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# CNN Fusion Based Brain Tumor Detection from MRI images using Active Contour Segmentation Techniques

Rajesh Babu.K<sup>1</sup>, L.S.P. Sairam Nadipalli<sup>2</sup>, C. Sai Tejaswini<sup>3</sup>, G. Bharath Kumar<sup>4</sup>, P. Vasantha<sup>5</sup>

<sup>1, 2, 3, 4, 5</sup> Department of Electronics and Communication Engineering, KLEF, Guntur, AP.

[saitejaswini0303@gmail.com](mailto:saitejaswini0303@gmail.com)

**Abstract:** Early diagnosis of a brain tumor may increase life expectancy. Magnetic resonance imaging (MRI) accompanied by several segmentation algorithms is preferred as a reliable method for assessment. This manuscript presented the performance analysis of clustered based and fusion-based segmentation techniques intended to detect the tumor from human brain MRI images in an efficient manner. Four primary steps are involved in this work such as pre-processing, clustering, segmentation, and fusion techniques. The main clustering methods such as K-means and fuzzy c-means (FCM) were first applied to the pre-processed MRI images, and then, the clustered images were segmented directly using the active contour segmentation techniques such as chan-veese (C-V) and level set method (LSM). Then in the next step, the clustered images were fused by using the non-sub sampled contour transform (NSCT) and convolution neural network (CNN) fusion methods, and then, the fused images were segmented by using the C-V and LSM segmentation methods again. The results of both clustered based and fusion-based segmentation in terms of structural similarity index measure (SSIM), dice coefficient (DC), computational time, sensitivity, precision, and segmentation accuracy revealed that CNN fusion-based C-V segmentation performs better than without fusion (clustered based or direct segmentation) to detect the tumors from the MRI images. The results indicate that C-V performs better with CNN as compared with the LSM. Finally, the fusion-based segmentation is an efficient approach to detect the tumor from the MRI images with minimal information loss and high segmentation accuracy over the clustered based segmentation.

**Keywords:** Brain tumor, clustering, chan-veese model, level set method, CNN, and NSCT.

## 1. Introduction

In biomedical sciences, medical image analysis acts an important role in the study analysis, and interpretation of problems from datasets obtained through different imaging technologies (like CT-scan, MRI, ultrasound, and X-ray) using mathematical and analytical approaches [1]. These approaches were allowing medical experts to derive and obtain valuable biological data and developing a suitable approach for treatment. The unregulated growth, replication, and collection of anomalous cells of the brain is known as brain tumor [2].

The brain tumors were broadly categorized into two groups, benign (noncancerous) tumors that are less violent, gradually developed, and often isolated from underlying normal tissues [3]. These do not migrate throughout the brain or human body and surgically easier to remove the tumor. Malignant (cancerous) tumors were not so easily distinguishable from normal tissues. It is maybe sometimes difficult to remove them completely without affecting the brain and these tumors may be transforming into brain cancer that leads to death[4]. Hence early identification and treatment of brain tumors may help improve the survival rate of patients. Recently, MRI is one of the reliable modalities for assessment and diagnosis purposes[5,6].



MRI is a popular non-invasive medical imaging technique used to detect and examine anomalies, internal structures, and disorders such as brain tumors. MRI not only provides a detailed quantitative analysis of soft tissues with high spatial resolution, and high contrast but also provides the mechanism of development of adult brains along with the knowledge on size, nature, shape, and location of tumors for clear diagnosis[7]. Brain tumor segmentation techniques play important part in the identification of tumors from brain MRI images that distinguish the tumor from normal brain tissues and provides the user details for proper diagnosis and therapy during the clinical procedure [8].

Segmentation is one of the challenging tasks due to poor contrast and variations in the texture during the acquisition or transmission of images from any modality or channel. To identify the tumors by the physicians are expensive, and time-consuming so, the segmentation techniques was a vital role in the identification of the tumors from MRI brain images [9]. Nowadays, advanced computational techniques for extracting the therapeutic data from medical images are consistently attracting further recognition.

Recently, various algorithms for brain tumor identification have been published in literary works, including region-based , threshold-based, classification, deep learning, and deformable methods. In this paper, we present a fusion-based brain tumor segmentation technique to identify the brain tumor for early diagnosis.

## 2. Related work

In literature, several automated procedures are introduced in the domain of medical imaging for the detection of anomalies in lungs and brain , skin cancer, and more [10, 11]. From all of these, many techniques are presented for early detection and classification of brain tumors. Richa Gautam and Shilpa Datar (2019) contributed their research towards the application of image fusion techniques on medical images. They performed different fusion methods on three data sets and observed that the curvelet fusion [12] using max selection rule gives improved results than other existing methods.

