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ANALYSIS AND SURVEY ON MEDICAL IMAGE SEGMENTATION USING DIFFERENT CLUSTERING ALGORITHMS

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ABSTRACT: Breaking down the medical image in image preparing is the most significant research territory. Catching the image are dissected to recognize distinctive medical imaging issues is the normal factor in this field. Powerful organ segmentation is an essential for computer-aided diagnosis (CAD), quantitative imaging examination, pathology detection and careful help. A portion of the organs in the human body have high anatomical changeability, so segmentation of such organs is exceptionally intricate. Medical images have had an incredible effect on medication, diagnosis, and treatment. The most significant piece of image handling is image segmentation. Many image segmentation techniques for medical image investigation have been exhibited in this paper. In this paper examined to different clustering strategy calculations specifically, K-Nearest Neighbor, K-Means and Fuzzy C-Mean. The Fuzzy C-Mean calculation is a superior execution of different calculations.

Keywords: [Segmentation, Medical Image, Clustering, Accuracy, Extraction.]

1. INTRODUCTION

Medical image segmentation alludes to the strategy for parceling found image information to a sequential of non covering locales .These areas mean totally extraordinary human tissue structures and apply proper technique for accuracy of clinical distinguishing proof. By and large the basic hypothesis of image segmentation could be a technique for apportioning a computerized image into numerous sections. The objective of segmentation is to adjust and change the representation of a picture into one thing that is extra significance and simpler to explore. Image preparing is any type of sign handling for which the information is an image, for example, a photo or video outline; the yield of image preparing might be additionally an image or a lot of uniqueness or parameters connected to the image. The larger part image-handling framework includes regarding the image as a two-dimensional sign and be fitting standard sign preparing usual way of doing things to it. Image handling generally alludes to advanced image preparing, however optical and simple image handling additionally are conceivable. This evaluate is about general usual way of doing things that apply to every one of them. The procurement of images (manufacture the info image in any case) is alluded to as imaging. In each exploration region they break down the issue, for the most part image examination includes move the image information to finish up exactly the data obligatory to answer a computer imaging issue. This examination is commonly part of a bigger procedure which includes preprocessing, characteristic extraction, segmentation, evacuate clamor information, and so forth, Image regulation in medical image is an incredible basic assignment to discover the issues in reality medical image. Image preparing are finished with the assistance of the advanced image, which is caught from the computerized organization, catching the image are utilized to distinguish the issue in the medical image. It is one of the regular factor in this factual world they were numerous issues jumped out at the general population. Catching their distinction and investigating the issue is the most basic undertaking for these fields, most basic factor in this field is to discover the issue in various zones, for example, mind, eye, stomach area, and so on. In certifiable individuals were affected by numerous sicknesses, the most tricky region is the eye ailment; without sight of individuals they can't do anything in their desolate time. Segmentation of image is a significant factor in image preparing. This paper utilizes the pancreas investigation of medical image. Segmentation of the pancreas is a significant advance in the improvement of computer aided diagnosis (CAD) frameworks that can give quantitative examination to diabetic patients and a required contribution for consequent systems for pancreatic malignancy detection. Mechanical segmentation of abundant organs in CT scans with high seeing, for example, the liver, heart and kidneys. Segmentation of the pancreas, high exactness in rehashed segmentation remains a defy. The pancreas demonstrates high anatomical deviation fit as a fiddle, size and setting that change from patient to persistent. The measure of instinctive fat tissue in the closeness can definitely shift the limit distinction also.

