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Implementation of multi dimensional medical image decomposition for exact disease diagnosis

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Abstract: Multi-dimensional image processing techniques are more helpful for medical image diagnosis process. In this research work brain MRI or CT scan images are collecting for input and attain the preprocessed image. Depending on scalability and integration on medical images we get multi model diagnosed image. The 2 scale multi dimensional sparse representation is applied on selected image for acquiring the original and de-noise image. This method improves the performance metrics such as accuracy 98.45%, recall 98.98% and throughput 97.58% have been improved.

Keywords:Image fusionMultimodal medical imagecontrast enhancement sparse representation

1. Introduction

Multi-modular medical image aggregate consolidates the complementary data as of various imaging modalities towardsobtaincorrect facts & upgrade the nature of a photo [1]. The fused photo improved the deceivabilityaimed at herbal eyes &computer investigation. Clinical picture mixture strategies are usually utilized in computer vision, medical remedy, AI, advanced imaging and layout acknowledgment with extensive programs through melding dissimilar systems of medical photos [2]. Multi-modal image synthesisoffersvariedModalities like CT, MRI, SPECT, PET and so on.,aimed at medical evaluation [2]. Over the maximum latest couple of years full-size measure of photo mixture plans has been acquainted with upgrade the combination execution. Picture combination have typically precept divisions i.e., spatial-location technique& exchange space system [3].

The spatial region strategies shape the twine picture through selecting the pixels/areas/squares of the supply pix without change [4]. This technique in addition ordered hooked on pixel founded [3] too locale primarily founded techniques [5]. Change location methods integrate the touching on alternate coefficients and apply reverse alternate to create the intertwined picture. Multi-scale trade (MST) combination method is mainstream in multimodality picture combination. In trade space approach, an assortment of modifications such as the separate wavelet alternate founded [6], double tree compound wavelet change grounded [7], contour let change founded [8], curvelet change primarily grounded[9], non-subsampled contourlet alternate founded [10] then meager portrayal based [11] methods had remained utilized in multi-method photo combination.

As of overdue, Multi scale trade (MST) & Sparse portrayal (SR) founded aggregate techniques consume pulled in top notch attention in alternate space strategies and accomplished efficaciously in image acknowledgment [12], photo grouping [13], photo great-aim 14], photo include removal [15], image item

ID [16]then multi-methodology records combination [17]. Nonetheless, it remains seen that SR-primarily founded techniques supply stepped forward execution than the MST-based totally strategies. By way of a change primarily based system, Li & Yang et al. [18] remained the opening to supplied the idea of photograph mixture by scanty portrayal. Li et al. [19] introduced a de-noising slant aimed at multimodal photograph combination through using bunch scanty portrayal, at the equal time, this plan changed into not dissected on shading scientific photos. Nikolaoset al. [20] offered a combination device for SR-based technique in which the facts snap shots are ordered into bunches utilizing the "sliding window" approach; this methodology indicates an unrivaled presentation in catching neighborhood putting highlights. Nejati et al. [21] & Yin et al. [22] introduced a KSVD primarily foundedmulti-center image mixture approach then created better mixture outcomes. Zhu et al. [17] brought a phrase reference knowledge primarily grounded image aggregate process, which progressed the presentation of picture subtleties be that as it may, this plan isn't always computationally effective as a result of the person making ready for sub word references also it remains tedious. Yin et al. [23] presented a image combination strategy depending on joint spar city version, easy locales of this approach activates mistaken department and prompts negative unique visualizations. Li et al. [24] delivered a general use of numerous multi-scale change primarily founded procedures & presumes that exhibition of NSCT-based totally plan remains better than others strategies.

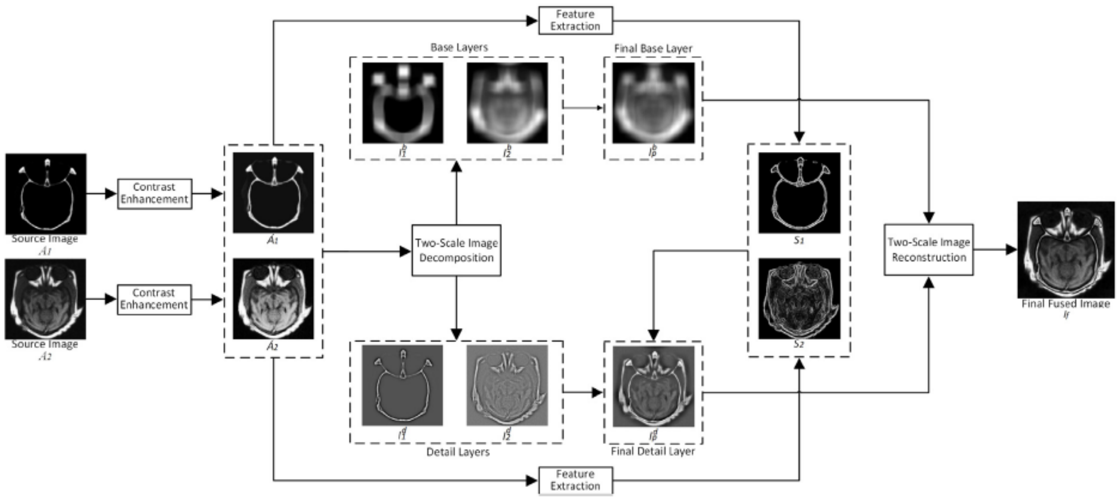


Figure 1.Schematic diagram of proposed method for image fusion algorithm.