Brij Bhan Singh et al. (2018) introduced the CLAHE enhancement and wavelet fusion [13] for efficient medical image enhancement. This paper provides different medical image fusion techniques. They reported the adaptive approach work efficiently for all medical images and able to adapt the optimal fusion law. Er. Kulvir Singh et al. (2017) proposed a new hybrid fusion technique. This paper suggested a hybrid solution that addresses the issue of preserving edges and precisely fused the images also. They are identified that the proposed method provides higher edge protection than the traditional techniques [14]

Yu Liu, Xun Chen, Hu Peng, and Zengfu Wang (2017), suggested a new multi-focus image fusion with a deep convolutional neural network. The key innovation in this proposed method is to develop a CNN model [15] to get a direct mapping between the source images and the target map. Saheli Majumder, Shekhar Anandite Anand, and Khatib Aqsa Javid (2016) showed the performance of K-means and FCM segmentation techniques in brain tumor images. They identified FCM gives the accurate tumor shape extraction of a malignant tumor. The proposed method gives a more accurate result. The simulation was performed on the MRI dataset, and a maximum segmentation accuracy of 99.5% was obtained in 21.15 s with FCM as compared with K-means[17]

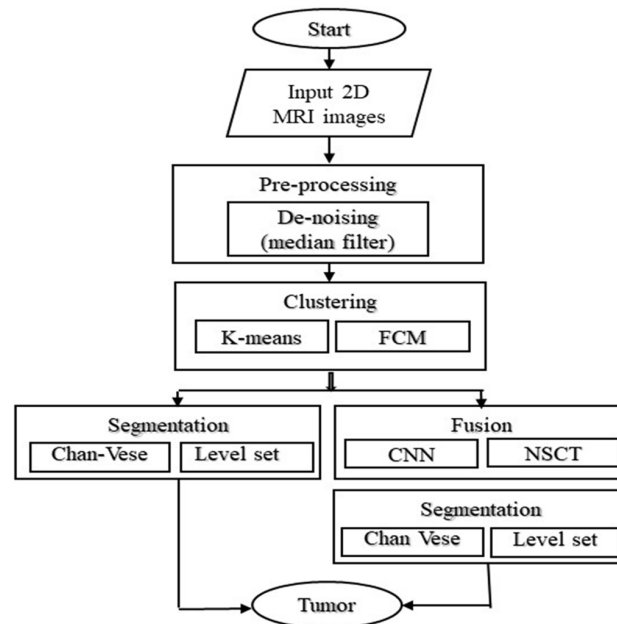
Unnati, R. Raval, and Chaita Jani (2016) presented the modified K-means clustering algorithm. They described how to determine the initial centroids and assigning data points to its nearest clusters with more accuracy and with less time complexity of the traditional K-means. They worked out on the initial value of the K (number of clusters) to improve the accuracy of the clustering. Finally, they obtained better improvement in the performance as compared with the traditional K-means approach [18].

The main aim of this study is to reveal a correlation between the differences in the abilities of segmentation techniques without and with fusion technique along with the clustering techniques and their impact on the efficacy of segmentation techniques used to segment brain tumor MRI images from different datasets. In this study, the performances of the segmentation techniques accompanied by the with and without fusion techniques after clustering techniques were compared in terms of segmentation accuracy.

## 3. Materials and methods

The algorithms were applied to detect the brain tumor images from a T1w MRI dataset. Benchmarked simulated T1w MR images of the brain obtained from the BrainWeb: Simulated Brain Database at the McConnell Brain Imaging Centre of the Montreal Neurological Institute, McGill University, were used because of the unavailability of segmentation ground truth for real MRI images [19]. This dataset consists

of 82 images in the axial plane with a resolution of 1 mm<sup>3</sup>. Furthermore, an MR image dataset containing 100 images was obtained from the Multimodal Brain Tumour Image Segmentation Benchmark (BRATS) 2017 database [20] and used in this study for evaluation. For implementing the segmentation of brain tumors from MRI images, 2020a software was run on a Core i6 (2.4 GHz) dell system. Initially, the  $256 \times 256$  images from the MRI data sets are denoised using a median filter (MF). The MF is a non-linear digital filtering technique often used to remove noise from an image. Such noise reduction is a typical pre-processing method to enhance the efficiency of subsequent processing. The MF preserves edges while reducing noise relative to other filtering strategies.



