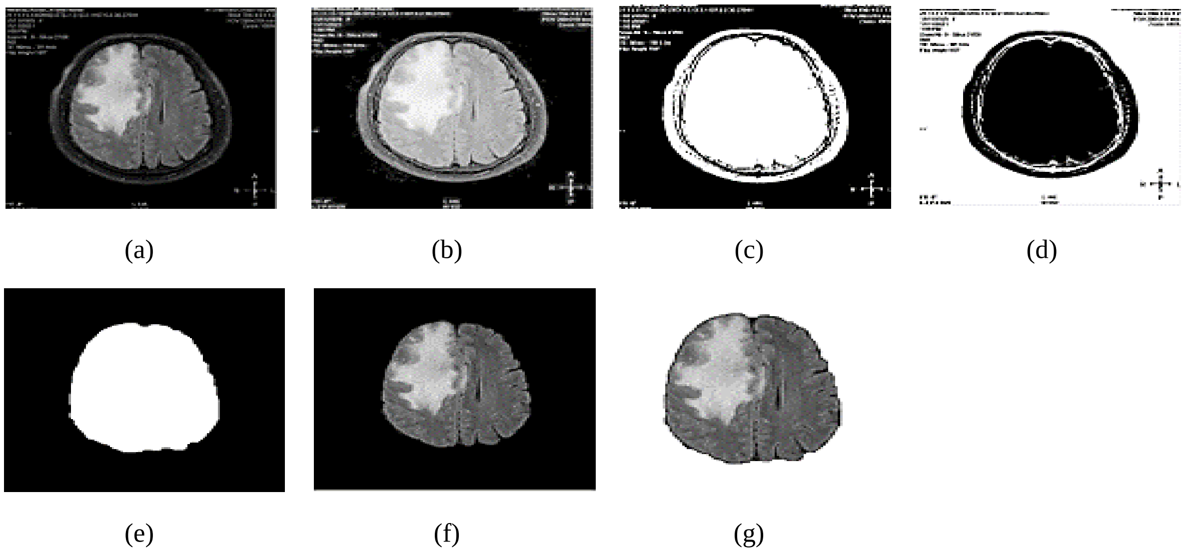


Figure 3. Steps of skull stripping: (a) original image, (b) correct gamma, (c) binarization, (d) image complement, (e) great mask, (f) image multiplications, and (g) skull stripping

Algorithm 1. Skull stripping

Input: BrainImg height, width
Output: Skull
Step 1: Apply inverse of gamma transform with $\gamma = 2.5$

$$Newimg = 255 \times (255/BrainImg)\ \text{^}\ (1/\gamma) \quad (1)$$

Step 2: The binarization creates a binary image using a threshold got using Otsu's method
BinImg = imbinarize (Newimg, TH)
Step 3: Perform image complement to BinImg
CompImage = imcomplement (BinImg);
Step 4: Create mask
Step 4.1: Perform image closing and opening on CompImage
Step 4.2: Mask = imcomplement (CompImage)
Step 5: Perform image multiplication between the mask and original image BrainImg
Skull = immultiply (mask, BrainImg)
Step 6: Skull with a white background
for i = 1 to width
for j = 1: height
if ((Mask (i, j) <> 0))
Skull2 (i, j) = BrainImg (i, j);
else
Skul2 (i, j) =255;
endif
end for j
end for i

3.3. Tumor segmentation

The segmentation method is incredibly significant in image processing. The findings of segmentation will be utilized to extract quantitative information from images, such as grouping and thresholding [26]. The suggested method used enhanced techniques to highlight the tumor region of interest (ROI) (i.e., tumor region), while morphological operators are used to remove unwanted features and recreate the tumor's shape and texture. The steps of tumor segmentation are listed in Algorithm 2.

Figure 4 shows the results provided by algorithm 2 which is drawn from the extracted tumor region and segmented outcome. Figure 4(a) original image, Figure 4(b) after skull stripping, Figure 4(c) correct gamma, Figure 4(d) after filling and addition, Figure 4(e) binarization, Figure 4(f) morphological operations, Figure 4(g) segment tumor region, and Figure 4(h) boundary of tumor in original image.