Be that as it may, SR and MST primarily based mixture techniques have completed exquisite execution, but, have some dangers in scientific picture combination. The foremost disadvantage is the "most L1" aggregate rule can also sources spatial variance inside the multimodal scientific intertwined picsas soon as the information pix remainoccupiedthrough using unique imaging modalities [25]. Multi-scale exchange (MST) channel [25] implemented towards scanty portrayal grounded totally photograph mixture manner. Despite the truth that, it has some constraints on disintegrating specific types of pictures. The subsequent downside is the tricky shape of information pics that can't be precisely spoken to by means of the organized phrase reference [19]. For this downside, Kimet al. [26] accrued a preparation tests by using k-implies method into some constructional gatherings and for each collecting specific sub-word reference is ready that suits the unique shape. The total word reference has a solid portrayal potential. K-implies systemremains applied towards fix the portions of bunch previously grouping. In [27], Wang delivered a multi-phantom photograph aggregate aimed at panchromatic imageswhich can independently shaped longitudinal& unearthly word reference. How-ever, this technique finished uniquely in apparent then infrared image synthesis.

In this paper, any other mutlimodular photo aggregate strategy is genius supplied. This method utilizes differentiate extending and spatial slopes to extricate stepped forward edges subtleties from the source pics. Two-scale picture disintegration manner is utilized for photo aggregate calculation. At long ultimate, within the wake of making ready the supply images, conclusion charts& making use of the mixture instruction the intertwined photo remains shaped. Expert offered strategy provides higher mixture effects aimed at multimodal photograph dataset than prevailing methods.

The remaining of the paper remains prepared by way of follows. In segment IIthe comprehensive strategy of projected structure remains clarified. Area III portrays the aggregate measurements. Area IV consists of trial effects and examination &Segment V closes this paper.

2. Proposed multi-modality image fusion method

Let Aibe the basis photo consuming measurements M × N where, m = 1, 2, 3, . . ., M, n = 1, 2, 3, . . ., N also I ∈ [1, 2] indicates CT & MRI pix, separately. Fig. 1 show off the development technique of projected system.

2.1.Pre-processing

Processing Histogram leveling remains maximum broadly way towards address upgrade the little differentiation photos. The first photograph may be deliberate by way ofadjacent as practicable towards the unchanging dispersion in the histogram nighttime out procedure. Non-Parametric Improved Histogram Equalization (NMHE) [28], remains consolidated by way of a pre-managing challenge towards recoup & protect the regular differentiation of the primary pictures Ai, i.e.,

$$\acute{A}_i \overset{\text{NMHE[28]}}{\longleftarrow} A_i \qquad (1)$$

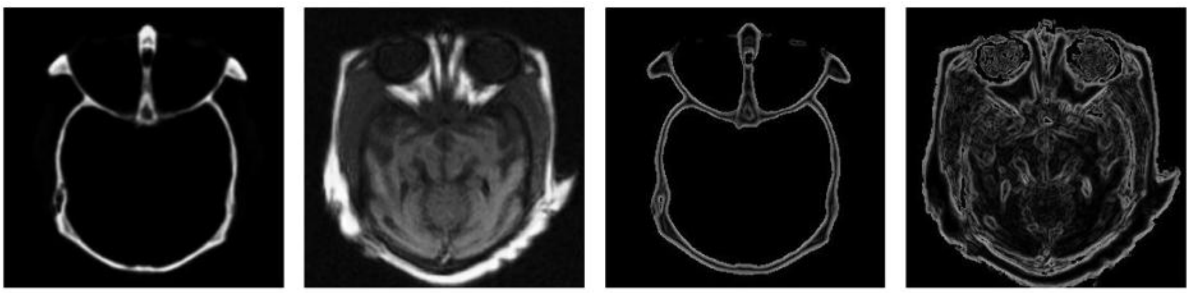
NMHE is carried out to supply pictures to get the differentiation upgraded pix' Ai. Differentiation upgrade activates higher force dispersion and improves the subtleties in a image. The development in aspect facts is regarded in Fig. 2. The major line suggests precise basis CT (Fig. 2(a)) & MRI (Fig. 2(b)) images, by their separate edge charts (Fig. 2(c, d)). The subsequent line incorporates the complexity upgraded CT (Fig. 2(e)) and MRI (Fig. 2(f)) pix by their perspective charts (Fig. 2(g, h)). It very well may remain observed that near may be an outstanding development inside the facet info of differentiation upgraded pix while contrasted with precise pix.

