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Performance Analysis of Fusion Based Brain Tumour Detection Using Chan-Vese and Level Set Segmentation Algorithms

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ABSTRACT: Brain tumour shortens the life expectancy of the diseased if not identified at early stages. Accompanied by variety of segmentation algorithms, MRI has been widely used as one of the identification procedures. But no single technique is commonly accepted for accurate segmentation that correlates with pathological studies. This paper highlights the effectiveness of CNN fusion followed by Chan-Vese active contour based segmentation intended for the detection of brain tumour and compares it performance with other contemporary approaches using various metrics.

Key words: Fuzzy C-Means, K-Means, CNN, CT, NSCT, MWGF, GFF, Chan-Vese, Level Set.

I. INTRODUCTION

Pathological assessments of brain tumours augmented by non invasive imaging modalities like Magnetic Resonance Imaging (MRI), Ultrasonography and Computed Tomography etc., empower the early detection of tumours and

facilitates in proper diagnosis to provide effective treatment essential for the survival of patient [1]. Being capable to present good contrast and also parameter adjustable to provide different gray levels to different tissues, Magnetic Resonance Imaging (MRI) has been recognized as a reliable imaging modality among the contemporary techniques of neuropathology. Detection of tumours in MRI can be done by the separation of cancerous cells from non cancerous cells by virtue of their contrast variations in the scanned image with a suitable segmentation which stands as a basic frame work for perceiving the details. Last few decades witnessed a wide utilization of various Partial Differential Equation (PDE) based methods for extraction of tumour regions in images using Active Contour Model (ACM).

In order to improve the data analysis and further extraction of enhanced details, an image segmentation approach has been followed by fused data after clustering. This paper highlights the fact that segmentation after fusion is exploring better details than segmentation alone as verified by various contemporary similarity metrics.

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II. METHODOLOGY

In order to enhance segmentation prospects, test MRI data is denoised using median filter. Further post processing has been carried in three stages. In the first stage, clustering process is achieved by employing clustering algorithms like K-Means and Fuzzy C-Means.

Here fusion is performed using five different algorithms named Convolution Neural Network (CNN), Curvelet Transform (CT), Non-Subsampled Contourlet Transform (NSCT), Multi-scale Weighted Gradient-based Fusion (MWGF), and General Fusion Filtering (GFF) in the second stage. Third stage includes segmentation employed over fused images by using active contour methods namely Level Set and Chan-Vese. Clustered MRIS with components of fusion based segmentation methods are discussed in this section.

In the next stage tumour detection followed by fusion is compared with segmentation alone for test MRI specimens.

2.1 Clustering Methods of an Image

2.1.1 K-Means Clustering Algorithm

In this data patterns are reprasented with related predetermined number of clusters called unsupervised learning algorithm.

Using the minimized squared error function as given by

$$F = \sum_{i=1}^{k} \sum_{j=1}^{n} \left\| x_j - \mu_i \right\|^2 \qquad (1)$$

Where, xj is input data point , □i□□is the mean and the quntity of fuzziness is denoted by m i.e m > 1.

2.1.2 Fuzzy C-Means (FCM) Clustering Algorithm

In FCM the iterative process of moving cluster centers nearer to input values. For minimizing the sum of the least square error function to fin the centroids given by

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

Where, uij is membership value dij is the distance between jth data point and ith cluster center ci; k is given as the number of clusters; and n is the