2. LITERATURE SURVEY

[1] Sen Liang, Rongguo Zhang, Dayang Liang, Tianci Song, Tao Ai, Chen Xia, Liming Xia and Yan Wang et.alproposed a novel system architecture to envision IDH genotype dependent on multimodal MRI imaging information, which called M3D-DenseNet. Non-intrusive prediction of isocitrate dehydrogenase (IDH) genotype plays a significant activity in tumor glioma diagnosis and theory. Starting late, examine has demonstrated that radiology images can be a potential instrument for genotype prediction, and fusion of multi-methodology information by profound learning techniques can further give integral data to improve prediction accuracy. Be that as it may, in any case it doesn't have a convincing profound learning architecture to predict IDH genotype with three-dimensional (3D) multimodal medical images. Proposed model, a novel multimodal 3DDenseNet (M3D-DenseNet) model to predict IDH genotypes with multi modular magnetic resonance imaging (MRI) information. It connected a 3D profound learning system using DenseNet as the structure square, and utilized a multi-channel strategy to coordinate multimodal information data. To assess its generalizability, they fine-tuned a similar model to predict WHO evaluation status. The two preliminaries accomplished high prediction accuracy. Our M3D-DenseNet can prepare by all the way, consequently extract highlights from multi-methodology images, and have more prominent generalizability. With further approval on more information, our models for IDH genotype prediction and WHO evaluation status prediction may can possibly be a significant procedure that can be stretched out to other multi-modular radiogeinomics issues and fill in as a basic leadership instrument to enable pros to improve treatment plans. They accomplished 84.6% accuracy (zone under the bend (AUC)=85.7%) on the approval dataset. To assess its generalizability, they connected exchange learning strategies to anticipate World Health Organization (WHO) grade status, which likewise accomplished a high accuracy of 91.4% (AUC = 94.8%) on approval dataset. With the properties of programmed include extraction, and practical and high generalizability, M3D-DenseNet can fill in as an accommodating strategy for other multimodal radiogenomics issues and can possibly be connected in clinical basic leadership.

[2] Yuqian Lia, Xin Liua, Feng Weia, Diana M. Simab, So fie Van Cauterc,d, UweHimmelreiche, YimingPia, GuangHuf, Yi Yaog and Sabine Van Huffelb et.alproposed a novel fusion plan dependent on NMF and wavelet disintegration for cerebrum tumor tissue differentiation. It improves the MRSI goals and tumor tissue segregation capacity by fusing point by point data from traditional MRI. In the meantime, the bio-compound data from MRSI information is defended as much as possible through rehashing the image fusion strategy inside NMF internal cycle of MRSI deterioration. They displays a propelled information fusion conspire for mind tumor diagnosis using both MRSI and MRI information to improve the tumor differentiation accuracy of MRSI alone. The plausibility of the proposed casing work is approved by contrasting and the ace outlines, giving mean connection coefficients for the tumor wellspring of 0.97 and the Dice score of tumor district cover of 0.90. These outcomes contrast positively against those acquired and an as of late proposed NMF strategy where MRSI and MRI are incorporated by stacking the MRSI and MRI highlights. Test results on in vivo information from inferior glioma patients demonstrated an improvement upon those gotten by performing source detachment on stacked highlights direct. This fusion plan could be stretched out to make usage of more highlights from different MR modalities, which may further expand its presentation for tumor detection and depiction. A similar fusion plan ought to likewise have the ability to work for high evaluation glioma, for example glio blastoma multiforme (GBM), if NMF is performed progressively.

[3] RuiShen, Irene Cheng and AnupBasu et.alproposed a CS fusion rule, which picks an ideal arrangement of coefficients for every disintegration level and certifications intrascale and interscale textures. Joint investigation of medical information assembled from different imaging modalities has transformed into a typical clinical practice. There-fore, image fusion systems, which give an efficient method for joining and upgrading data, have drawn expanding consideration from the medical system. In this examination, the creator proposed a novel cross-scale fusion rule for multiscale-decay based fusion of volumetric medical images considering both intrascale and interscale textures. An ideal arrangement of coefficients from the multiscale portrayals of the source images is discourage mined by incredible abuse of neighborhood data. An efficient shading fusions chemeis likewise proposed. Investigations exhibit that their fusion standard produces preferred outcomes over existing principles. Examinations on volume tricmedical image fusion showed the convincing ness and flexibility of our fusion rule, which made entwined images with higher quality than existing principles. An efficient shading fusion plot sufficiently utilizing monochrome fusion results was likewise proposed.

