BRAIN TUMOR EXTRACTION FROM MULTIMODAL MRI OF HUMAN HEAD SCANS USING IMAGE FUSION TECHNIQUES

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Abstract
The proposed work extracts the tumor portion using an image fusion technique from a Multimodal MRI of Human brain tumor images. The proposed work fused the MRI modalities Flair, T2, and T1C to enhance the tumor portion from other surrounding portions in the brain slice. Preprocessing of brain tumor images are done by pseudo coloring. Modalities such as Flair, T2, and T1C are assigned three color channels, red, green, and blue, respectively and then these colored images are fused together. This enhances the tumor portion with better contrast. Gray scale transformation is applied with a fused color image for further enhancement of the tumor portion and thus separates them from the surroundings. Finally, the tumor portion is extracted by applying Largest Connected Component (LCC) algorithm. Experiments are done using BRATS 2019 dataset and estimated with entropy (EN), structural similarity index metric (SSIM), peak-signal-to-noise ratio (PSNR), mean squared error (MSE), and dice coefficient (DC), which evaluate thesimilarity between ground truth and extracted whole tumor. Better results are produced for the proposed image than the existing method.

Keywords: Magnetic Resonance Imaging, Image Fusion, Pseudo Coloring process, Binary Transformation, Largest Connected Component, Segmentation.

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1. Introduction

In medical imaging techniques, MRI is the superior imaging technique to produce human body parts images with good quality [1]. In MRI scans, tissues of the normal brain: white matter (WM), graymatter (GM), and Cerebrospinal Fluid (CSF) are present in better contrast with multimodalities. MRI produces four modalities Flair, T1, T2, and T1c. These high-definition images produce in-depth information to analyze the human brain tissues normal and abnormal. Tissues of the abnormal brain which are tumor tissues appear with high-intensity variation in the MRI slice.

In the medical field, MRI is used for brain tumor diagnosis. An abnormal growth of cells developed in brain tissues is considered a brain tumor. It is classified as primary and secondary brain tumors. A primary brain tumor is the genesis of the brain and will reside in the brain itself. The secondary brain tumor started anywhere in the body and then it will affect the brain. The whole brain tumor region consists of active tumors, edema, and necrosis or dead cells.

Extraction of tumor portion in brain MRI is essential in medical diagnosis, surgical planning, and prognosis. In Figure 1, sample MRI multimodal images of brain tumor is given. T2 images clearly outline the edema region and produce bright signals for the tumor portion on the images. In the Flair image, signals of water molecules are suppressed since the edema region is well distinguished from CSF. Healthy tissue of the brain is structured in a T1 image. In T1 contrast-enhanced image (T1c), tumor boundaries become brighter around the tumor region. In this range, the active and non-active (necrotic) tumor regions are distinguished easily.

Brain tumor portion extraction separates tumor cells and normal cells from MRI brain tumor images. In multimodal MRI brain images, tumor portions are heterogeneous in appearance, shape, and size as shown in Figure 1. The image fusion technique integrates these different appearances of the tumor portion in multimodal images and produces a whole tumor portion for diagnosis [2]. Image fusion is specific in medical diagnosis, specifically for tumor treatment and it combines twoor more images having maximum features than one image [3, 4]. Different levels of image fusions such as pixel, features, and decision level are used to unite the multimodal images to improve the clinical accuracy of decisions [5, 6].

Pixel-level fusion relates the picture element in the images. Feature-level fusion extracts feature like regions, edges, and objects in source images and combine them to produce the fused image. Decision-level fusion techniques are based on the outcomes obtained from different algorithms.

Pixel-level fusion preserves more critical information than feature level and decision level because it directly merges the pixels from multiple images [7], as shown in Figure.2. Different types of pixel-based image fusions are available in the literature. Averaging method is one such simple and fastest pixel-level fusion method that considers the average of respective pixels of the input images [8]. It is defined as,

$$F(A,B) = \sum_{x=1}^{n} \sum_{y=1}^{m} (A(m,n) + B(m,n))/2 \qquad (1)$$

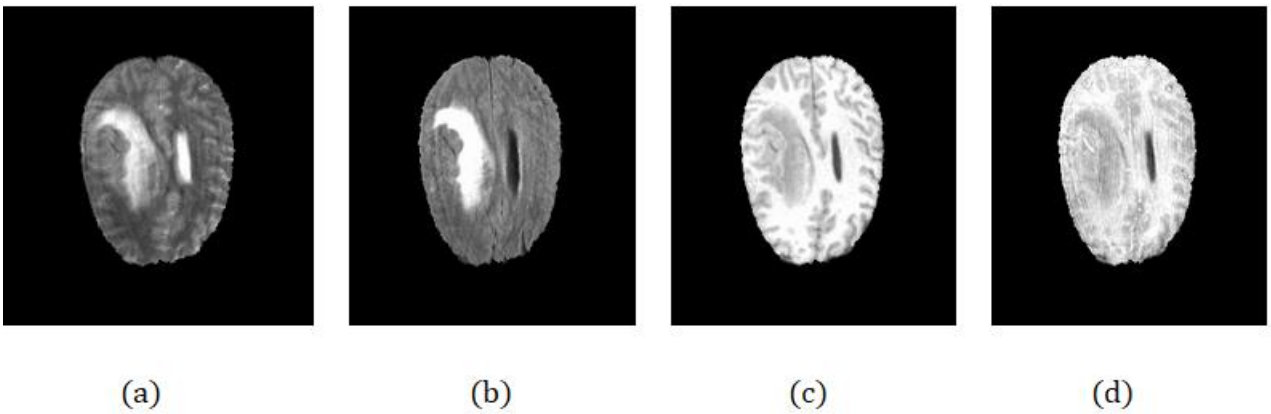

Figure 1: Sample MRI Multimodal Images of Brain Tumor (a) T2 (b) Flair (c) T1 (d) T1c

Where, A and B are single images of size m x n and F is a fused image.

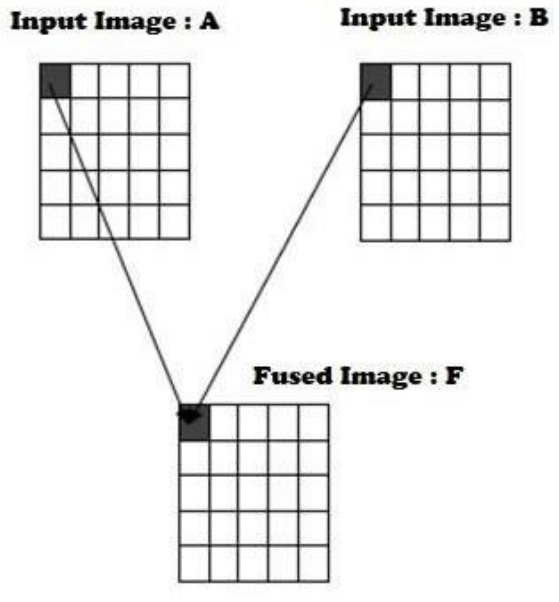

Figure 2. Pixel-Level Image Fusion

In the proposed work, modalities of MRI brain images are fused using a pseudo-coloring process to extract the tumor portion. Modalities of MRI brain images Flair, T2, and T1C, are mapped to three color channels R, G, and B respectively, and produce a color image. Formerly image transformations are implemented to extract the tumor region from the brain image. Finally, extracted tumor portion is compared with ground truth, qualitatively and quantitatively using evaluation parameters.