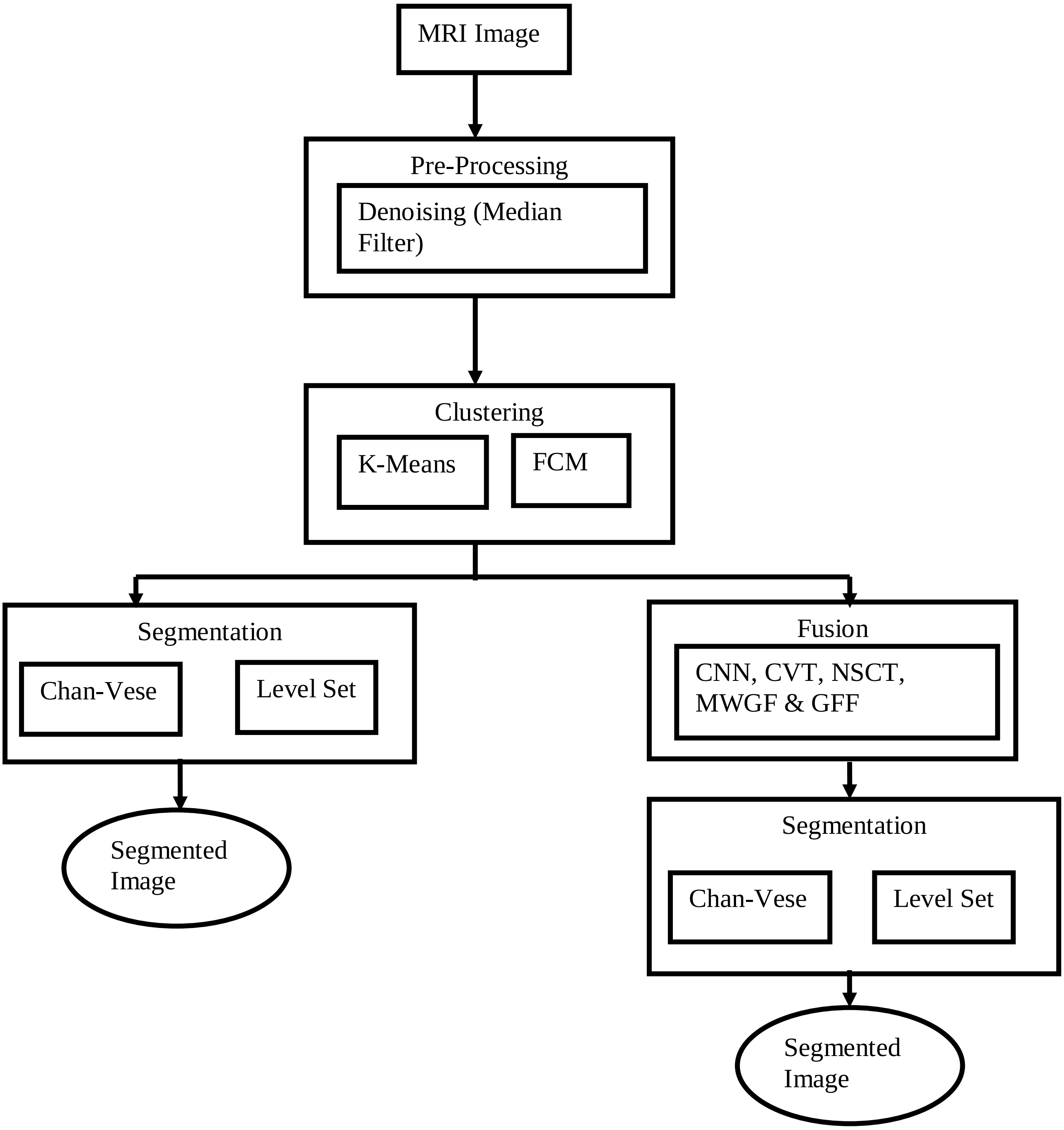

Fig. 1 Flow chart for fusion based segmentation

Number of data patterns similar to the terminations used in K-Means.

2.2. Fusion Algorithms

2.2.1 Convolution Neural Network (CNN)

CNN is a Siamese network in which the weights of the two branches are constrained to the same.

Each branch consists of one max-pooling layer and three convolutional layers.
The algorithm can be performed in four steps. These are 1.CNN-based weight map generation 2.Pyramid decomposition 3.Coefficient fusion 4.Laplacian pyramid reconstruction.

2.2.2 Curvelet Transform (CT)

Curvelet is a multiscale and multidirectional change competent to speak to bend as an arrangement of superimposed elements of different lengths and widths. It depends on multi scale ridgelets with a band pass sifting to isolate a picture into disjoint scales. The side length of the limiting windows is multiplied at each other dyadic sub band for keeping up the essential property of the Curvelet change.

2.2.3 Non-Subsampled Contourlet Transform (NSCT)

The multiscale property of the NSCT is accomplished by the Non-Subsampled Pyramid (NSP), which utilizes Non-Sub sampled Filters (NSFs) to part the recurrence plane into a low-recurrence sub band and a few annular high-recurrence subbands. In the interim, the multi-directional property is gotten by the Non-Subsampled Directional Filters (NSDFs) which additionally incorporate high-recurrence coefficients into wedge-molded directional sub bands.

2.2.4 Multi-scale Weighted Gradient-based Fusion (MWGF)

The point of the inclination based combination is subsequently to blend all the imperative slope data from the information pictures and move it into the melded picture. It depends on a "circuit then-break down" system, in which inclination channel is utilized to play out a superior component choice in the slope area, and after that exploit the traditional multiresolution technique to reproduce the intertwined picture. The weighted inclination based combination strategy is proficient to distinguish the most essential nearby structures in the info pictures and render them into the intertwined picture.