[4] Chuong T. Nguyen and Joseph P. Havlice et.alintroduced a linear adaptive fusion (LAF) calculation for heterogeneous sensors vision framework. The interweaved image is figured as a weighted linear mix of detectable and infrared data images. To exploit the fascinating working characteristic of infrared sensors, they partition the fusion plot into two parallel systems: lowpass fusion and highpass fusion. The weighting coefficients of every methodology are dictated by boosting the SSIM-based no-reference fusion quality measure. The authors exhibited the ampleness of the proposed calculation quantitatively and subjectively. The trial results demonstrate that LAF reliably passes on preferred execution relative over seven contending strategies. They are starting at now assessing the presentation of LAF under boisterous and high contortion situations.

[5] Jifeng Sun and JianhuiKuang et.alproposed a novel method to encode the images. This plan can supplant the commonplace image pressure strategy dependent on the excess evacuation. The self comparability of a static image is investigated in order to execute image pressure on premise of similitude and fusion instead of repetition expulsion since the previous is dynamically like visual characteristic of people. Image fusion can be ordered into sign dimension image fusion, pixel-level image fusion, highlight level image fusion and image level image fusion. The regular looks into are image fusion dependent on wavelet change, image fusion dependent on PCA and image fusion dependent on BEMD. Barnsley's fractal image pressure technique and Jabos change based image coding is simply the outcome of combining the similitude and fractal Geometry. Test result demonstrates the plan showed can has a potential execution on image and video coding. A couple of preliminaries are done to exhibit the likelihood and ampleness of this new plan of image pressure.

3. CLUSTERING METHODS

The activity of clustering calculations resembles a characterization procedure with the main distinction that clustering calculations needn't bother with preparing information. These calculations are known as unsupervised learning techniques. These calculations work like thickness estimation in measurements which implies that an unsupervised learning calculation endeavors to outline and present information by their primary highlights. Numerous information mining calculations have been utilized in clustering. In this section, we clarify three prominent clustering calculations: k-implies, fluffy C-mean, and expectation amplification. As to strategies that don't utilize learning information, they needn't bother with more opportunity to get ready sectioned example information. One of the benefits of these strategies is that they expend less time. As a detriment, we can't allude to spatial data. Like the characterization approach, these calculations don't observe the spatial data; in this manner, they can be delicate to commotion and power in homogeneities.

3.1 K-NEAREST NEIGHBOUR

K-closest neighbor (k-nn) is an ordinary non-parametric and regularly utilized grouping technique. This strategy is known as a non-parametric technique on the grounds that the k-nn calculation does not require any data about measurable properties of pixels. The k-nn calculation needs a lot of test information which are named as preparing information. Every pixel is grouped by the quantity of closest neighbors which are characterized before as preparing information. In this calculation, k is the quantity of closest neighbors. To arrange new information with k ¼ 4, it should discover four closest neighbors. This set incorporate three information from class 2 and one information from class 1. Hence new information is delegated class 2. To order new information with k ¼ 9, new information with same principle is characterized in class 2. Underneath, we clarify the k-nn calculation.

Algorithm:

Set labelled training data X_D¼ fx_1;. . .;x_{nD}g where ^{X}D 2^Mfunc·

Choose k neighbours to find.

Choose d :R^pR^p!$R^þ$ any metric (distance measure) on R^p.

For any vector z in R^p: using X_D¼ fx_ig

Calculate and sort the distances dðz;x_iÞ as fd_1 d_2d_k $d_{kþ1}d_{nD}$g.

Find the column in U_d corresponding to the k-nearest neighbour indices {1,2, . . . ,k}.