This article is structured as follows. Existing methods in image fusion and tumor extraction are discussed in section 2. Image fusion techniques are represented in section 3. The proposed brain tumor extraction method in multimodal images is addressed in section 4. In Section 5, materials and metrics are discussed. Section 6 describes the results and discussions. Conclusions as well as future work are addressed in section 7.

2. Literature survey:

Kalaiselvi and Kalaichelvi,[3] developed a method to extract the tumor portion using multimodal MRI scans of brain tumor images. Sequences of MRI T2, Flair, and T1c are used in the segmentation process. The proposed method is performed in three phases. In the first phase the preprocessing work is done using Fuzzy-c means clustering algorithm to enhance the tumor portion. In the second phase, the substructure of tumor region enhancing tumor, edema, and necrotic regions are segmented using region-wise set operation. The post-processing work is performed in phase III with a segmented tumor image with 3D visualization. Here BraTS 2013 dataset with 20 HGG and LGG is used for the experiment. The proposed method was evaluated by validation metrics such as dice, sensitivity, specificity, and accuracy and also this method is compared with 19 existing works. The evaluation parameters give 77% dice value, 53% sensitivity, and 59% specificityfor the proposed method. The result for HGG appeared well than the result of LGG.

Kalaiselviet.al.,[4] developed a novel method to combine the multimodality of MRI imagesto form a RGB image. In the RGB image, the tumor portion is enhanced with better contrast. The grayscale image of Flair, T2, and T1c is built with Red, Green, and Blue channels to form an RGB. Here substructure of the tumor portion is also separated using color range. In RGB images, tumor substructures such as enhanced tumors appeared in golden yellow color and necrotic appeared in white respectively. Then the substructures are extracted from the RGB image. The experiment was done with BraTS 2012 high glioma dataset. Quantitative analysis is done with accuracy and similarity index for the resultant images which produced better results with 0.99 and 0.82 values respectively. The proposed method segregates the tumor region in MRI brain images for the segmentation and classification process. Multiple tumors cannot be detected by this method. Thisis the limitation of this method.

Ranjinikanthet.al.,[6] proposed a method to detect abnormalities in MRI brain images using the computer-assisted technique(CAT). Here, preprocessing work is done by image fusion technique and thresholding function. Multimodalities of MRI brain tumor images are T1, T2, T1c, and flair, these are processed in a hybrid manner. These modalities of images are fused by DWT- PCA image fusion techniques. Then, social group optimization thresholding is applied to enhance the tumor portion. Post-processing work is implemented using a watershed algorithm, to segment the enhanced tumor portion. These modalities are taken as individual and as well as a combination of different modalities such as Flalir+T1c, Flair+T2, and Flair+T2+T1c used for the pre and post-processing work. The experiment was done using

BraTS 2013 dataset with 105 slices. Evaluation parameters used here are Jaccard, dice, sensitivity, specificity, and accuracy giving 84.33%, 90.86%, 99.93%, 90.67%, and 95.74% respectively. Based on the results, Flair+T2+T1 gave better results when compared with other combinations.

Kalaiselvi et al., [7] proposed a new work to segment the whole tumor portion using k- means and image fusion techniques. The fused image contains more details than a single image. They fused the multimodality MRI images to segment the tumor portion and fetch the required texture details. The modified k-means algorithm is employed in diffusion tensor image (DTI) to segment cerebral spinal fluid (CSF), gray matter, and white matter to extract the tumor portion. Quantitative analysis was done by specificity, sensitivity, and dice coefficient metrics. The dice value gives up to 0.93 for all images in the proposed method. They represent that the proposed method consumes less time and does not exceed 1.44 seconds. The results indicate that the proposed method gave better performance.

Methodology

The proposed multimodal brain tumor extraction method using the pixel-level fusion technique is based on the following five steps, and its flowchart is given in Figure 3.

Input : MRI brain modalities Flair, T2, and T1C

Step 1 : Preprocessing using Pseudo-coloring process is done by assigning eachmodality to separate color channels: Flair with the Red channel, T2 with the Green channel, and T1C as the Blue channel.

Step 2 : Apply the pixel level average Fusion rule on color images of multimodal.

Step 3 : Image Transformation.