**Figure 1.** Flow chart for fusion-based segmentation

Further processing has been done in three stages. In the first step, the clustering mechanism is achieved by using clustering techniques namely K-means and FCM. In the second stage, the output images of both clustering techniques were segmented (C-V and LSM) without fusion techniques. In the third phase, the segmented images were fused by using the NSCT and CNN fusion methods. Finally, we have segmented the tumor, before and after applying the fusion methods from the clustered and pre-processed MRI images. The proposed flow chart for shown in Fig.1. The segmentation techniques for both clustering and fusion methods are discussed in this section. The next stage of tumor detection followed by fusion is compared to segmentation alone for the different MRI images datasets.

**Pre-processing:** The MR images have some noise due to thermal effects. Therefore, prior to the segmentation of the brain tumor, the removal of noise is important. To this reason, first remove the potential noise without loss of edge information by using the suitable pre-processing technique [21]. The median filtering used for this purpose, by modifying the median value of an adjacent pixel. This process is named "way" pixel sliding for the full image and sorting the values from the window to calculate the median of the image, and then, replaces the pixel with middle value. So, the median filter will be more useful to remove noise [22].

**Clustering methods:** The clustering methods were classified into supervised and unsupervised method of learning is a method by which we create references from datasets which consisting of input data without labeled responses. It is commonly used as a tool to identify the meaningful structure, explanatory mechanism, generative features, and groupings inherent in a collection of examples [23]. But in case of supervised learning method we maintain the input data with labeled responses. The aim of the clustering is split the population or data points into many groups, so that that data points in the same groups are more similar to other data points in the same group and different to the data points in other groups [24].

Clustering is a set of objects which are focused on similarity and dissimilarity between them. The techniques of clustering commonly categorized in to two groups, such as K-means and FCM.

**K-means clustering algorithm:** K-means clustering is a vector quantization technique, based on image processing it is prominent for cluster analysis in data mining. The goal of K-means clustering is to segment  $n$  observations into  $K$  clusters in which each observation belongs to a cluster with the nearest mean serving as a cluster reference [25]. K-means helps to reduce within-cluster variances (Euclidean squared distances), but not normal Euclidean distances, which would have been the more complicated with major issues: the mean optimizes square error, while the geometric mean minimizes Euclidean ranges [26]. The accompanying fixed number of clusters in this data pattern is considered an unmonitored programming algorithm. This algorithm minimizes the objective function that is represented by the below equation

$$\text{Objective function} = F = \sum_{i=1}^k \frac{1}{n_i} \sum_{j=1}^{n_i} \|x_j - \mu_i\|^2 \quad (1)$$

Here,  $x_j$  is input data point  $\mu_i$  shows the mean i.e. the middle of  $i$ th cluster, therefore  $\|x - \mu\|$  gives a distance measurement from  $j$ th data point to center were,  $i = 1, \dots, k$  and  $j = 1, \dots, N$  [27].

**Fuzzy c means clustering algorithm:** Fuzzy clustering is a clustering method to which each data point may belong to more than one cluster. Also referred to as soft clustering or soft k-means. Clustering or cluster analysis means assigning data points to clusters in such a way that items in the same cluster are as similar as possible, while items belonging to different clusters are as different as possible [28]. Clusters are characterized by similarity tests. Similarity measures include distance, connectivity, and strength. Various similarity tests may be chosen based on the data or the procedure. In FCM, the iterative method for moving cluster centers closer to input values. [29]. To significantly reduce the sum of the mean square error function, and to reduce the error, the objective function is given by:

$$O(U, c_i) = \sum_{i=1}^k O_i = \sum_{i=1}^k \sum_{j=1}^n \mu_{ij}^m d_{ij}^2 \quad (2)$$

Here,  $\mu_{ij}$  represents membership value  $d_{ij}$  denotes distance among  $i$ th point &  $j$ th cluster center  $c_i$ ; the number of clusters  $k$ ; fuzziness is denoted by  $m$  i.e.,  $m > 1$  and the number of information patterns  $n$ ; indistinguishable to the conclusions used as in K-Means [30]. The cluster centers for every information points are updated frequently while waiting for the perfect converge happens to minimize the objective function ( $O$ ), it includes the degree of similarity and the membership function [31].

**Fusion algorithms:** The image fusion process is of combining important information from the number of images into a single image. This one image, which contains all the required information, is more informative and accurate than any other source image. In computer vision, multi-sensor image fusion integrates specific data from two or more pictures into a single image [32] and provides the resultant image with a greater amount of informativeness than any other input source images. The purpose of the image fusion is not merely to minimize the quantity of data but also for the creation of more appropriate and readable images for human and machine processing [33].