Compute the label vector U(*|z) = (u(1|z), u(2|z), ….,u(c|z)) withk-nnlabels fromU$_d$:

$$u(i|z) = \sum_{j=1}^{k} \frac{uD,ij}{k} fori = 1,2,\ldots\ldots,c$$

Decide $x \in i \leftrightarrow D_{nn,k}(z) = e_i \leftrightarrow u(i|z) = \max\{u(i|z)\}$,

where z is the new data, X_D is the training data, Rp is the domain, and p is the dimension of data. The term d is the Euclidean distance between two vectors in Rp and is declared as follows:

$$d(z,x_i) = \|z,x_i\| = \sqrt{(z,x_i)^T(z,x_i)}.$$

Here we present the standard k-nn. Three parameters which affect the k-nn results are as follows: (1) finding a suitable k to classify the data, (2) selecting the mea-surement for distance (like Euclidean distance), and (3) the method of counting votes.A fuzzy rule has been applied on k-nn and a new algorithm implemented. In fuzzy k-nn, each datum belongs to a class with some weights.

3.2 K-MEANS

k-implies is a generally utilized unsupervised technique which parcels the image into k sections dependent on the mean of each section. In the first place, information are partitioned into k groups and after that the mean for each bunch will be determined. Every datum is placed in the group which has the closest separation to the mean of bunches utilizing the Euclidean separation. The info information is a vector and the yield is a k vector. So as to apply k-implies on MRI images which are two dimensional, pixels ought to be placed in one vector.

Algorithm: Input (k, data)

Choose k random positions in the input space

Assign the cluster centres m_j to those positions

For each x_i2 data

(a) Compute the distance Distðx$_i$;m$_j$Þ for each m_j

(b) Assign x_i to the cluster with the minimum distance

(4)For each m_j: Move the position of m_j to the mean of the points in that cluster:

$$mj¼Nji¼1xi;$$

where k is the number of clusters, N_j is the number of data in a cluster j, and m_j is the mean of cluster j and some of square errors which determine the condition of the repeat loop as

$$SSE = \sum_{j=1}^{k}\sum_{i=1}^{n} dist(x_i,c_j)^2$$

One of the inconveniences of this calculation is the quantity of bunches. Client should select the k incentive to portion the image. Another issue is affectability to anomalies, commotions, and introductory qualities. The underlying qualities are selected haphazardly from the information vector. A few refinements have been done on this calculation to improve the issue and an upgraded calculation has been introduced.

3.3 FUZZY C-MEAN

Fluffy C-mean (FCM) clustering is an unsupervised calculation which has been performed effectively on medical images. This method depends on the mean of each bunch and gathering comparable information esteems in similar groups. Covering for the most part exists in many dark scale medical images for various tissues. FCM is one of the reasonable clustering techniques for medical image segmentation. A few FCM clustering applications have been exhibited for MRI segmentation of various pieces of body.

Let X ¼ fx$_1$;. . .;x$_n$g be a data set where x_i2 R^d and assume there are k clusters and c_j is the centroid of cluster j. Then, we havec$_1$; c$_2$;. . .; c$_k$ k clusters; c$_j$: j ¼ 1;. . .; k:

Let w be a weight matrix where each value belongs to each cluster with a specific value.

$$w = \begin{bmatrix} w_{1,1} & w_{n,1} \\ w_{1,k} & w_{n,1} \end{bmatrix}, w_{i,j} \in [0,1].$$

This method has the following two restrictions:

$$\sum_{j=1}^{k} w_{1,1} = 1\ \forall x_i$$

$$0 < \sum_{j=1}^{n} w_{i,j} < 1$$

We have provided some preliminary information about FCM. Given below is an explanation of the FCM algorithm.

Algorithm:

(1) Initialize a fuzzy partition and set the weight W (for all W_{ij})

(2) Repeat

(a) Calculate the centre of clusters using the fuzzy partition.

(b) Update the fuzzy partition, i.e., W_{ij}.