Step 4 : Whole Tumor Extraction

Output: Complete tumor portion

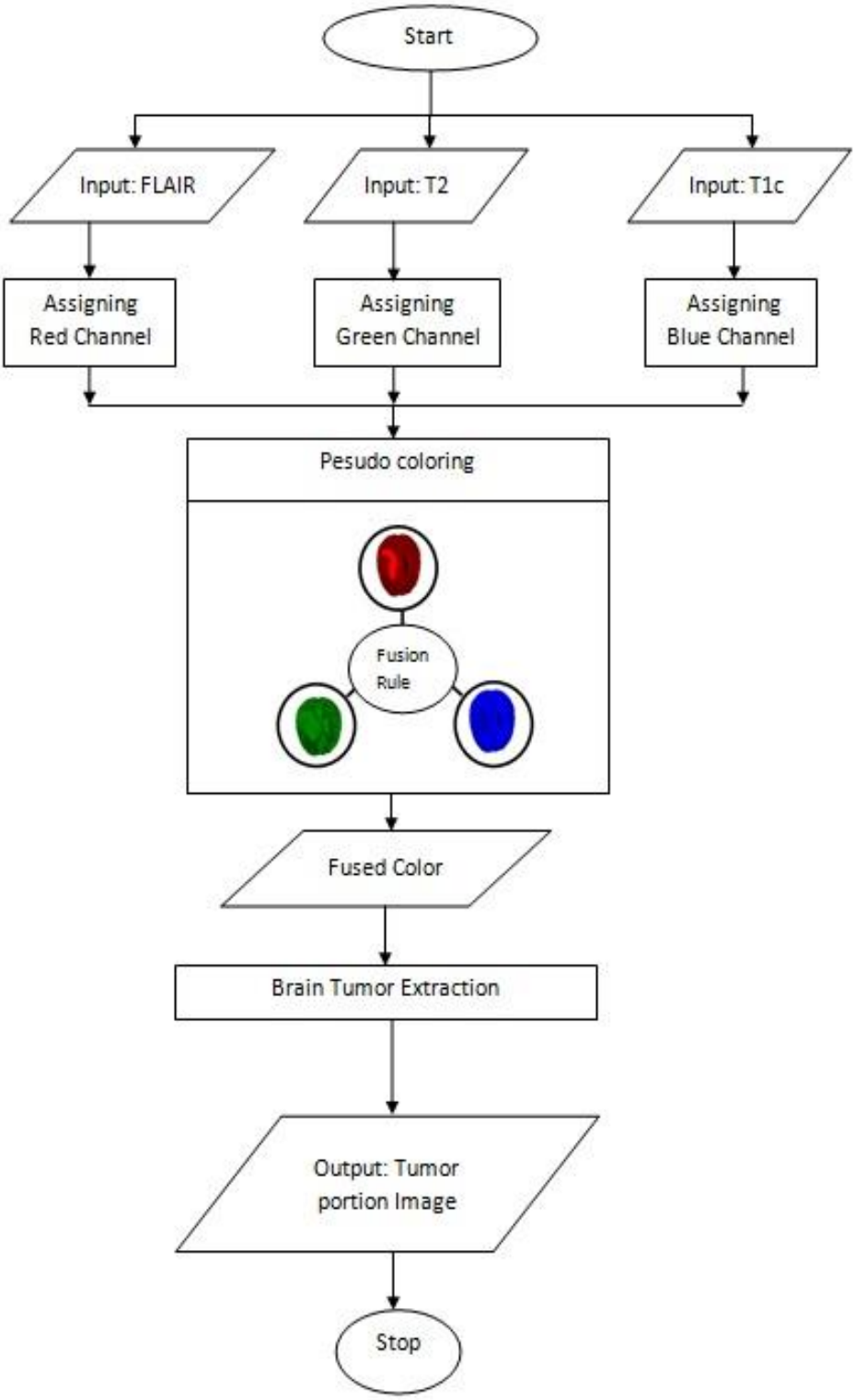

Figure 3. Flow Chart of Proposed Method

The multimodal MRI brain tumor images Flair, T2, and T1C have different appearances of tumor portions in each modality as shown in Figure 4(a), 4(b), and 4(c) respectively. Color channels red, green, and blue are assigned to Flair, T2, and T1C, respectively, as shown in Figures 4(d), 4(e), 4(f). The entire structure of the tumor portion with high-quality information is produced by combining these modalities using the image fusion rule. Averaging fusion rule is applied to merge the three color images, which produces the fused color image, as shown in Figure 5. The resultant fused color image as shown in Figure 6(a) is translated to grayscale transformation with enhanced tumor portion, as given in Figure 6(b). Binary transformation function with a gray image to separate the tumor portion pixels from other pixels shown in Figure 6(c). To extract the tumor portion, the largest connected component (LCC) is applied on the threshold image, and then the extracted tumor portion is shown in Figure 6(d). The resultant tumor portion image is compared with the ground truth as shown in Figure 6(e).

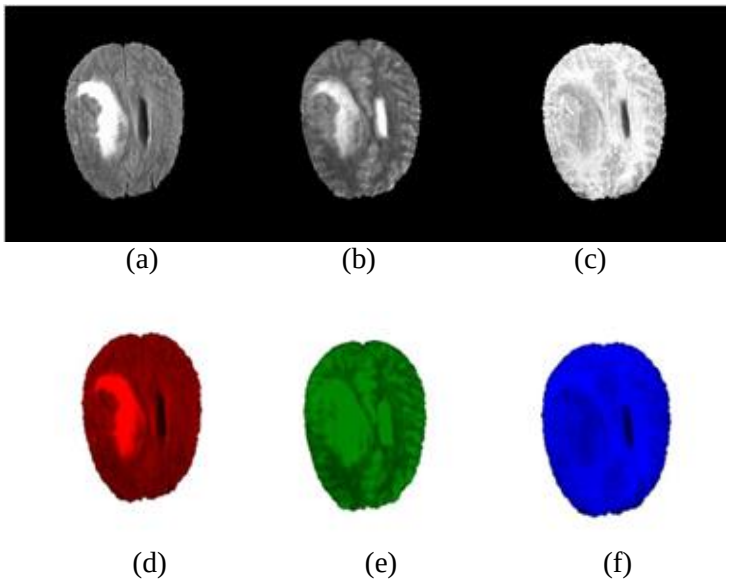

Figure 4. Assigning multimodal images to color channels a) Flair b) T2 c) T1C d) Flair – Red e) T2 - Green f)T1C – Blue

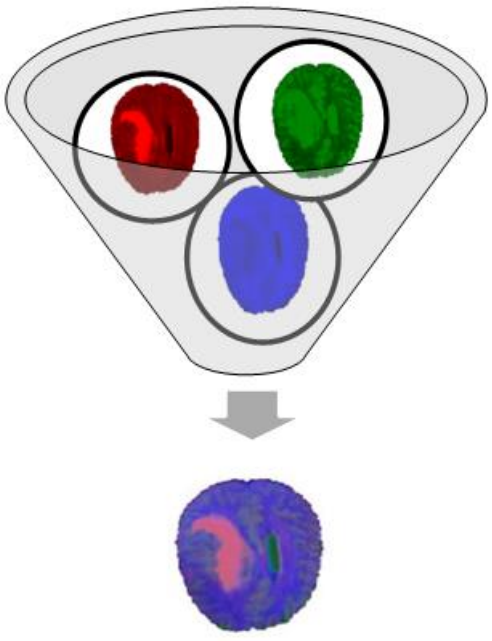

Figure 5. Fused color image

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

Figure 6. a) Fused Color Image b) Gray Scale Transformation c) Binary Transformation d) Extracted Tumor Portion e) Gold Standard Image

3. Material and Metrics:

Multimodal Brain Tumor Segmentation Challenge (BraTS) repository contains a massive, publicly available dataset of brain tumor images agreed upon by the expert team [9]. In the experiment, BraTS 2019 dataset with 11 volumes is used with 135 images of each modality. The configurations used for the experiments are 8 GB RAM, Windows 10, 64-bit, Intel(R) Core(TM) i5 Processor, and Python 3.10. The evaluation parameters used in our experiment are DC, EN, SSIM, PSNR, and MSE.

Dice – Coefficient measures the similarity among the fused segmented and ground truth images [10,4,14]. Its range from 0 to 1. If the value nearest to 1 means the segmented image similar to referenced image. It is calculated by,

$$DC = \frac{2|A \cap B|}{|A|+|B|} \quad (2)$$

Where A is the resultant image and B is the ground truth image.

Entropy (EN) calculates the depth of information obtained in the fused image. It ranges from 0 to 8 [11]. If the entropy value is near 8 then the resultant image has a maximum depth of value. If the value is near 0 then it indicates that the resultant image has less amount of information. It is calculated by,

$$EN = -\sum_{L=0}^{L-1} p_L \times log_2 p_L \quad (3)$$

Where L represents the gray level and p_L represents the probability of each gray value L.

Structural Similarity Index Measures (SSIM) calculate the structural similarity among resultant fused images and ground truth images [11, 15]. SSIM ranges from 0 to 1. If the SSIM value is nearest to 1, it indicates that the resultant image has the same structure as the gold standard image.

$$SSIM_{(A,F)} = \frac{(2\mu_A\mu_F+C_1)(2\sigma_{AF}+C_2)}{(\mu_A^2+\mu_F^2+C_1)(\sigma_A^2+\sigma_F^2+C_2)} \quad (4)$$

Where, μA and μF are the mean value of A and F. σ_A^2 variance of A, σ_F^2 variance of F, σ_{AF} covariance of A and F. Then $c_1$and c_2 are two variables to stabilize the division with weakdenominator.

Peak-Signals to Noise-Ratio (PSNR) calculates the ratio of peak power and noise value between the resultant image and ground truth image [2, 3, 12]. The highest PSNR value indicates that the resultant extracted tumor portion image is as much as closer to the ground truth image and has less distortion during the fusion process. It is measured by,

$$PSNR = 10log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (5)$$

Where MAX stands for a maximum value of gray level pixels in the resultant image and MSE is the mean squared error between the resultant image and ground truth image.

Mean Squared Error (MSE) calculates the error projection among the resultant and ground truth image [13]. If MSE gives 0, then it indicates that the images are identical. The following equation calculates it,

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij} - B_{ij}\right)^2 \quad (6)$$

Where A stands for the resultant image and B represents the ground truth image.

Results and Discussion:

The quantitative analysis is done by the evaluation parameters EN, SSIM, PSNR, MSE, and DC between fused extracted tumor portion and ground truth image in every 11 volumes. The average value calculated for each parameter is given in Tables 1 to 5.

The entropy value is calculated for the fused extracted tumor portion image for each volume shown in Table 1. The computed values range from 0 to 8, and this value indicates the resultant image quality. The Entropy value is computed for each multimodal MRI brain tumor images Flair, T2, T1c, and fused grayscale image, shown in Figure 8. In that analysis, the entropy value of the fused grayscale image gives a higher value than other modalities.