**Convolution neural network (CNN):** CNN is a Siamese network in which the two branches weights are correlated to the same. Each branch has one max-layer and three convolutional layers. The algorithm can be applied in four steps. These are the 1. CNN weight map generation 2. Decomposition of the pyramid 3. Coefficient of fusion 4. Reconstruction of the Laplacian pyramid [34]. The convolutional neural network consists of both input and output layer, and multiple hidden layers. The CNN invisible layers typically consist of a series of convolutional layers which coexist due to multiplication or other dots [35]. CNN is mainly used to fuse high-level image information. In this, a max-pooling layer follows each convolution segment, and all the hidden layers use a rectified linear unit as an activation function. The window size of the max-pooling layer is  $2 \times 2$  [36, 37]. The activation function is usually a RELU layer, which is subsequently accompanied by additional convolutions such as pooling layers, completely linked layers which normalization layers, referred to as hidden layers because the activation function and final convolution hide their inputs and outputs [38].

**Non-subsampled contourlet transform (NSCT):** The NSCT multi-scale properties are achieved via the non-subsampled pyramid (NSP) which uses the non-sub sampled filters (NSFs) to partition the plane into a higher-recurrence sub-band and a few annular high-recurrence sub-bands. [39]. Meanwhile, the multi-directional properties are obtained by the non-subsampled directional filters (NSDFs) which additionally

implement a high-recurrence c-band. The non-sampled contourlet transformation (NSCT) was developed mainly because the contourlet transformation is not invariant in shifts. The reason for this lies in the up sampling and down-sampling of the Laplacian pyramid as well as the directional filter banks [40]. The method used in this variation was inspired by the non-sampled wavelet transformation or the stationary wavelet conversion. The output image is produced by widening the gap between images at adjacent pyramid levels and framing the image between adjacent resolution levels to allow pixel-wise differences to be measured [41].

**Segmentation algorithms:** In computer vision, image segmentation is the way a digital image is partitioned into multiple segments (pixel sets, also known as image objects). The segmentation is intended to simplify and/or alter the representation of an image into something more meaningful and easier to analyse [42]. Image segmentation is typically used in images to identify the objects and boundaries (lines, curves, etc.). More specifically, the method of assigning a label to each pixel in an image is image segmentation such that pixels with the same label share similar characteristics [43].

**Chan-veze model:** Chan-Vese display in complex shapes is astoundingly capable of packing various kinds of images, including those that are difficult to section by existing division techniques. Common methods are approaches based on threshold values and gradient-based techniques. The Chan-veze shows depend on the realistic division of Mummmford-Shah. [44]. The Chan-veze model is commonly used as part of medical imaging, especially in the brain, heart, and trachea regions. This model relies on the energy minimization problem that can be reformulated in the level formula. The algorithm description by different steps is given below.

1. Download the MRI image
2. Create the initial mask using the image dimensions and initialize it.
3. Make the image and mask smaller for fast computing.
4. Convert the image to a gray level 2D dual matrix.
5. Create a signed mask distance map.
6. Get the small band of the curve and the inner and outer mean.
7. Using gradient descent to push the curve.
8. Take the mask out of the stage package.

**Level-set method:** The level set method is commonly used to capture interface creation, especially when the interface experiences to the topological changes. The LSM approach has been used for the segmentation of images over the last decades. In this, surfaces or contours are a collection of set of a higher dimensional function called a level-set function at the zero-level [45].

It can be used to depict surfaces or contours with complex topology and to alter the form of their topology inherently. It uses partial differential equations and the Hamilton Jacob method to solve the segmentation problem [46].

To deal with the strength of inhomogeneity, we find the Image  $I$ , which can be modeled as

$$I = b J + N \quad (3)$$

When  $N$  is AWGN, ' $J$ ' is an input that is assumed to be a piecewise refinement constant, and ' $b$ ' is a bias field that can be interpreted to be an approximation constant for the neighborhoods with radius [47].

#### 4. Performance evaluation metrics.

**Dice coefficient:** The dice coefficient will be used to prove the degree of similarity between the harvested tumor and the manually segmented tumor region [48].

$$\text{Dice}(X, Y) = 2 * \frac{|X_1 \wedge Y_1|}{(|X_1| + |Y_1|)} \quad (4)$$

If the value of the dice coefficient value is 1 it performs the same overlap between  $X$  and else if its value is 0, then  $X$  and  $Y$  do not overlap.