Until the centres do not change. In this algorithm, cj is

$$C_J = \frac{\sum_{I=1}^{N} W_{IJ}^{P}.x_i}{\sum_{I=1}^{N} W_{IJ}^{P}}$$

which is an extended edition of the centroid formula which is used in k-means. The difference is just the degree of membership for each pint belonging to e ach cluster. Weights are defined as

$$C_J = \frac{1(1/dist(x_i, C_J)^2)^{\frac{1}{1-p}}}{\sum_{j=1}^{k} 1(1/dist(x_i, C_J)^2)^{\frac{1}{1-p}}}$$

Some of square errors which determine the condition of repeat loop is

$$SSE = \sum_{j=1}^{k} \sum_{i=1}^{n} W_{IJ}^{P} dist(x_i, c_j)^2$$

where p is a factor which specifies the impact of the weights and p e [0 . . .1]. If p > 2, then the power 1/(p1) reduces the weight of clusters which are near to the point. If p goes to 1, then the power goes to 0. This leads to the result that weights tends to 1/k. If p goes to 1, the power increases the membership weights of points to which the cluster is close. As p goes to 1, the membership tends to 1 for the closest cluster and it tends to 0 for other clusters (same like k-means). The FCM algorithm has been effectively used in medi-cal images and has proved useful in producing effec-tive results in the case of bad or corrupted images. It produces rapid and reliable results for MRI images with limited human interaction, but it needs enough experience to apply significantly.

4. EXPERIMENTAL RESULTS FEATURE EXTRACTION

K-Nearest NeighbourAlg	K-Means Alg	Fuzzy C-Mean Alg
22	7	35
27	15	39
35	20	44
44	22	56
51	26	60

Table 1: Comparison table of Feature Extraction

The comparison table of Feature Extraction of K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm shows the different values. While comparing the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm the Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 22 to 51 the K-means Algorithm values starts from 7 to 26 and the Fuzzy C-mean Algorithm values starts from 35 to 60. Every time the Fuzzy C-mean Algorithm gives the great results.

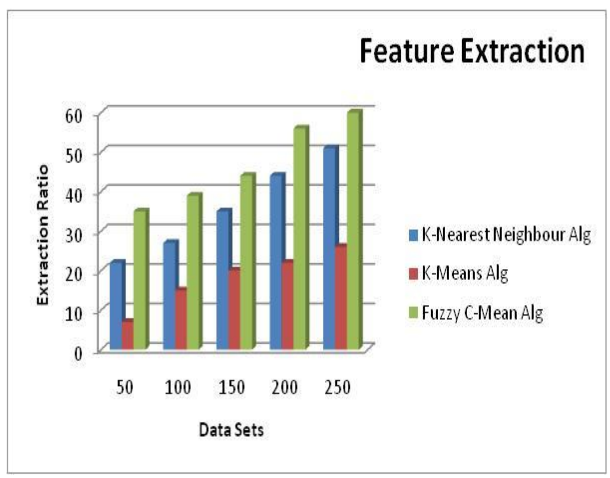


Figure 1: Comparison chart of Feature Extraction

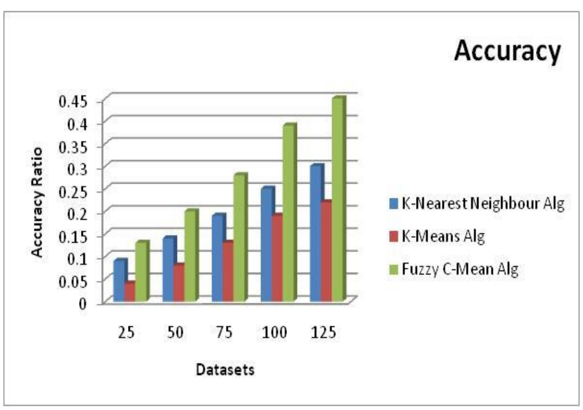
The comparison chart of Feature Extraction is demonstrates the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm. Data sets in x axis and Extraction ratio in y axis. The Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 22 to 51 the K-means Algorithm values starts from 7 to 26 and the Fuzzy C-mean Algorithm values starts from 35 to 60.