The average SSIM value of each volume is calculated among the ground truth image and fused extracted whole tumor image shown in Table 2. The average SSIM value given near 1 shows that the proposed result is similar to the ground truth image and it has been calculated for each multimodal MRI brain tumor images Flair, T2, T1c, and fused grayscale image, shown in Figure 9. The PSNR value of each volume is calculated and the average is given in Table 3. The highest value of PSNR indicates the highest ratio between the fused extracted tumor portion and the ground truth image. The PSNR value is calculated for each multimodal MRI brain tumor images Flair, T2, T1c, and fused grayscale image, shown in Figure 10. MSE between fused extracted tumor portion and ground truth images of each volume is calculated and the average value is listed in Table 4. The low MSE shows that the resultant image and ground truth image comparison have fewer errors. The MSE value is calculated for each multimodal MRI brain tumor images Flair, T2, T1c, and fused grayscale image, shown in Figure 11. Here among other modalities, fused extracted tumor portion gives betterresults.

The average DC for each volume is primarily high, indicating that the resultant image of the proposed whole tumor portion is similar to ground truth, which is listed in Table 5. The extracted tumor portion of each modality and fused image with DC value are shown in Figure 12. When comparedto the ground truth image, the tumor portion extracted in the fused brain tumor image gives a better structure than other modalities. The fused extracted brain tumor image given a high percentage of DC value and that indicates its high similarity to the ground truth image.

Table 1. Entropy value for each volume

Volume NO	AverageValue
BraTS19_CBICA_AAB_1	3.924364313
BraTS19_CBICA_AAG_1	4.504969719
BraTS19_CBICA_AAL_1	3.502420789
BraTS19_CBICA_AAP_1	4.392585743
BraTS19_CBICA_ABB_1	4.065744881
BraTS19_CBICA_ABE_1	4.117618457
BraTS19_CBICA_ABM_1	3.938612109
BraTS19_CBICA_ABN_1	4.405225472
BraTS19_CBICA_ABO_1	3.644481062
BraTS19_CBICA_ABY_1	3.677889613
BraTS19_CBICA_ALN_1	4.404781145
Average	**4.052608482**

Table 2. SSIM value between Fused Extracted Tumor Portion Image and Ground Truth image

Volume NO	AverageValue
BraTS19_CBICA_AAB_1	0.8419555
BraTS19_CBICA_AAG_1	0.8877330
BraTS19_CBICA_AAL_1	0.8106572
BraTS19_CBICA_AAP_1	0.9334444
BraTS19_CBICA_ABB_1	0.9364711
BraTS19_CBICA_ABE_1	0.9750512
BraTS19_CBICA_ABM_1	0.9287683
BraTS19_CBICA_ABN_1	0.9077809
BraTS19_CBICA_ABO_1	0.9670474
BraTS19_CBICA_ABY_1	0.8538984
BraTS19_CBICA_ALN_1	0.9674087
Average	**0.9100196**

Table 3. PSNR value between Fused Extracted Tumor Portion Image and Ground Truth image

Volume NO	Average Value
BraTS19_CBICA_AAB_1	64.24617298
BraTS19_CBICA_AAG_1	65.49755139
BraTS19_CBICA_AAL_1	61.17031603
BraTS19_CBICA_AAP_1	65.12109452
BraTS19_CBICA_ABB_1	63.61354273
BraTS19_CBICA_ABE_1	68.72133782
BraTS19_CBICA_ABM_1	65.96299691
BraTS19_CBICA_ABN_1	67.51988384
BraTS19_CBICA_ABO_1	68.67932792
BraTS19_CBICA_ABY_1	61.30457173
BraTS19_CBICA_ALN_1	67.22302626
Average	**65.36907474**

Table 4. MSE value for each volume

Volume NO	Average Value
BraTS19_CBICA_AAB_1	0.05142482
BraTS19_CBICA_AAG_1	0.07379333
BraTS19_CBICA_AAL_1	0.14277945
BraTS19_CBICA_AAP_1	0.06220241
BraTS19_CBICA_ABB_1	0.04590072
BraTS19_CBICA_ABE_1	0.04918518
BraTS19_CBICA_ABM_1	0.04987525
BraTS19_CBICA_ABN_1	0.06229784
BraTS19_CBICA_ABO_1	0.08685995
BraTS19_CBICA_ABY_1	0.08322273
BraTS19_CBICA_ALN_1	0.02246823
Average	**0.06636454**

Table 5. Average DC value for each volume

Volume NO	Average Value
BraTS19_CBICA_AAB_1	0.8385875
BraTS19_CBICA_AAG_1	0.9351171
BraTS19_CBICA_AAL_1	0.8603299
BraTS19_CBICA_AAP_1	0.9555183
BraTS19_CBICA_ABB_1	0.9705055
BraTS19_CBICA_ABE_1	0.9821131
BraTS19_CBICA_ABM_1	0.9568032
BraTS19_CBICA_ABN_1	0.9433151
BraTS19_CBICA_ABO_1	0.9767357
BraTS19_CBICA_ABY_1	0.9252075
BraTS19_CBICA_ALN_1	0.9835583
Average	**0.9388902**

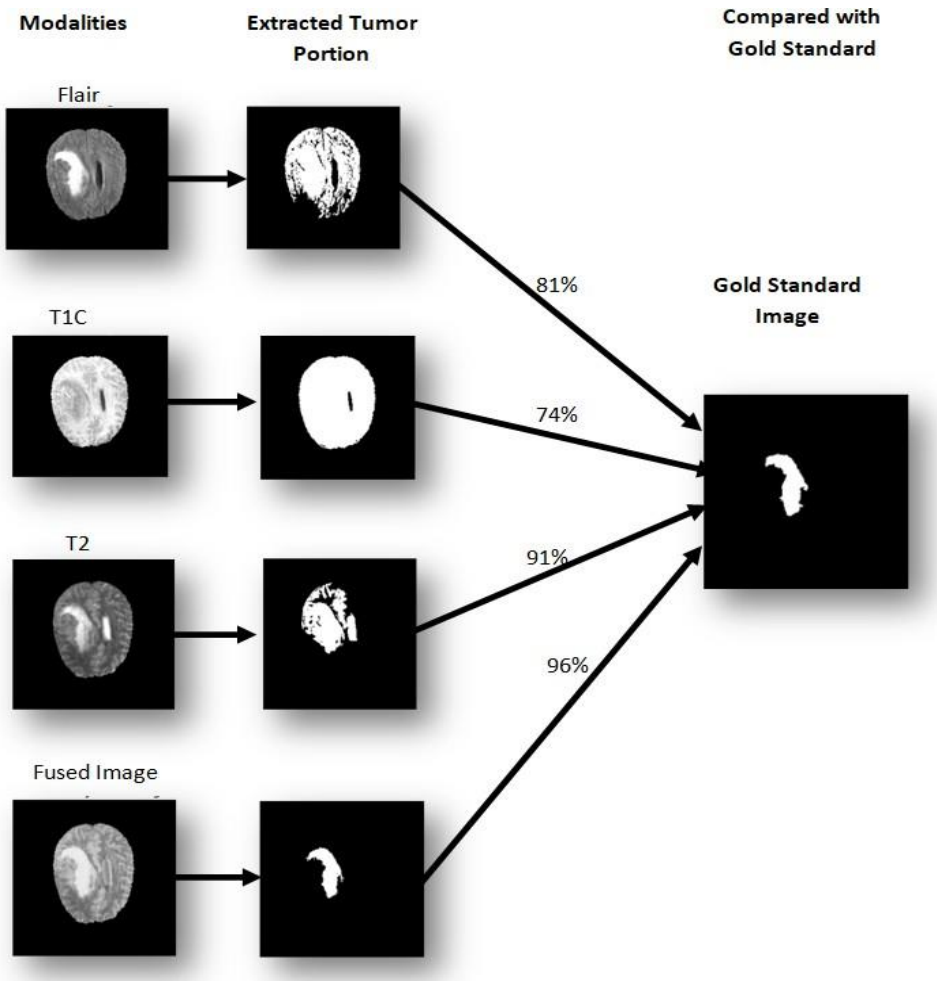

Figure 7. Comparison between extracted tumor portion of fused and other modalities

As early mentioned the tumor-extracted images of each modality Flair, T2, T1c, and fused brain tumor portion extracted images are shown in Figure 7. The evaluation parameters EN, SSIM, PSNR, MSE, and DC are applied to these images for comparative analysis. Here among other modalities, fused extracted tumor portion gives better results.