2.2.Feature Extraction

Spatial Stimuli Incline Sketch Typical (SSGSM) [29], remains usedtowards get the boundaries guide of every complexity improved pictures. The edge statistics in a combined image ought to consume high difference. Thisinforemains moreover applied in processing the action stage charts whichcomprise the middle records in altogether of the photographs. The magnitude of the community improvements remains decided through using locating the nearby intensity in the obvious beauty on the spatial regions.The professed brightness, Ciof a specified image $\acute{A}_i$, remains expressed by way of

$$C_i = \eta \log_{10}(\acute{A}_i) \qquad (2)$$

Where, $\acute{A}_i$ indicates the source images & η denotes the scaling factor.



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

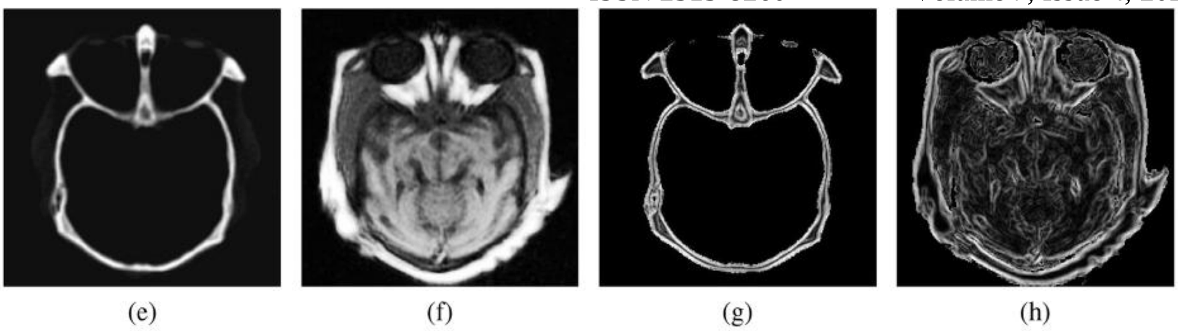


Figure 2. The "CT and MRI" basis pictures focused on differentiate improvement. (a,b) Basis pictures, (c,d) Inclines of (a,b) got through SSGSM [29], (e,f) Dissimilarity extended utilizing NMHE[28], (g,h) Inclines of (e,f) acquired thru SSGSM [29].

Gradients signifiesthe sharp strength types in the image. The slope remains a formula of dimensional separation estimation comparative with the deliberate limited fluctuation of the entomb pixel. The length numerically determined as the internet comparison of the plain beauty end to end m & n headings. The power styles of Ci along m (ξ_i^m) & n (ξ_i^n) allianceremainindicatedthrough Z_i^m then Z_i^n. This cansremainformulated as,

$$[Z_i^m, Z_i^n] \overset{\text{gradient}}{\longleftarrow} C_i \tag{3}$$

$$\xi_i^m = Z_i^m(e^{-|Z_i^m|}); \xi_i^n = Z_i^n(e^{-|Z_i^n|}) \tag{4}$$

The extent of local enhancements Si can remain determined through using,

$$S_i = \sqrt{(\xi_i^m)^2 + (\xi_i^n)^2}$$

2.3.Two-scale Image Decomposition

The pictureSiformerly disintegrated hooked on ignoble coatings I_m^b at that point disintegrated into base layers I_m^dm having little scope varieties. Base layer is finished with the aid of looking after the accompanying difficulty.

$$I_m^b = arg\min ||S_i - I_m^b||_F^2 + \delta(||h_x * I_m^b||_F^2 + ||h_y * I_m^b||_F^2) \tag{6}$$

Where, hx= [-1 1] remains the even inclination administrator, hy= [-1 1]R remains the vertical slope administrator &δsuggests the regularization boundary. The element layer I_m^d m remains finished through way of deduction.

$$I_m^d = S_i - I_m^b \tag{7}$$

2.4.Detail Layer Fusion

The scanty constant charts Sm,n, n ∈ {1,...,N} of every part layer I_m^d m remains accomplished through knowledge the CSR version by method in [30]:

$$S_{m,n} = arg\min \frac{1}{2}||\sum_{n=1}^{N} k_m * S_{m,n} - I_m^d||_2^2 + \lambda \sum_{n=1}^{N} ||S_{m,n}||_1 \tag{8}$$

Let, Sm,1: N (x, ydesignates substance of Sm,nonposition (x, y). TheSm,1: N (x, y) is N dimensional vector. The approach used in SR based totally photograph aggregate approach [11], the l1-standard ofSm,1: N(x, y) is acquire because the movement stage share of the advanced descriptions. There-front, the movement levelmap$\bar{P}$m(x, y) is executed through way of

$$\bar{P}_m(x, y) = ||S_{m,1:N}(x, y)||_1 \tag{9}$$

At that point, a remaining action degree manual is received by way of making use of window prepare averaging approach with admire to$\bar{P}$m(x, y).

$$\bar{P}_m(x, y) = \frac{\sum_{k=-q}^{q} \sum_{l=-q}^{q} P_m(x+k, y+l)}{(2q+1)^2} \tag{10}$$

Wherein, q decides the window size. By the more estimation of q this method remains moreover lively towards is-enrollment, be that as it is able to, concurrently some minor subtleties might be lost. A little scope detail for the most element exist in multimodal image combination, as a consequence, it is increasingly useful to get a littler q.