ACCURACY

K-Nearest NeighbourAlg	K-Means Alg	Fuzzy C-Mean Alg
0.09	0.04	0.13
0.14	0.08	0.2
0.19	0.13	0.28
0.25	0.19	0.39
0.3	0.22	0.45

Table 2: Comparison table of accuracy

The comparison table of accuracy of K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm shows the different values. While comparing the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm the Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 0.09 to 0.3 the K-means Algorithm values starts from 0.04 to 0.22 and the Fuzzy C-mean Algorithm values starts from 0.13 to 0.45. Every time the Fuzzy C-mean Algorithm gives the great results.



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The comparison chart of accuracy is demonstrates the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm.Data sets in x axis and accuracy ratio in y axis. The Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 0.09 to 0.3 the K-means Algorithm values starts from 0.04 to 0.22 and the Fuzzy C-mean Algorithm values starts from 0.13 to 0.45.

TIME DELAY

K-Nearest NeighbourAlg	K-Means Alg	Fuzzy C-Mean Alg
0.09	0.23	0.02
0.14	0.28	0.05
0.19	0.31	0.09
0.25	0.34	0.14
0.3	0.44	0.19

Table 3: Comparison table of time delay

The comparison table of time delay of K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm shows the different values. While comparing the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm the Fuzzy C-mean Algorithm is gives the minimum time delay values to complete the algorithm. Therefore, the Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 0.09 to 0.3 the K-means Algorithm values starts from 0.23 to 0.44 and the Fuzzy C-mean Algorithm values starts from 0.22 to 0.19. Every time the Fuzzy C-mean Algorithm gives the great results.

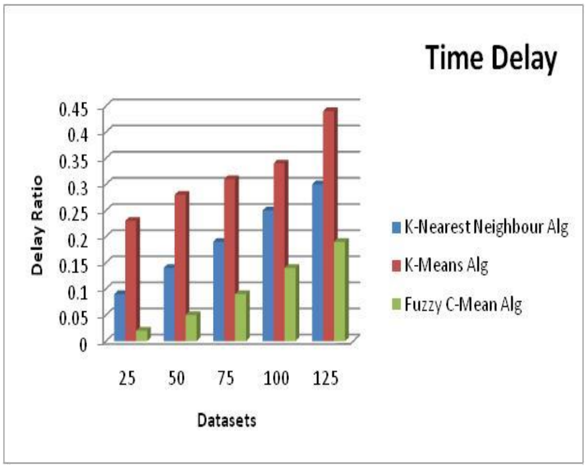

Figure 3: Comparison chart of time delay

The comparison chart of time delay is demonstrates the K-Nearest Neighbour Algorithm, K-means Algorithm and Fuzzy C-mean Algorithm. Data sets in x axis and Delay ratio in y axis. the Fuzzy C-mean Algorithm is gives the minimum time delay values to complete the algorithm. Therefore, the Fuzzy C-mean Algorithm is gives the better results. The K-Nearest Neighbour Algorithm value starts from 0.09 to 0.3 the K-means Algorithm values starts from 0.23 to 0.44 and the Fuzzy C-mean Algorithm values starts from 0.22 to 0.19.

CONCLUSION

Various current image preparing methods which are broadly utilized in medical image examination. The calculations and their applications in medical image investigation are introduced. Some of them have been connected in MRI images, particularly for the knee bone. The portrayal of every method will encourage in selecting the appropriate segmentation method. A fitting segmentation method can be selected based on various parameters, for example, the objective of the investigation, image type, and image characteristics. We ordered these methods in four gatherings: region-based method, clustering method, classifier method, and half and half method. Thresholding (worldwide, neighborhood, Otsu) and region developing whereupon region-based methodologies are based are additionally clarified. This class is delicate to clamor, however they are easy to execute. They don't have great outcomes in MRI without preprocessing however are effective for CT images which have less commotion. X-ray is more valuable than CT imaging for delicate tissues.

REFERENCES

[1]. Sen Liang, Rongguo Zhang, Dayang Liang, Tianci Song, Tao Ai, Chen Xia, Liming Xia and Yan Wang, “Multimodal 3D DenseNet for IDH Genotype Prediction in Gliomas”, Genes 2018, 9, 382; doi:10.3390/genes9080382 www.mdpi.com/journal/genes.