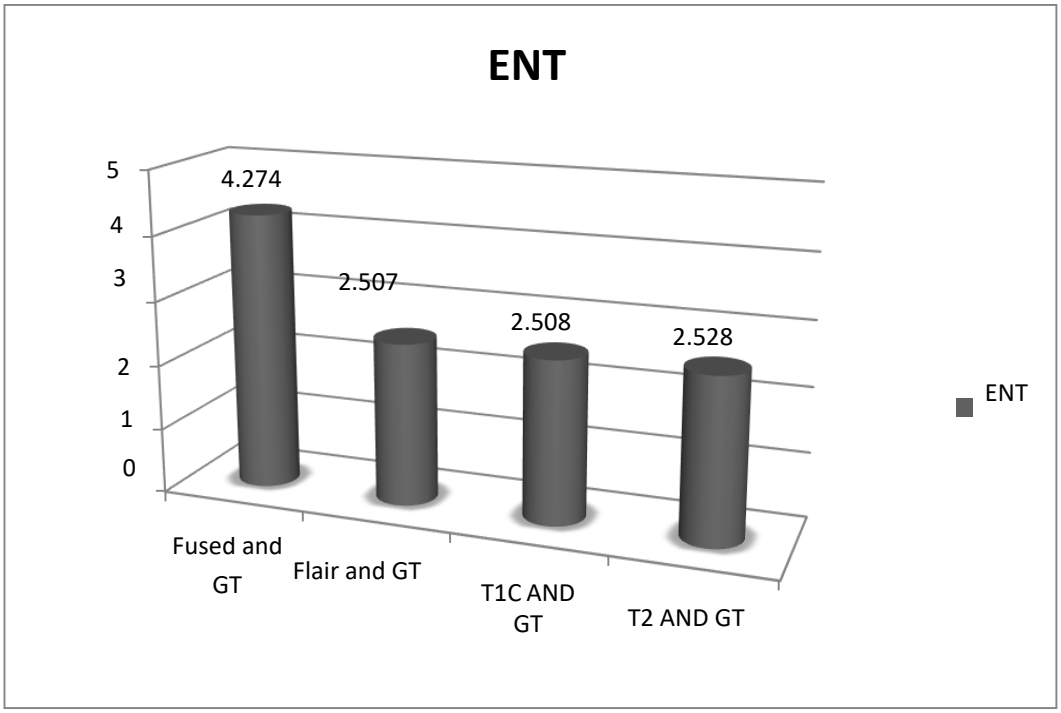

Figure 8. Comparative analysis of Entropy value for each modality extracted tumor portion and fused extracted tumor portion in MRI brain image

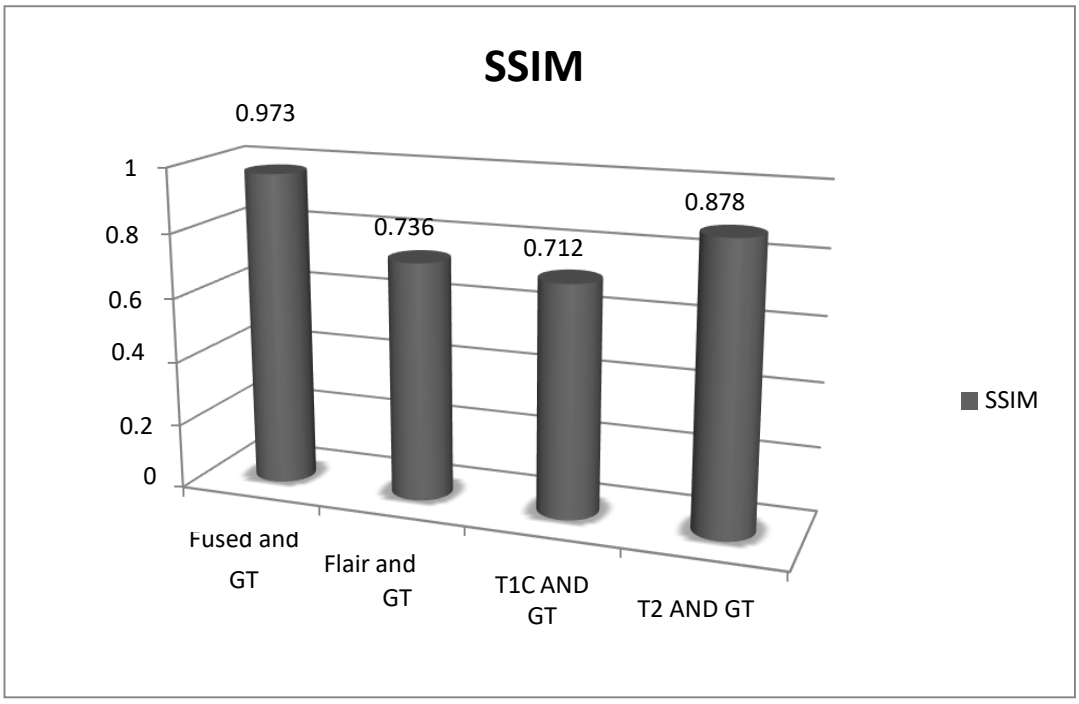

Figure 9. Comparative analysis of SSIM value for each modality extracted tumor portion and fused extractedtumor portion in MRI brain image