Algorithm 2. Tumor segmentation

Input: MI // Brain image
Height, width
Output: ROI: localized ROI region
Step 1: Read brain image MI of size W×H
Step 2: Apply algorithm 1 for skull stripping and return brain image brain
Step 3: Apply contrast stretching to increase Brain intensity values using the (2)

$$Ebrain(x,y) = \begin{cases} 0 & Brain(x,y) \le Low \\ 255 \times \frac{Brain(x,y)-Low}{High-Low} & Low < Brain\,(x,y) < High \\ 255 & Brain\,(x,y) \ge High \end{cases} \quad (2)$$

Where Ebrain (x, y) is the enhanced image and brain (x, y) is the brain image.
Low and high levels are chosen through trial and error.
Step 4: The enhanced brain image Ebrain is recorded using Gamma correction demarcated by the (3)

$$Gbrain = ((Ebrain/255)\hat{}\ \alpha) \times 255 \quad (3)$$

Where Gbrain is a gamma image, Ebrain for medical image (MI), and α gamma factor for gamma factor.
When the value is between 0 and 1, it improves contrast in bright areas, and when it is greater than 1, it improves contrast in dark areas.
The number of 2.5 was chosen to brighten the medical image and make the ROI region more distinct.
For the greatest results in this phase, choose this value.
Step 5: Fill gaps and apply image addition between the addition Gbrain after region filling and Ebrain to highlight tumor region
Step 6: Apply global thresholding to segment the tumor image
Step 7: Apply morphological operation. For a binary image, use the morphological closure operator The closing filter operation smoothes the edges, reduces minor inner collisions, ties narrow joints, and fills small gaps caused by noise.
Step 8: segment the tumor region
Completes tumor segmentation by evaluating each spatially split area in image space discretely. Area free of the lesion are unconcerned. with those regions remains labeled as a tumor. The subsequent image is considered the last tumor segmentation.
Step 9: Contour boundary of tumor in the original image

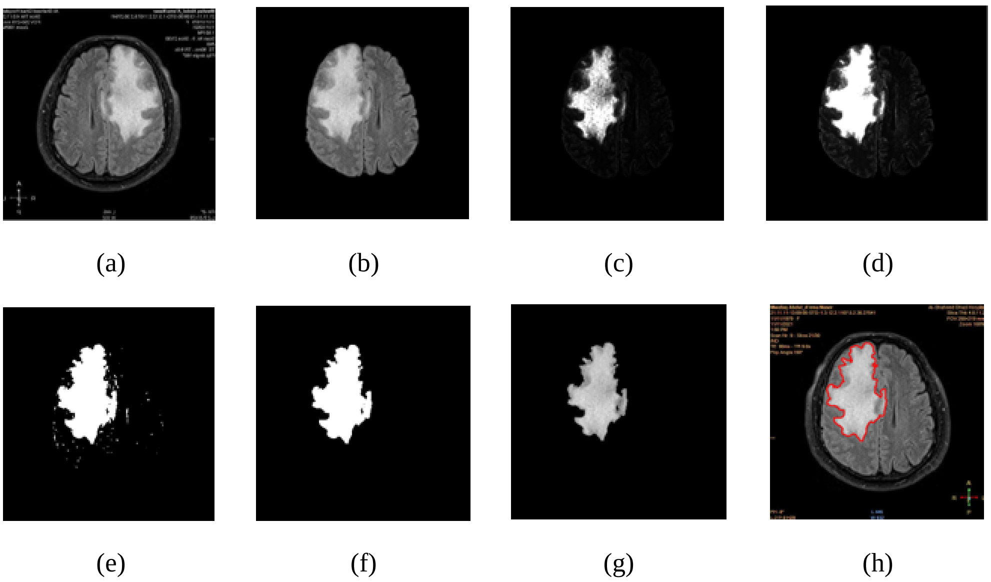


Figure 4. Steps of tumor segmentation: (a) original image, (b) after skull stripping, (c) correct gamma, (d) after filling and addition, (e) binarization, (f) morphological operations, (g) segment tumor region and (h) boundary of tumor in original image