2.2.5 General Fusion Filtering (GFF)

GFF strategy can be called as high-pass sifting technique (HPFM). It lessens time by finishing separating in flag area by keeping away from FFT calculations.

It comprises of three primary advances: low picture insertion, combination itself performed in an unearthly/Fourier space lastly histogram coordinating. Flag preparing view enabled us to join initial two stages into one by unearthly combination actualized in Fourier space. General Framework for picture Fusion (GFF) is well reasonable for a combination of multi-sensor information, for example, optical-optical and optical-radar symbolism [2].

2.3. Segmentation Algorithms

2.3.1 Chan-Vese Model(C-V):

Chan-Vese display in dynamic shapes is amazingly capable and can parcel various sorts of pictures including the pictures which are difficult to section by established division techniques. The traditional procedures are Threshold based strategies and Gradient based techniques. The Chan-Vese shows relies upon Mummford-Shah practical division [3].
Chan-Vese model is broadly utilized as a part of medical imaging mainly to segment brain, heart and trachea. This model depends on an energy minimization issue, which can be reformulated in the level set formulation. The description of algorithm is given below

Step 1: *Load the MRI image*
Step 2: Create initial mask by using dimensions of image and initialize it.
Step 3: Make the image and mask smaller for fast computation
Step 4: Convert the image into gray level 2D double matrix
Step 5: Create a signed distance map from mask i.e., SDF.
Step 6: Get the curve's narrow band and interior and exterior mean.
Step 7: Evolve the curve by using gradient descent.
Step 8: Get the mask from level set.

2.3.2 Level-Set Method (LSM):

Level-Set methods have turned out to be broadly utilized for capturing interface development particularly when the interface experiences outrageous topological changes. This Level- Set method is used in image segmentation for past decades. In this, the surfaces or contours are treated as the zero-level set of a higher dimensional function, called as a level set function. It can be used to represent surface or contours with complex topology and change their shapes their topology in the natural way. It uses Partial Differential Equations and Hamilton Jacob method to solve segmentation problem [4].

To deal with intensity inhomogeneity, we consider an Image I, which can be modelled as

I □ b J □ N (3)

Where N is AWGN, 'J' is input which is assumed as piecewise approximation constant and 'b' is bias field that can be considered as approximation constant for neighbourhood with radius □□as defined by $O_y = [X : |X - Y| \le \rho]$

$$b(X) \cong b(Y) \; for X \in O_y$$

3. Performance Evaluation Metrics

3.1 Mean Square Error (MSE):

Mean square error is a measure of image fidelity [5], used to find the similarity between two images by providing the quantitative score.
For image M*N the MSE can be calculated as

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]^2 \tag{4}$$

Where I (i, j) is input image and K (i, j) is output image.

3.2 Peak Signal-to-Noise Ratio (PSNR):

It is used to evaluate the nature of reconstruction of processed image and it is characterized as

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{2^n - 1}{\mathrm{MSE}}\right) \tag{5}$$

3.3 Standard Deviation (SD):

It is the second central moment describing probability distribution of an observed population and can serve as a measure of inhomogeneity. A higher value indicates better intensity level and high contrast of edges of an image.

$$\mathrm{SD}(\sigma) = \sqrt{\left(\frac{1}{m \times n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left(f(x,y) - M\right)^2} \tag{6}$$

Where f(x, y) is the input image and M is the mean of an image

3.4 Entropy (E):

Entropy is the quantitative measure of disorder and an extensive property [6]. Entropy indicates the information content of the image. It is sensitive to noise and high value of entropy and indicates high information content in the image. It is calculated to characterize the randomness of the textural image and is defined as

$$E = -\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\log_2\left(f(x,y)\right) \tag{7}$$

The segmentation performance has been improved for higher values of entropy.

3.5 Mutual Information (MI):

The mutual information of two discrete random variables X and Y can be formally defined as:

$$I(X;Y) = \sum_{y \in Y}\sum_{x \in X} p(x,y)\log\left(\frac{p(x,y)}{p(x)\,p(y)}\right), \tag{8}$$

Where, joint probability function p(x, y) is function of X and Y, and p(x){\displaystyle p(x)} and p(y){\displaystyle p(y)} are the marginal probability distribution functions of X and Y respectively.

3.6 Dice Coefficient (DC):

Dice similarity coefficient is used to show the similarity level of extracted tumour region with respect to the manually segmented tumour region [7]. It is mathematically formulated as

$$Dice(A,B) = 2 \times \frac{|A_1 \wedge B_1|}{(|A_1| + |B_1|)} \tag{9}$$

Where □ is tumour region extracted from algorithmic predictions and □ is the expert's ground truth. If the Dice coefficient value is 1, then it shows the perfect overlap between A and B. Else if its value is 0, then there is no overlap between A and B.