**Structural similarity index measure:** The SSIM is a perceptual parameter that means that data compression, lack of data transmission, or other means of image processing can trigger deterioration in

the image quality. This expression is given by :

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (5)$$

Where  $\mu_x$  and  $\mu_y$  are mean,  $\sigma_x$  and  $\sigma_y$  is variance and  $\sigma_{xy}$  is the covariance of  $x$  and  $y$ . The  $c_1$ ,  $c_2$  are constants. A lower SSIM value ensures greater luminance, contrast, and structural material quality [49].

**Accuracy:** It is an ability to find the correctness or closeness of a tumor. It is calculated by

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (6)$$

Where TP is truly positive. The FP and FN indicate false positive and negative, respectively [50].

**Precision:** It refers to the correctness of two or more values. The formula for precision is

$$Precision = \frac{TP}{TP + FP} = \frac{TP}{TPP} \quad (7)$$

Where TP is the true positive and FP is the false positive [51].

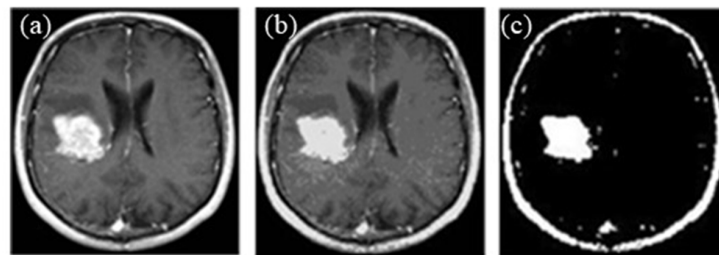
**Sensitivity:** It is an ability to find the tumor or any affected place. The mathematical equation is

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

Where TP is true positive. The FP and FN are the false positive and negative, respectively [52].

## 5. Results and discussion

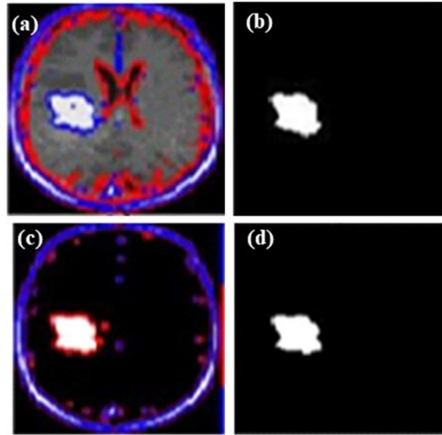
In this study, the performances of the segmentation techniques accompanied by the with and without fusion techniques after clustering techniques were compared in terms of segmentation accuracy. Tests were planned in three phases after pre-processing (denoising) the original MRI images. The first phase consisted of the clustering mechanism is achieved by using the clustering algorithms, namely K-means and FCM. In the second phase, the output images of both clustering techniques were segmented by using the segmentation techniques, namely C-V and LSM by without fusion techniques. In the third phase, the segmented images were fused by using the NSCT and CNN fusion methods and then segmented by using both segmentation algorithms. Finally, we have segmented the tumor, before and after applying the fusion methods from the clustered and pre-processed MRI images.



**Figure 2.** Results of clustering methods (a) MRI Image, (b) K-means, and (c) FCM

To determine the improvement in the segmentation accuracy, the pre-processed images were clustered by using the K-means and FCM. The results are shown in Fig. (2). The main difference between the two clustering techniques is the partitioning process. FCM implements to be in each group with a membership function varying from 0 to 1, whereas K-means assigns every data point to just a single cluster and is therefore complicated to cluster. Clustering using K-means and FCM algorithms based on the number of peaks in the histogram of the original image size  $256 \times 256$ . To determine the number of clusters, the histogram of the original image taken that represents the probability of the occurrence of the intensity level of each pixel in the image. Around three peaks are supposed to represent probable clusters.

According to the original image's histogram, the number of clusters was taken as a five ( $k = 3$ ). FCM produces more positive outcomes than K-means. Because its output is limited by the center's initial locations, there is no guarantee that K-means will always provide the optimal solution.



**Figure 3.** Segmentation without fusion (a) level set of K-means, (b) Chan-Vese of K-means, (c) level set of FCM, and (d) Chan-Vese of FCM

But in the case of the FCM algorithm that continuously updates the cluster centers to reduce the sum of the squared error function given in Eqn. (2).