The melded coefficient maps remain obtained with the aid of applying “choose-max” approach.

$$S_{p,1:N}(x, y) = S_{m^*,1:N}(x, y),\ m^* = arg_m \max(\bar{P}_m(x, y)) \tag{11}$$

At final, the element layers mixture end result is reproduced by using

$$I_p^d(x, y) = \sum_{n=1}^{N} k_m * S_{p,n} \tag{12}$$

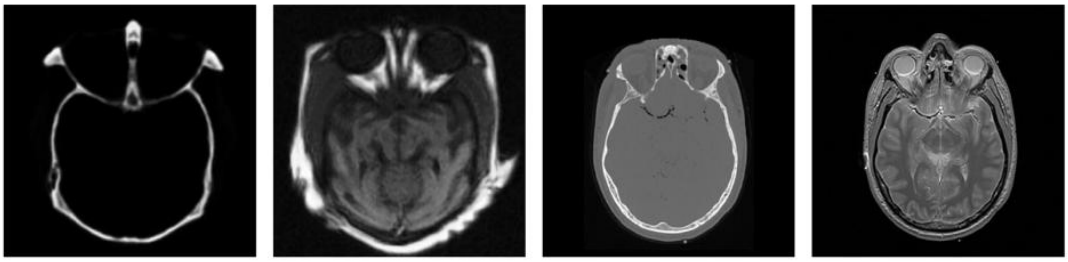
Where, I_p^d is a final detail layer.

2.5.Base Layer Fusion

The bese around mixture instructionremainspracticaltowards multimodal photograph mixture towardintertwines the ignoble coating.

$$I_p^b(x, y) = \frac{1}{M} \sum_{m=1}^{M} I_m^b(x, y) \tag{13}$$

Where, I_p^b is a final improper layer.