3.7 Structural Similarity Index (SSIM):

SSIM is a perceptual metric that signifies that the degradation in image quality may be caused by data compression or losses in data transmission or by any other means of the image processing. It is defined as

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{10}$$

Where μ_x and μ_y is mean, σ_x and σ_y is variance and σ_{xy} is covariance of x and y. c_1, c_2 are constants.

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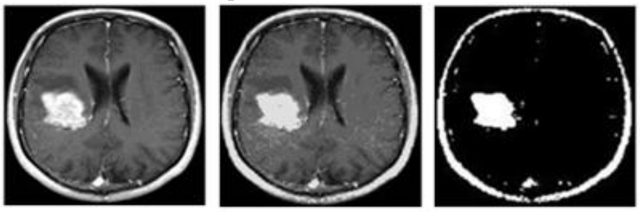
A Higher value of SSIM indicates better preservation of luminance, contrast, and structural content.

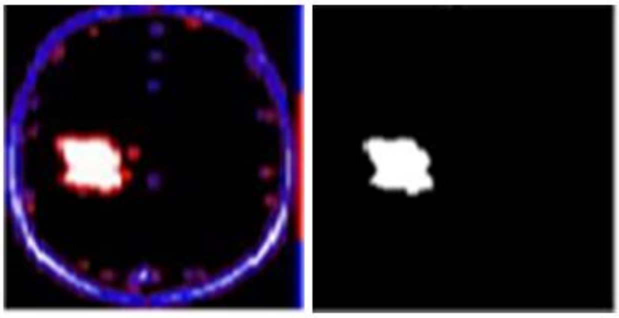
4. RESULTS AND DISCUSSION

In this present study, the iterations have been conducted on patient MRI images who suffered from a malignant brain tumour dataset intended to detect tumour accurately. Before applying the methods, all images were pre-processed to remove possible noises with median filtering method. This noise reduction technique is used to further improve the MRI image quality to enhance detection performance of the tumour.

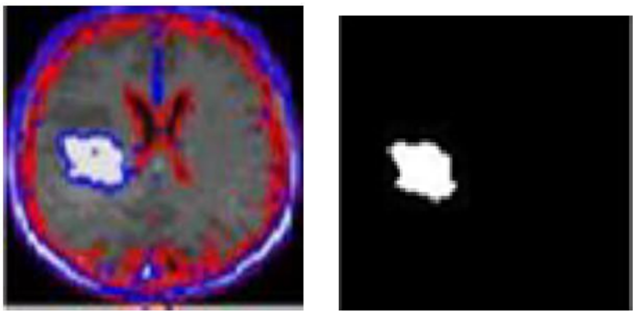


(a) (b) (c)

Fig: 2 (a) MRI Image (b) K-Means (c) Fuzzy C-Means



(a) (b)



(b) (d)

Fig: 3 Segmentation without fusion (a), (c)

After pre-processing the images, the clustering methods were employed on the filtered MRI images and then both segmentation algorithms were applied before fusion. Further their performance metrics were calculated. The visual descrption of results are given in Fig. 2 and 3.

Clustering using K means and Fuzzy C-Means (FCM) algorithms as per the number of peaks in the histogram of the original image of size 512x512 shown in Fig.2 followed by segmentation of whose quantitative performance metrics have been computed as given by Table.1.

Segmentation applied after fusion by using different types of fusion methods as visualized in Fig.4 represent the fused image of different fusion method in the first column. Whereas second and third column indicates level-set and Chan-Vese based segmented images of whose performance metrics were presented in Table 2. Similarly Level-Set segmentation has been performed over the fused images and subsequent calculated values are tabulated in Table 3.

Table 1: Performance metrics of Chan-Vase and Level-Set segmentation without fusion methods

Method	**Chan-Vese**		**Level Set**	
	K-Means	**Fuzzy C-Means**	**K-Means**	**Fuzzy C-Means**
PSNR	12.16	16.14	10.52	11.43
MSE	3.02	1.98	5.06	4.96
SD	61.16	48.19	72.18	66.41
Entropy	0.9	1.6	0.65	2.6

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MI	1.43	2.32	1.33	1.56
DC	0.45	0.79	0.4	0.82
SSIM	0.89	0.97	0.8	0.93

As observed from the Fig. 2 & 3 and Table 1, it can be claimed that as compared K-Means algorithm FCM algorithm is more successful. Since its performance is bounded with the initial positions of the centres, but there is no assurance that the K-Means algorithm always finds the optimal solution. As observed from few metrics values Chan-Vese gives better results than level-set segmentation before fusion.