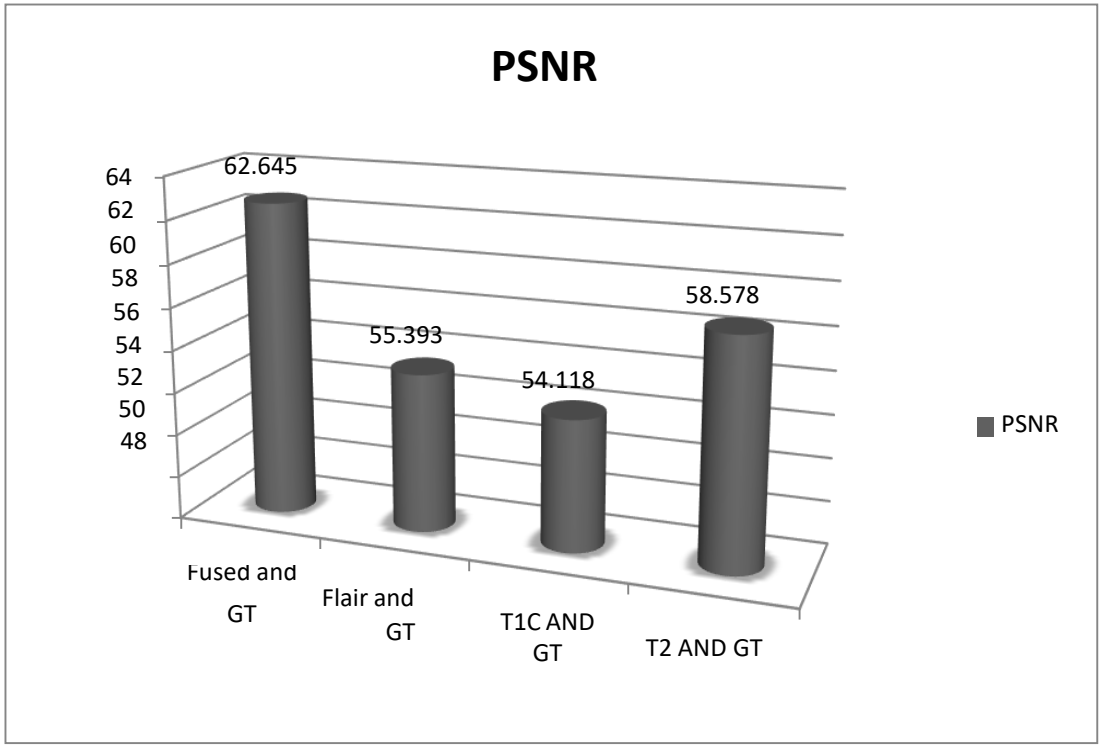

Figure 10. Comparative analysis of PSNR value for each modality extracted tumor portion and fused extracted tumor portion in MRI brain image

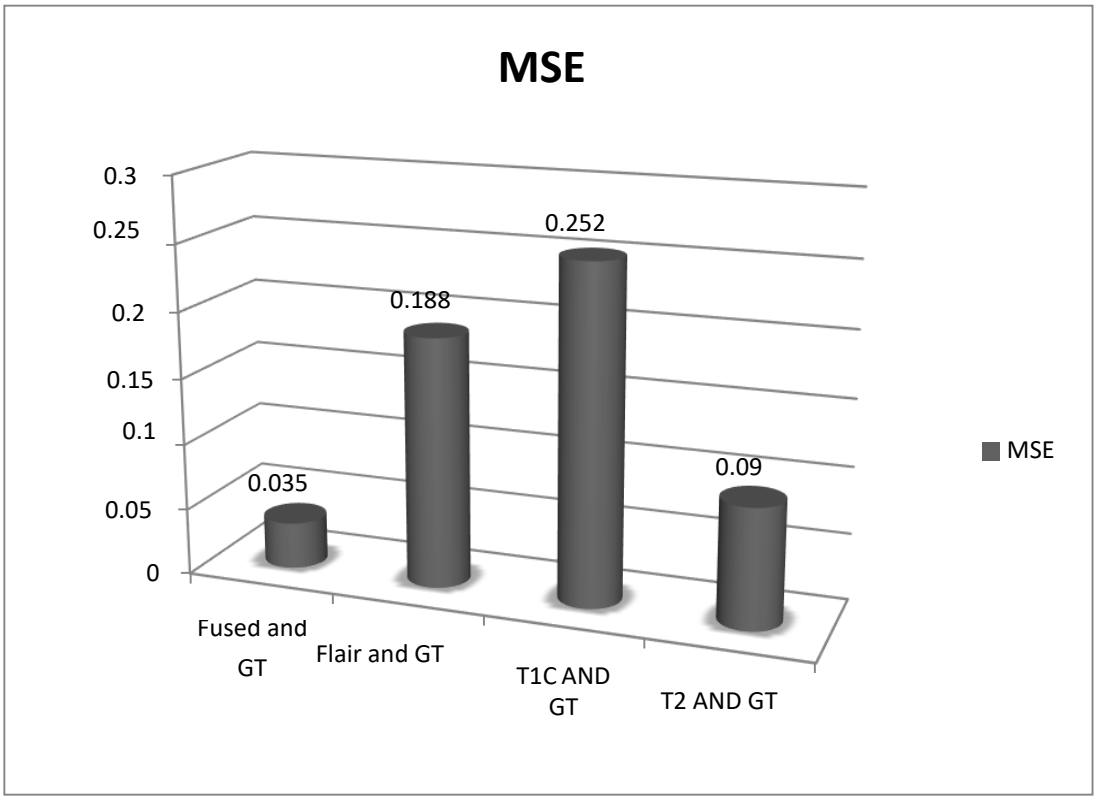

Figure 11. Comparative analysis of MSE value for each modality extracted tumor portion and fusedextracted tumor portion in MRI brain image

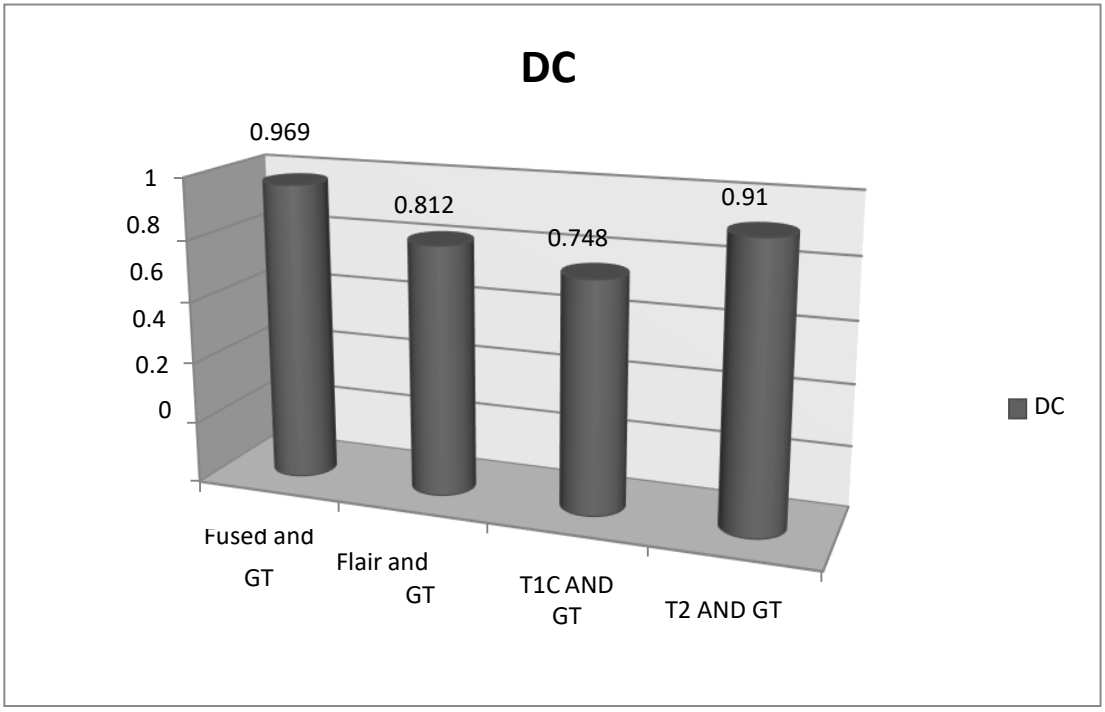

Figure 12. Comparative analysis of DC value for each modality extracted tumor portion and fused extracted tumor portion in MRI brain image

The result of the proposed method compared with existing methods of brain tumor extraction and listed in Table 6. In that, the DC value of the proposed method and different existing methods of brain tumor extraction methods used the same dataset of BraTS. Here the proposed method dice score is better than the traditional brain tumor extraction methods.