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

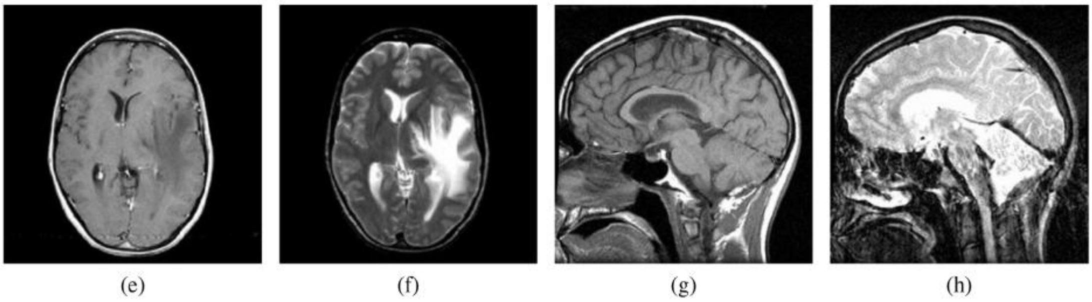


Fig. 3 multimodal medical image dataset

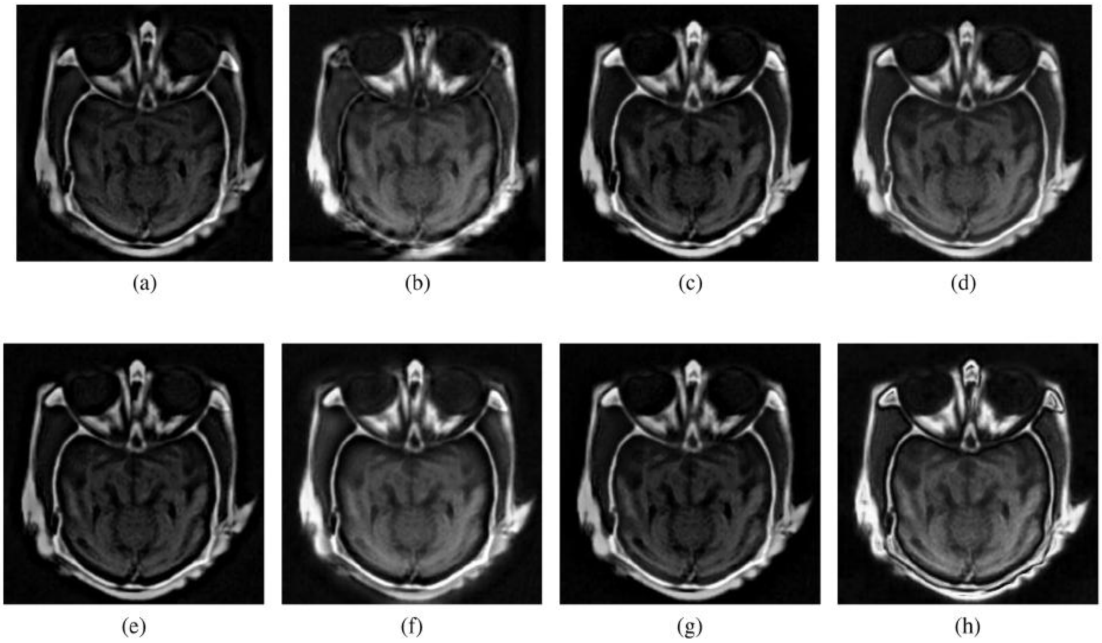


Figure 4: The “Med-1” source image. Fused images obtained using DTCWT

2.6.Two-scale Image Reconstruction

The fused image If(x, y) remains framed through using the direct coordination of final melded detail layer $I_p^d(x,y)$ and combined base layer $I_p^b(x,y)$.

$$I_f(x, y) = I_p^d(x, y) + I_p^b(x, y) \tag{14}$$

Picture combination is applied to defeat the obstacle in a multi-modular imaging, empowering endeavor & expectation of the lacking facts from MRI. The endeavor of a photograph gives a sharp, new picture, and moreover solves particular records at better scales. The MRI along special modalities while utilized at the side of photo aggregate method have regarded to improve the imaging exactness, and common-sense scientific relevance.

3. Objective Evaluation Metrics

To check the adequacy of other photograph aggregate conspires, nearlymeasurable estimations remain utilized towardssubstantiate the presentation. Five measurements remain applied aimed at quantitatively assessment, remain Entropy (EN) [25], dimensionalOrganizationalComparison (SSS) QAB/F[31],CommonInfo (MI) [32], Feature CommonInfo (FMI)[33] &GraphicInfoLoyalty (VIF) [34] towards test the flawlessness & predominance of the projected multimodal picture mixture technique. For these measurements, the bigger worth for the most component shows a superior outcome.

4. Experimental Results

4.1. Experimental setup

The proposed picture combination system remains contrasted by a few further latest calculations with affirm the viability & principal ity on multi-modular scientific photographs. The datasets aimed at multimodality picture combination received as of [17]. The analyses remain made on a PC in MATLAB R2016b too on a QuadrangleEssential Intel(R) 2.4GHzprocessor by 4GB RAM. To control the predominance of genius supplied technique an examination remains finished by prevailing picture combination techniques i.e., discrete wavelet alternate (DWT) [6], double sapling complicated wavelet trade (DTCWT) [7], Palladian pyramid(LP) [35], guided separating founded totally aggregate (GFF) [36], non-subsampled contour let trade (NSCT) [10], NSST-PAPCNN [37] then convolutionsparsityfounded totally morphological section investigation (CSMCA)[38]. The ciphers of altogether of the previously mentioned strategies remain freely handy. The length of supply photographs utilized remains 256×256.

4.2. Fusion results of medical images

Four sets of multimodality clinical pictures remain utilized by way of dis-played in Fig. Three. Utilizing the reducing facet calculations, the aggregate consequences are represented in Figs. 4–7. The predominance of the combined image is predicated upon both the visible belief & target assessment.

4.3. Visual observation of medical image fusion

Visual fine investigation of "Medications 1" photo dataset got through using DTCWT, DWT, LP, GFF, NSCT, NSST-PAPCNN, CSMCA mixture techniques then the projected conspire remains proven in Fig. Four(a)- (h)correspondingly. The supply MRI picture shows delicate tissues whilst CT photograph clarifies the bone systems to the hard tissues. For the higher determination, it's far mandatory towards consolidate entirely the important records of those photos hooked on one melded photo. The visual excellent & difference of the DTCWT (Fig. Four(a)) also DWT (Fig. Four(b)) aggregate plans remain on as much as stamp. LP & CSMCA techniques lost a few precise records for the most element within the covering quantities of CT & MRI pix also moreover containing a few visual twists within the melded picture. Combination consequence of GFF (Fig. Four(d)) & NSST-PAPCNN (Fig. 4(f)) remain outwardly superior to the relaxation of the techniques. Be that as it can, the proposed multimodal photograph mixture technique (Fig. Four(h)) gives well-known visible nature of the threshold subtleties and the differentiation than different strategies i.E., the sensitive tissues extensively cut loose the bone construction.