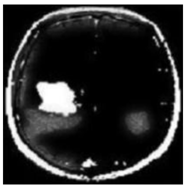
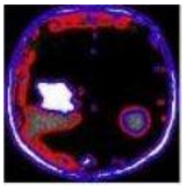
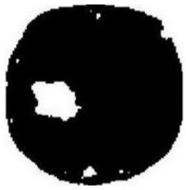
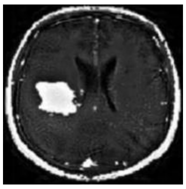
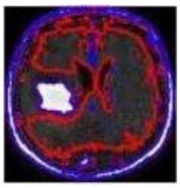
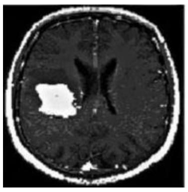
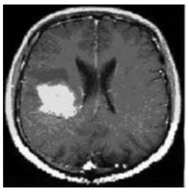
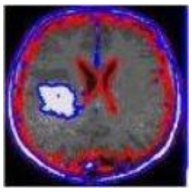
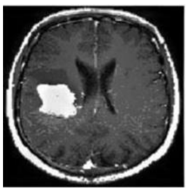
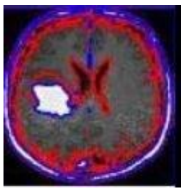
S. No	**Fusion Method**	**Fused Image**	**Level-Set**	**Chan-Vese**
1	CNN			
2	CVT			
3	NSCT			
4	MWGF			
5	GFF			

Fig. 4 Output images of fusion, C-V and Level Set methods

From the results concluded that CNN is the most powerful method for the fusion of images without loss of information. Secondarily, the Chan-Vese segmentation algorithm achieves strong results to detect the tumour for all fusion methods compared with Level-Set method.

Table.2: Performance metrics of Chan-Vase segmentation with fusion methods

S. No	**Method**	**MSE**	**PSNR**	**SD**	**SSIM**	**MI**	**Entropy**	**DC**
1	CNN	0.59	35.02	28.92	0.978	0.78	3.21	0.98

2	CVT	0.61	33.90	31.46	0.945	0.35	1.89	0.76
3	NSCT	3.06	26.32	73.69	0.915	0.72	2.26	0.93
4	MWGF	2.42	34..24	36.68	0.936	0.44	1.80	0.95
5	GFF	1.46	30.09	54.24	0.963	0.45	1.65	0.94

The CNN fusion method is compared with other recently proposed medical image fusion methods.

Table.3: Performance Matrices of Level Set Segmentation with fusion methods

S. No	Method	MSE	PSNR	SD	SSIM	MI	Entropy	DC
1	CNN	3.59	20.59	52.92	0.91	1.75	6.39	0.95
2	CVT	4.34	20.08	85.64	0.87	1.58	5.43	0.94
3	NSCT	5.62	20.39	73.70	0.91	0.92	4.66	0.76
4	MWGF	3.75	20.17	70.03	0.88	1.35	6.12	0.94
5	GFF	4.24	20.03	74.75	0.87	1.17	6.21	0.93

It can be seen that the NSCT method could extract sufficient spatial details from source images, but the fused images suffer from some undesirable artifacts which degrades the visual perception to some extent. The Curvelet Transform and Spatial based methods can well prevent visual artifacts, but it tends to lose the energy contained in source images, leading to

decreasing brightness and contrast of some regions in the fused image. The main defects of

the General Fusion Filtering method is its limited ability in detail preservation, and it can be observed that many small details of the source images are blurred in the fused images.

The CNN fusion method generally do well in both detail and energy preservation without introducing undesirable visual artifacts.

It is observed that due to segment images with intensity inhomogeneity, the global energy function used as the global term and incorporates both local spatial information and local intensity information to handle intensity inhomogeneity, Chan–Vese (C–V) model gives the better performance than Level-Set model shown in Table 2.

5. CONCLUSION

Image segmentation is performed over clustered and fused images of MRI with the intent for identification of brain tumours. In this paper, the authors compared the performance between fusion based segmentation and direct segmentation through clustering and also recognized Fuzzy C-means method gives better clustering of image than K-Means clustering method. It is identified from the performance metrics, Chan-Vese segmentation algorithm provides better performance in the case of fusion based segmentation with CNN fusion method as compared to direct segmentation. Fusion based segmentation is exhibiting an edge over direct segmentation in tumour detection.

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