Even FCM applied may be some unwanted area will be appeared the abnormal brain image. So, the next active contour applied to the result of the noise removed image. After clustered by both clustering techniques, the output images were segmented separately by using the C-V and LSM segmentation methods, respectively. We can observe the outcomes in Fig. (3). The performance metrics of C-V and LSM presented in Table 1. Here iterations, computational time, DC, and SSIM was calculated for K-means and FCM with both segmentation algorithms (C-V and LSM) to detect the brain tumor from the pre-processed images without any fusion techniques, respectively. As per the Table 1., computational time values and similarity point of view, the C-V segmentation technique with FCM technique takes less time (fewer iterations) and more similar with golden standard images compared to the LSM with FCM (multiple clusters) and K-means (single cluster) clustering algorithm to detect the tumor.

Finally, simply we may say that the C-V method provides better results than the level set segmentation before fusion with the FCM clustering technique as compared with the K-means. Because the C-V model is based on the Mumford-shah segmentation function and an energy minimization problem, that can be reformulated in the level set, which leads to an easier way to solve the problem and, in particularly, the C-V model has gained popularity due to its efficiency in contour detection without considering the problem of curve initialization.

**Table 1:** Performance metrics of C-V and LSM segmentation without fusion methods.

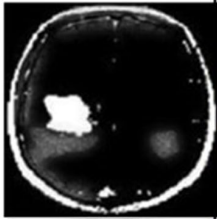
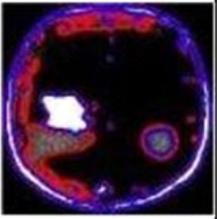
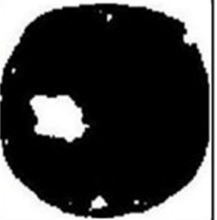
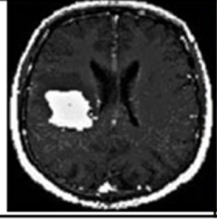


LSM	C-V
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Method	K-means	FCM	K-means	FCM
Iterations	15	12	11	7
Time	1.57	1.45	0.42	0.34
DC	0.88	0.90	0.92	0.95
SSIM	0.89	0.92	0.93	0.96

Next, segmentation techniques were applied after fusing both K-means and FCM output by using CNN and NSCT fusion methods. The results and performance metrics are shown in Table 2 and Table 3, respectively. Here, the same metrics were measured to evaluate the performance of detection of the tumor by applying the segmentation techniques before and after the fusion methods. The comparison between segmentation techniques to detect the tumor before and after applying the fusion techniques, shown in Fig. (3).

**Table 2:** Result of C-V and LSM segmentation with CNN and NSCT fusion methods.

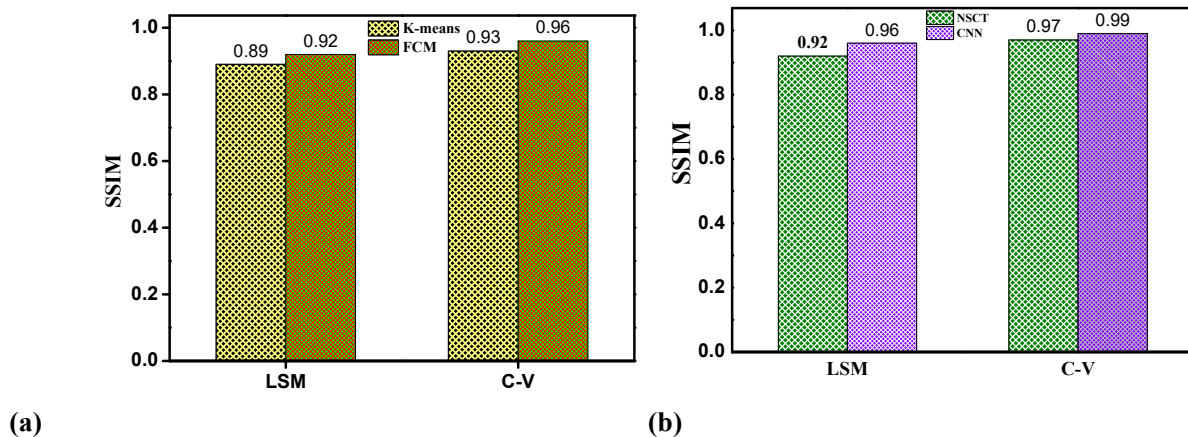
S.No	Fusion method	Fused image	LSM	C-V
1	CNN			
2	NSCT			

The graph is shown in **Fig.3.(a)** drawn for SSIM values to the segmentation of brain tumors without and with fusion methods. Before fusion, the C-V segmentation technique along with FCM and K-means clustering techniques takes less time and performs better than the LSM segmentation technique to detect the tumor. The SSIM values for LSM with FCM and C-V with FCM were 92% and 96% respectively as compared with K-means. The C-V method effectively segments the noisy images without smooth boundaries by combining the edge function. But here also these methods do not detect the tumor accurately due to inhomogeneities lower dimension contours and, non-convex. So, the out images were fused by using the NSCT and CNN methods, then segmented by both segmentation algorithms (LSM and C-V). The CNN fusion method overcoming the difficulty of missing effective resolution and ambiguous prediction at boundaries.