Visual exceptional correlation of "Drug 2" photograph dataset making use of numerous mixture plans is shown in Fig. 5. Source photos of "Prescription 2" dataset remains appeared in (Fig. Three(c, d)). The aggregate consequences of different strategies DTCWT, DWT, LP, GFF, NSCT, NSST-PAPCNN and CSMCA remain proven in (Fig. 5(a)- (g)), one at a time. Proposed photograph combination conspire is added in (Fig. Five(h)). Since (Fig. Three(a, b, d)),DTCWT, DWT and GFF calculations no longer incorporated all the widespread records and can misfortune some reciprocal records while contrasted with source pix. CSMCA approach offers quality results whilst contrasted with special techniques and coordinated all fundamental statistics and convey outwardly first-rate photograph. Notwithstanding, the aggregate effect of proposed approach gives outwardly more subtleties when contrasted with NSST-PAPCNN and CSMCA strategies. The genius offered picture mixture differentiate is extremely captivating while contrasted with different aggregate strategies.

Combination aftereffects of "Medications 3" photo dataset by means of extra mixture plans to the projected conspire remain delivered in Fig. 6. The DWT (Fig. 6(b)) & NSST-PAPCNN (Fig. 6(f)) consequences created positive antiquities inside the area. The GFF (Fig. 6(d)), NSCT (Fig. 6(e)) & CSMCA (Fig. 6(g)) strategies offer improved execution also intertwined photograph gives practically entirely the sizable info. Notwithstanding, in big name offered approach (Fig. 6(h)) the rims are very an awful lot safeguarded and brought more subtleties information inside the melded photograph.

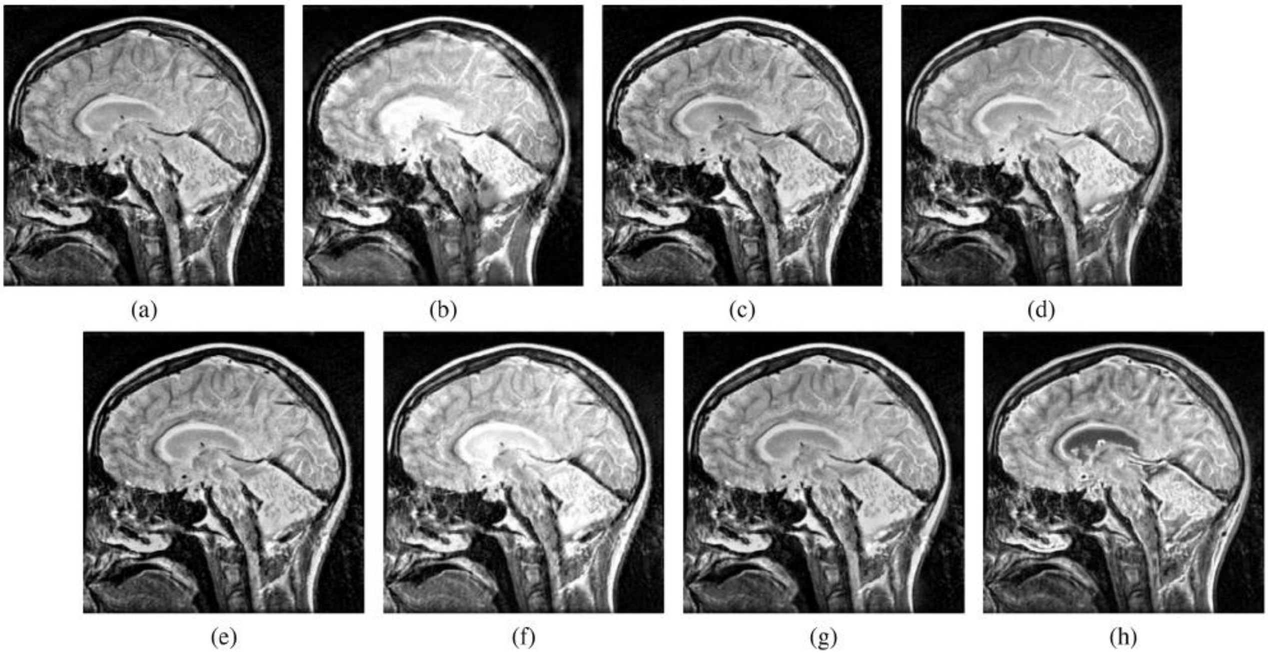


Fig. 6.The “Med-3” source image.