Table 6. Proposed and Existing methods comparison

Methods	**Dice Value**
Proposed	**96%**
Fuzzy – C means[3]	77%
DWT-PCA Image Fusion[6]	90.86%
K-Means Clustering Technique [7]	87%
Histogram based fully automatic brain tumor segmentation method [14]	79%
GLCM and DWT [15]	87%
Local Independent Projection-based Classification (LIPC) [16]	84%
Maximum A Posterior Expectation Maximization (MAP-EM) [17]	92%
Wavelet-based Extraction [18]	88%

CAD System:

Using image fusion techniques, Computer aided diagnostic (CAD) system was developed for the extraction of brain tumors using MRI images. The main screen of the brain tumor analysis tool is shown in Figure 13. The tool is presented as a Graphical User Interface (GUI), capable of processing, analyzing, and segmenting the brain tumor portion from MRI images. The CAD system is an endeavor to develop one automatic system that helps the doctor view and analyze the extracted whole brain tumor portion with better structure in MRI tumor images during clinical diagnosis.

This system contains five stages. In the first stage, multimodal MRI brain tumor images Flair, T2, and T1care were selected as shown in Figure 14 and then assigned with three color channels, red, green, and blue, respectively, using the Pseudo Coloring process and merged by image fusion techniques as shown in Figure 15. In the second stage, a fused color image is converted to grayscale. Here, the tumor portion is displayed with good contrast as shown in Figure 16. In the third stage, the grayscale image is transformed into binary form using image threshold processing. Then LCC is applied to extract the final tumor portion. In the fourth stage, extracted whole tumor portion is displayed separately as shown in Figure 17. Finally in the fifth stage, to analyze the proposed work performance, similarity evaluation parameters are calculated and displayed in the panel as shown in Figure 18.