**Table 3:** Performance metrics of C-V and LSM segmentation with CNN and NSCT fusion methods.

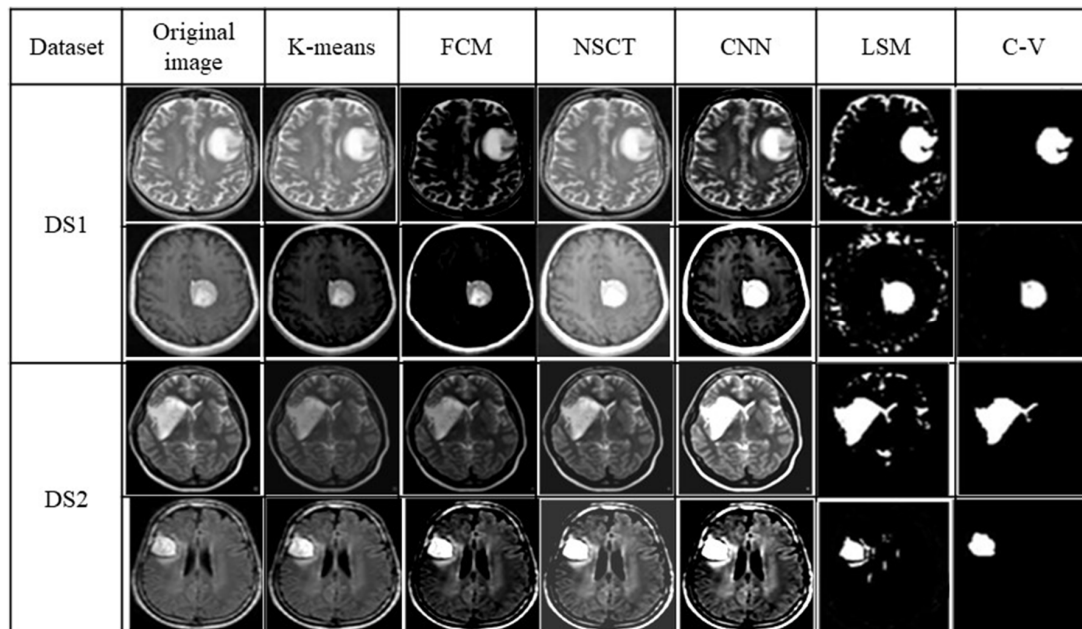
Type	LSM		C-V	
	NSCT	CNN	NSCT	CNN
Iterations	13	10	8	6
Fusion time	0.41	0.28	0.31	0.20
DC	0.95	0.97	0.98	0.99
SSIM	0.92	0.96	0.97	0.99

As seen in **Figure 4(a)**, the C-V method yields better results along with FCM and after applying the CNN fusion techniques as compared to LSM followed by FCM and NSCT. As can be seen from **Figure 4(b)**, the C-V segmentation technique along with the CNN fusion method segment the tumor with high similarity as compared to the LSM method.



**Figure 4.** The SSIM of the segmentation without and with fusion (a) Segmentation without fusion (b) Segmentation with CNN and NSCT fusion methods.

So, the CNN fusion method is the most efficient way to combine images without data loss as compared to the NSCT fusion method. The C-V segmentation algorithm also leads strongly in all the phases of fusion relative to the LSM to identify the tumor. Furthermore, FCM detects the tumor accurately as compared with the K-means clustering technique irrespective of time.

**Table 4:** The results of the main stages of the proposed framework applied to two data sets.

The CNN fusion approach is contrasted with other recently suggested methods for the fusion of medical images. The effectiveness of the CNN fusion technique along with the C-V segmentation technique and FCM clustering algorithm compared with the other was identified by measuring the sensitivity, precision, and segmentation accuracy for two different datasets.