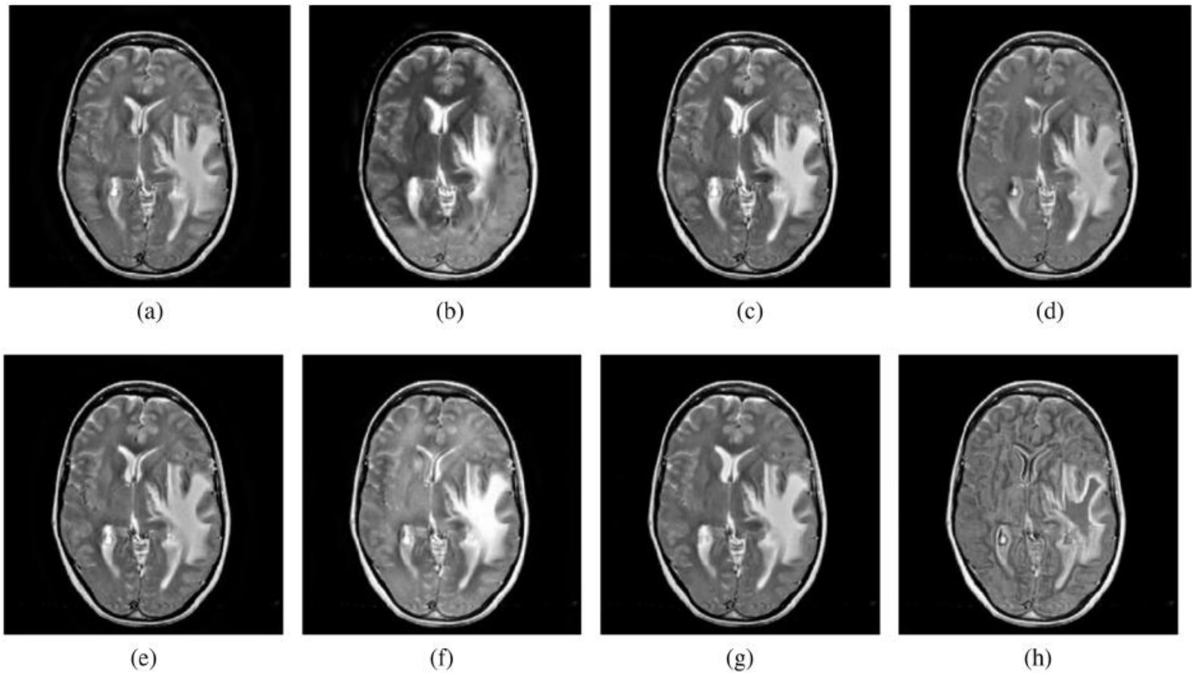
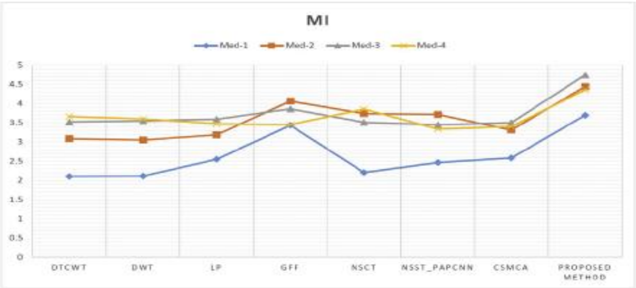


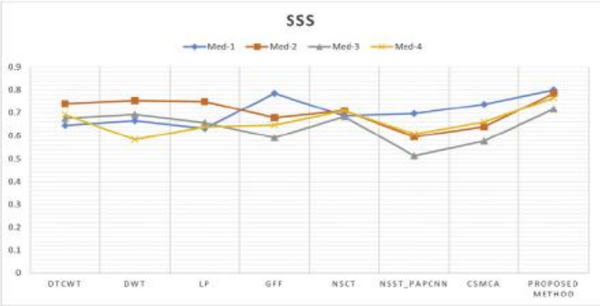
Fig. 7.The “Med-4” source image.

Another mixture execution is checked on "Med-4" picture informational index confirmed in Fig. 7. Melded image of the projected plot remains delivered in (Fig. 7(h)) which noticeably upgraded the ends then gives great distinction than different mixture techniques, as an example, DTCWT, DWT, LP, GFF, NSCT, NSSTPAPCNN and CSMCA techniques. Realistic portrayal of quantifiable evaluations of photograph datasets with various measurements remain appeared in Fig. 8(a)- (e).

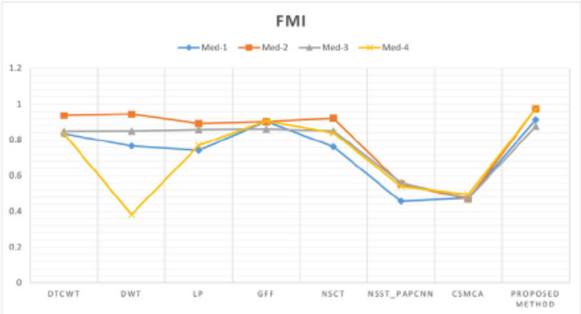
Subsequent to examining the quantifiable appraisal & visible nature of diverse plans, it's far reasoned that the proposed technique produces outwardly charming & awesome mixture bring about large a part of the cases and beat the present-day mixture plans for multimodal snap shots. Table 1 indicates that the professional offered method offers most well-known appraisal effects over present procedures.