[2]. Yuqian Lia, Xin Liua, Feng Weia, Diana M. Simab, So fie Van Cauterc,d, UweHimmelreiche, YimingPia, GuangHuf, Yi Yaog and Sabine Van Huffelb, “An advanced MRI and MRSI data fusion scheme for enhancing unsupervised brain tumor differentiation”, 81 (2017) 121–129, 0010-4825/ © 2016 Elsevier Ltd.

[3]. RuiShen, Irene Cheng and AnupBasu, “Cross-Scale Coefficient Selection for Volumetric Medical Image Fusion”, IEEE, 0018-9294/$31.00, VOL. 60, NO. 4, APRIL 2013.

[4]. Chuong T. Nguyen and Joseph P. Havlice, “LinearAdaptiveInfraredImageFusion”, 978-1-4799-4053-0/14/$31.00 ©2014 IEEE.

[5]. Jifeng Sun and JianhuiKuang, “An Image Compression Scheme Based Fusion and Disassemble”, 978-1-4244-6893-5 / 2010 IEEE.

[6]. PallaviBute and Asst.ProfRupaliSagar, “Performance Evaluation of Contrast Based Image Fusion Techniqe Over Medical Image”, 978-1-4673-2272-0/12/$31.00 ©2012 IEEE.

[7]. Om Prakash, RichaSrivastava, AshishKhare, “BIORTHOGONAL WAVELET TRANSFORM BASED IMAGE FUSION USING ABSOLUTE MAXIMUM FUSION RULE”, 978-1-4673-5758-6/13/$31.00 © 2013 IEEE.

[8]. UjwalaPatil and Uma Mudengudi, "Image fusion using hierarchical PCA", 978-1-61284-861-7/11/$26.00 ©2011 IEEE.
[9]. Gao Ting, "Study on Hierarchical Pre-treatment Image Fusion Algorithm of Complicated Sea and Airspace Background", 978-1-61284-881-5/11/IEEE, 2011.
[10]. ZHANG BinI ZHENG Yong-guo, FANG Wei and CUI Li-min, "A New Image Fusion Algorithm Based on Second Generation Wavelet Transform", 978-1-4244-7703-6/10/$26.00 ©201O IEEE .
[11]. Simeon E. Spasov, Luca Passamonti, Andrea Duggento, Pietro Li and Nicola Toschi, "A Multi-modal Convolutional Neural Network Framework for the Prediction of Alzheimer's Disease", 978-1-5386-3646-6/18/$31.00 ©2018 IEEE.
[12]. Ozan Oktay , Enzo Ferrante, Konstantinos Kamnitsas, Mattias Heinrich, Wenjia Bai, Jose Caballero , Stuart A. Cook, Antonio de Marvao, Timothy Dawes, Declan P. O'Regan, Bernhard Kainz, Ben Glocker, and Daniel Rueckert, "Anatomically Constrained Neural Networks (ACNNs): Application to Cardiac Image Enhancement and Segmentation", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 37, NO. 2, FEBRUARY 2018.
[13]. Milad Ghantous, Soumik Ghosh and Magdy Bayoumi, "A GRADIENT-BASED HYBRID IMAGE FUSION SCHEME USING OBJECT EXTRACTION", 978-1-4244-1764-3/08/$25.00 ©2008 IEEE.
[14]. Yu Song, Mantian Li, Qingling Li and Lining Sun, "A New Wavelet Based Multi-focus Image Fusion Scheme and Its Application on Optical Microscopy", 1-4244-0571-8/06/$20.00 C) 2006 IEEE.
[15]. Jiasheng HAO, Yi SHEN, Hongbing XU and Jianxiao ZOU, "Generalized Local Priority Based Medical Image Fusion Scheme", 978-0-7695-3762-7/09 $26.00 © 2009 IEEE DOI 10.1109/IIH-MSP.2009.978-0-7695-3762-7/09 $26.00 © 2009 IEEE DOI 10.1109/IIH-MSP.2009.214