4. RESULTS AND DISCUSSION

The suggested method is evaluated on two datasets: one is publicly available [27] and the second is a private dataset. The private dataset was compiled from 10 patients who are diagnosed as begin, malignant and metastatic brain tumors in Al-Yarmouk and Baghdad teaching hospitals in Baghdad-Iraq. All patients that enter study are between the ages of 18 and 60. Their MRI scans were saved in a database in a photo in the JPG, bmp, JFIF, and JPEG formats. The total number of tumor images for each MRI sequence investigated in this paper is 250 tumor images with T1, T2, T1c, and FLAIR modalities. The white color represents the suspicious area of the MRI image. This area of the image has the maximum intensity compared to the rest of the image. In this section, we looked at two different Brain MRI datasets for brain tumor segmentation. Figure 5 depicts some samples of the results for skull stripping. The results of skull stripping are depicted in Figure 5. The tumor segmentation testing results exhibit superior results, as illustrated in Figure 6 and Figure 7.

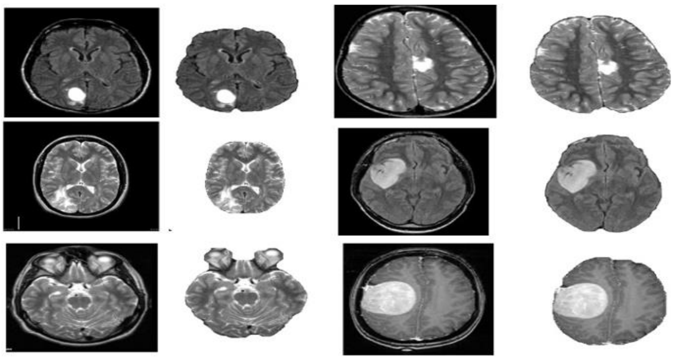


Figure 5. Samples of skull stripping process

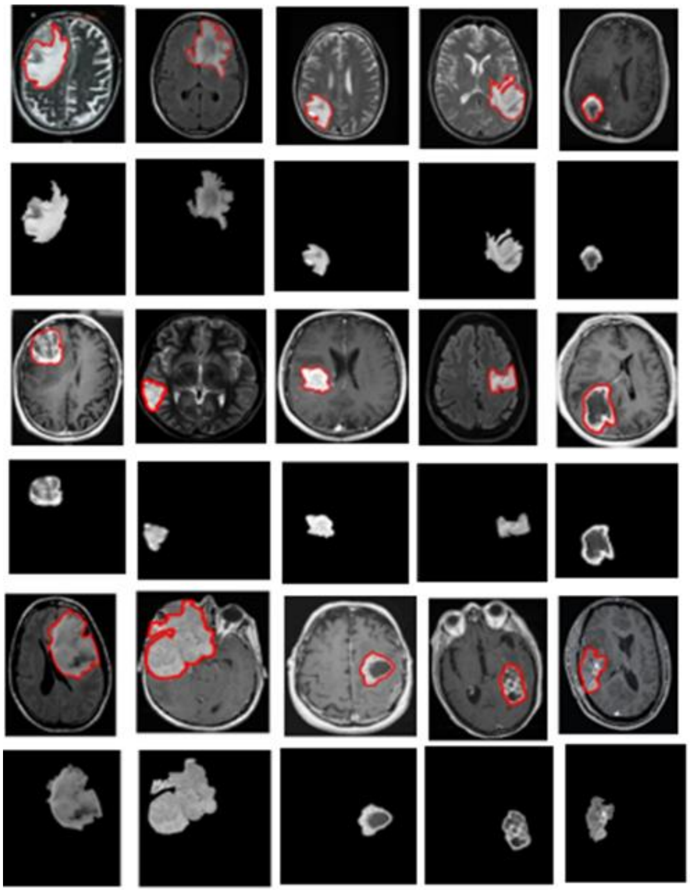


Figure 6. Samples of segmentation of brain tumours lesion from Kaggale

The algorithm proposed in this paper can successfully extract brain tumors with a 95% accuracy in various age groups, as calculated by the equation below. The accuracy of hybrid segmentation was compared to that of fuzzy and C-mean, fuzzy and K-mean, improved fuzzy and watershed algorithm, contrast correction, and intelligent mean shift, which were 85%, 86%, 88%, 89%, and 92% as shown in Table 1. We present the MATLAB2019b application of this context to validate the visual benefits of hybrid image processing approaches algorithm for localizing brain tumor in MRI images to show the results and theoretical construction proposed in this study. MATLAB is a widely used multifunctional numeric programming language that carried out higher-order mathematical calculations.