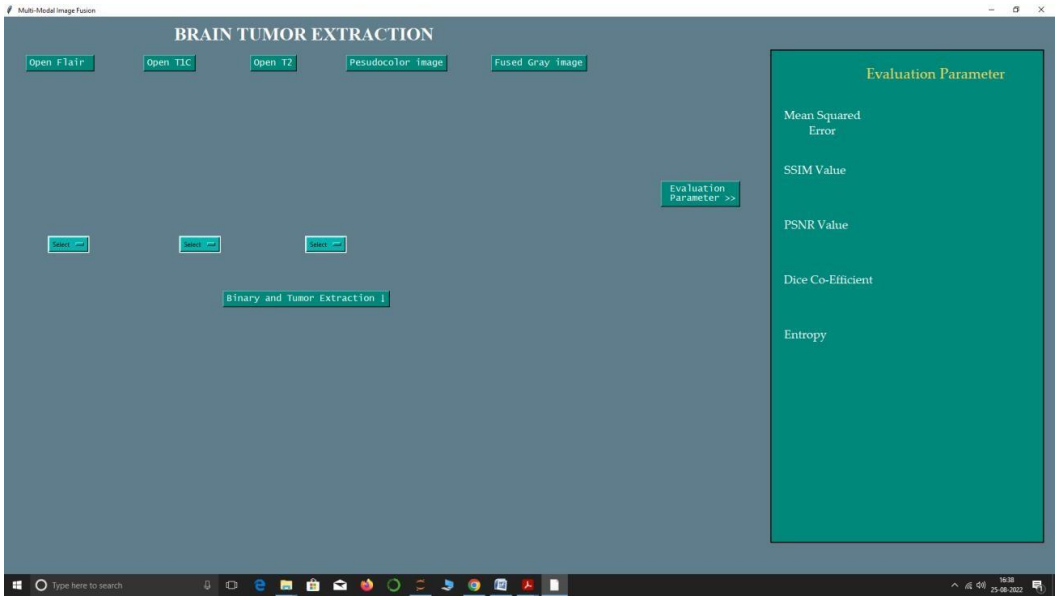

Figure 13. Brain Tumor Extraction Tool- Main Screen

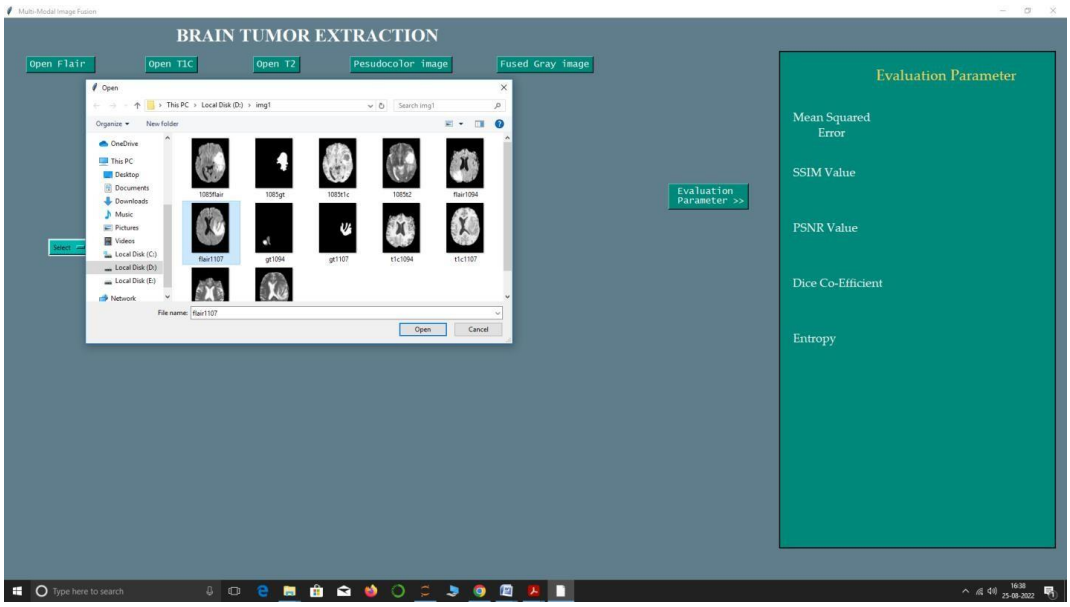

Figure 14. Image acquisition from the disk file

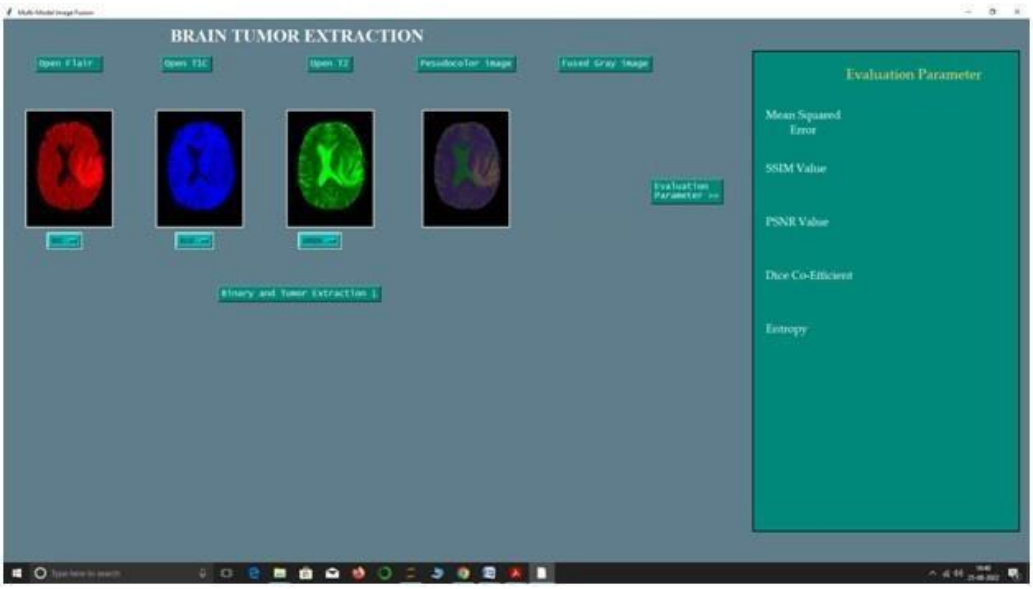

Figure 15. Pseudo coloring process

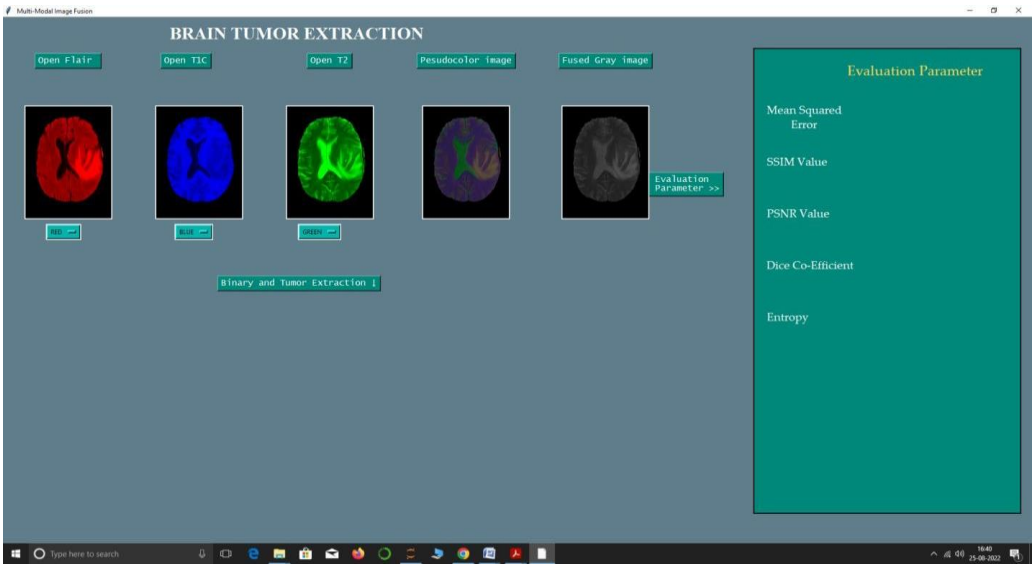

Figure 16. Grayscale conversion process

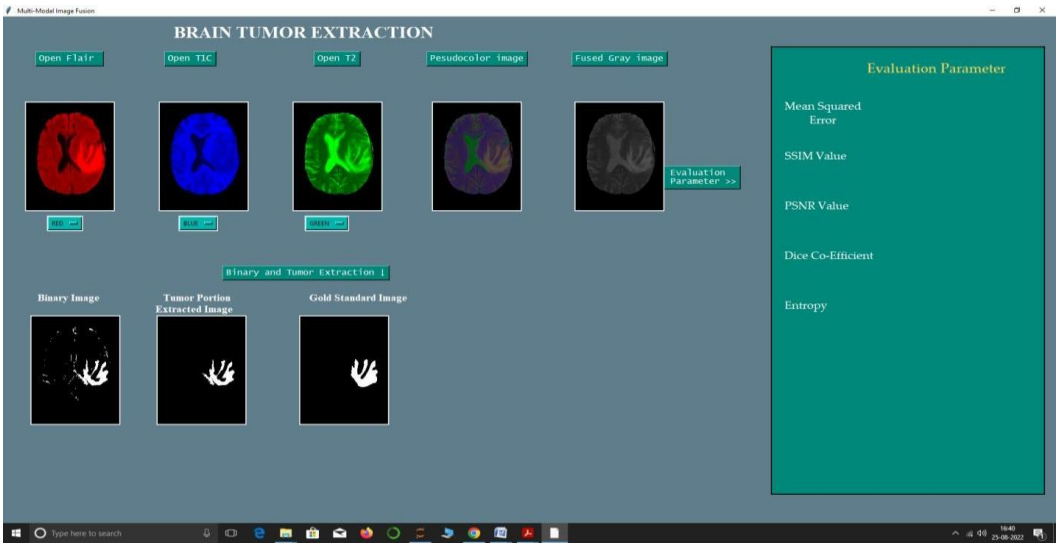

Figure 17. Binary Transformation Image, Extracted Tumor Portion Image, and Gold Standard Image

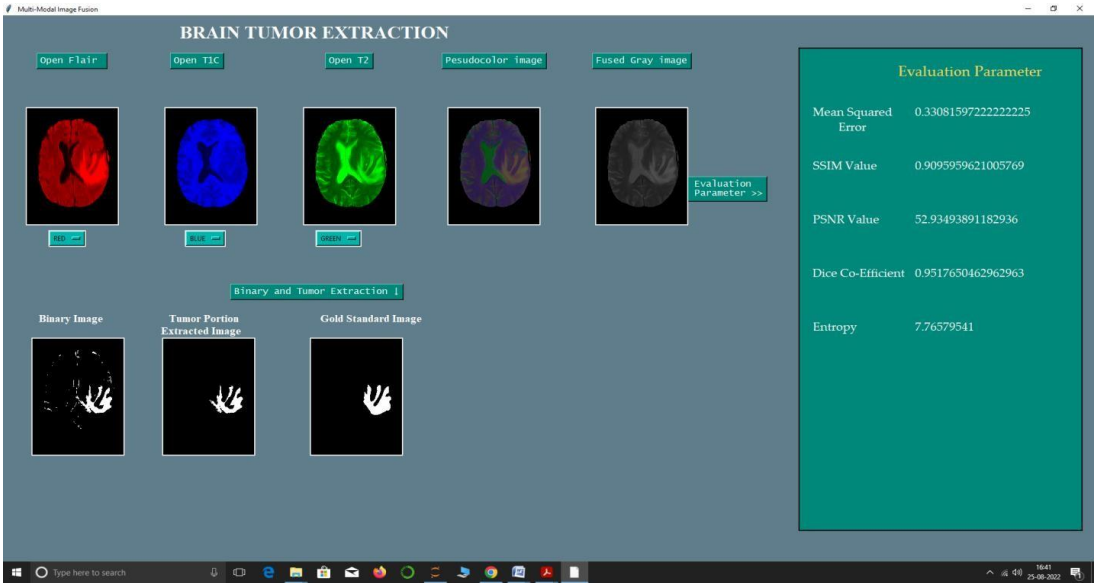

Figure 18. Evaluation Parameters

4. Conclusion:

The proposed work fused the multimodal MRI brain tumor images with a pseudo-coloring process by assigning color channels to each modality. The binary thresholding and LCC were applied to extract the tumor portion with better quality. The extracted tumor portion image is compared with the ground truth using several evaluation parameters such as EN, SSIM, PSNR, MSE, and DC. The proposed method gives better results. To help the doctors, we have developed a CAD system for brain tumor extraction. In the future, we are intended to implement multimodal brain MRI fusion using frequency domain techniques to get accurate results for brain tumor analysis.

Conflict of Interest:

None

Ethical Statements:

Not contain any studies with animals performed or human participants by any authors.

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