**Table 5:** Performance metrics with fusion techniques for dataset 1

DATASET -1 (20Normals_T1_8bit.tgz)				
Segmentation	LSM		C-V	
	NSCT	CNN	NSCT	CNN
Fusion				
Sensitivity	95.85	97.22	96.16	98.79
Precision	97.17	98.91	97.54	98.63
Segmentation Accuracy	96.11	97.63	96.03	98.76

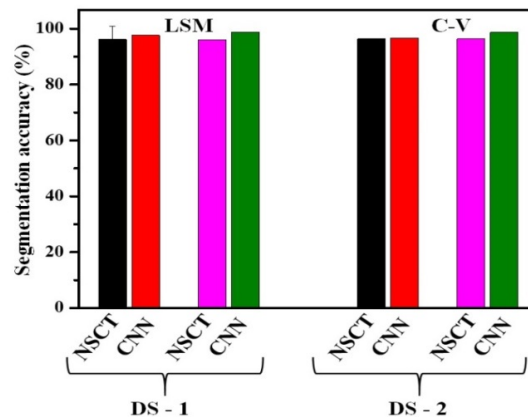
As per the flow chart, all the stages applied to the selected two sample quality images taken from each dataset. The results of each step of the total framework shown in Table 4.

**Table 6:** Performance metrics with fusion techniques for dataset 2

DATASET -2 (IBSR\_17parc\_ANALYZE.tgz)

Segmentation	LSM		C-V	
Fusion	NSCT	CNN	NSCT	CNN
Sensitivity	96.51	97.14	97.06	98.81
Precision	96.87	98.18	98.46	98.56
Segmentation accuracy	96.38	96.69	96.38	98.69

Using median filter denoising is done so that the noise can be removed from the images. These images are given as input for the FCM and K-means clustering techniques and the results are recorded.



**Figure.5** Segmentation accuracy of two datasets DS-1 and DS-2.

The obtained images are then fed as input for the segmentation methods such as LSM and C-V techniques. It has been observed that FCM has performed better than the K-means clustering method and C-V has shown better performance in tumor detection in the brain images as compared with the LSM. Then in the next step, results from both K-means and FCM fused by using the NSCT and CNN fusion methods. After that, fused images from both fusion techniques were segmented separately by using the LSM and C-V segmentation techniques. It has been observed that the C-V segmentation technique of fused images from the CNN fusion technique outperformed than others to detect the tumor from MRI images. The performance metrics of segmentation techniques with both fusion techniques for the datasets DS-1 and DS-2 shown in Table 5 and Table 6. On average, the segmentation accuracy of C-V with CNN is 98.8% as compared to the other techniques. The segmentation accuracy for two datasets was compared that is shown in Figure 4.

## 6. Conclusion

Segmentation plays a crucial role in brain tumor detection. To detect tumors, clustered T1w MRI brain tumor images were segmented before and after applying the fusion techniques. The T1w MRI images used in this study had an original size of  $256 \times 256$ . The main objective of this study was to evaluate the performance of clustered based segmentation and fusion-based segmentation in terms of structural similarity index, segmentation accuracy, and computational time. The K-means and FCM clustering processes were used to obtain high-level information about the image.

In this study, clustering algorithms were first applied to the pre-processed MRI images, and then, the clustered images were segmented directly. Then in the next step, the clustered images were fused by using the NSCT and CNN methods, and then, the fused images were segmented by using the C-V and LSM segmentation methods. The results of both clustered based and fusion-based segmentation in terms of SSIM, DC, computational time, sensitivity, precision, and segmentation accuracy revealed that CNN fusion-based C-V segmentation performs better than without fusion (clustered based or direct

segmentation) to detect the tumors from the MRI images due to overcoming the problem of losing effective resolution and uncertain prediction at boundaries by the CNN fusion method and the C-V technique was effectively segmented the noisy images without smooth boundaries by combining the edge function. The NSCT approach has been deriving the more spatial details from the source image, but the resulting images were suffering from unwanted features that degrade the degree of visual quality and the LSM segmentation technique suffers from the initialization of the curve. So, to detect the brain tumor the C-V segmentation better than LSM and CNN gives better features than the NSCT fusion method.

The results indicate that C-V performs better with the FCM method than K-means in terms of tumor detection. These clustering techniques depend on the initial conditions and way of portioning the clusters. FCM minimizes the error function by updating the clusters iteratively, unlike K-means. Therefore, C-V performs better with the CNN fusion method than LSM, and it is an efficient approach to detect the tumor with minimal information loss. Finally, the fusion-based segmentation has an advantage over the clustered based segmentation in tumor detection from MRI images.

## 7. Future scope

This work may be extended by using other fusion and hybrid techniques for efficient detection of a brain tumor while reducing the number of iterations and the computational time. The future work can also include the removal of the skull area in the MRI image so that the tumor detection may be more accurate.

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