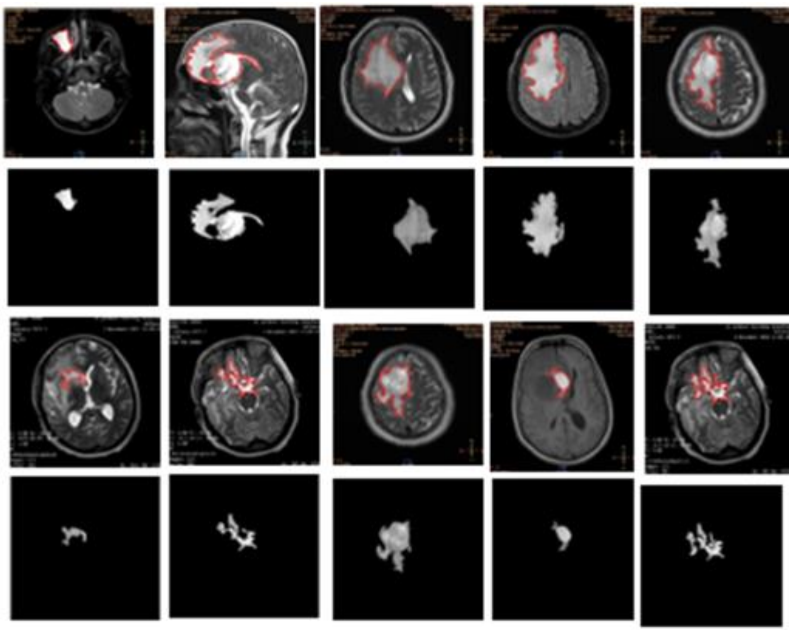


Figure 7. Samples of tumor segmentation for real patient Images

Accuracy is the measure of successful segmentation of the proposed algorithm has been calculated by the (4).

$$Accuracy(\%) = \frac{Number\ of\ correct\ data}{Number\ of\ all\ data} \times 100 \quad (4)$$

Table 1. Compression accuracy rate between proposed methods and other methods

Authors	Technique	Accuracy rate (%)
[28]	Intelligent mean shfit	92
[20]	Contrast corection	89
[29]	Improved fuzzy and watershed	88
[30]	Fuzzy and K-mean	86
[31]	Fuzzy and C- mean	85
Proposed method	Hybrid image processing technique	95

5. CONCLUSION

MRI images are commonly used in the diagnosis of brain benign and malignant brain tumor. The current study used advance modality which is of hybrid image processing techniques for segmenting of brain tumors from MRI brain images to minimizing the effect of artifact and for separation and segmentation of the suspicious area at the same time. These hybrid image processing approaches and procedures give excellent brain tumor segmentation outcomes with accuracy reaching 95% which is given the novality for this work in compare to previous studies, according to the results gathered. Pre-processing procedures could successfully remove enormous parts of the brain and some cerebrum areas. The initial step in the brain picture segmentation procedure is stripping off the skull. Cranium stripping is mandatory to remove the bone and the surrounding zone from the MRI. It is necessary for a thorough investigation of a brain tumor using MR imaging. Morphological procedures are primarily used as the filter in the proposed method to eliminate low-frequency pixels and border pixel tumor location.

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