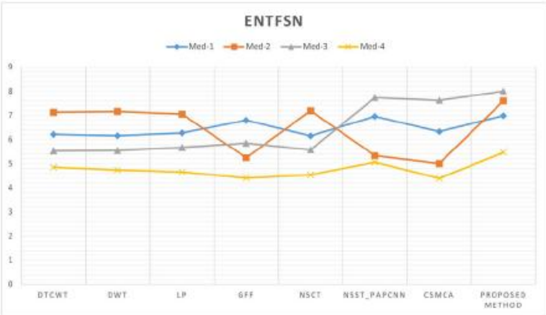
(a)



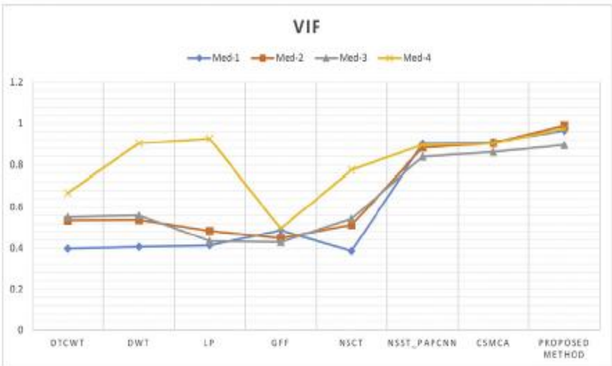
(b)



(c)



(d)



(e)

Fig. 8.image datasets using different metrics

Table 1: The quantitative assessment results of different fusion methods.

Images	Fusion methods	MI[32]	$Q^{AB/F}$[31]	$FMI_m^{x,y}$[33]	EN[25]	VIF[34]
Med-1	DTCWT[7]	2.1044	0.6454	0.8341	6.2074	0.3976
	DWT [6]	2.1141	0.6656	0.7654	6.1512	0.4065
	LP [35]	2.5508	0.6321	0.7412	6.2724	0.4141
	GFE [36]	3.4313	0.7849	0.9032	6.7971	0.4864
	NSCT [10]	2.2087	0.6872	0.7612	6.1488	0.3864
	NSSTPAPCNN [37]	2.4665	0.6968	0.4559	6.9551	0.9015
	CSMCA [38]	2.5863	0.7373	0.4751	6.3274	0.9088
	Proposed	**3.6949**	**0.7997**	**0.9116**	**6.9870**	**0.9645**
	NSCT [10]	3.5110	0.6837	0.8498	5.5703	0.5435
	NSSTPAPCNN[37]	3.4462	0.5136	0.5597	7.7278	0.8393
	CSMCA[38]	3.5008	0.5772	0.4728	7.6182	0.8615
	Proposed	**4.7421**	**0.7169**	**0.8756**	**7.9945**	**0.8951**
Med-2	DTCWT[7]	3.6632	0.6921	0.8339	4.8551	0.6679
	DWT [6]	3.5962	0.5835	0.3823	4.7393	0.9027
	LP [35]	3.4733	0.6391	0.7690	4.6547	0.9255
	GFE [36]	3.4514	0.6470	0.9047	4.4081	0.4961
	NSCT [10]	3.8544	0.7093	0.8395	4.5360	0.7769
	NSSTPAPCNN [37]	3.3372	0.6076	0.5401	5.0598	0.8960
	CSMCA[38]	3.4007	0.6601	0.4939	4.3896	0.9027
	Proposed	**4.3580**	**0.7654**	**0.9721**	**5.4681**	**0.9737**

5. Conclusion

A two-scale picture disintegration and insufficient portrayal primarily based multimodality picture mixture technique remains proposed. The source pictures remain pre-dealt with utilizing NMHE histogram evening out approach & their angles remain determined by means of SSGSM. Further the photos remain rotted hooked onsegments (base layer & element layer). Through which the extra element statistics too edge highlights may remain sent hooked on the mixed photo. Reenactment consequences on distinctive cases shows that the proposed photograph aggregate plot carried out unmatched and gives higher mixture execution each outwardly and quantitatively while contrasted with different combination methods. In future, the process of projected calculation determination sell beinspectedaimed at different photograph making ready packages.

References

[1] H. Li, Z. Yu, C. Mao, Fractional differential and variation method for imagefusion and super-resolution, Neurocomputing 171 (2016) 138–148.

[2] A.P. James, B.V. Dasarathy, Medical image fusion: A survey of the state of the art, Information Fusion 19 (2014) 4–19.

[3] S. Li, X. Kang, L. Fang, J. Hu, H. Yin, Pixel-level image fusion: A survey of thestate of the art, Information Fusion 33 (2017) 100–112.

[4] H. Li, H. Qiu, Z. Yu, B. Li, Multifocus image fusion via fixed window techniqueof multistage images and non-local means filtering, Signal Processing 138(2017) 71–85.

[5] M. Zribi, Non-parametric and region-based image fusion with Bootstrap sampling, Information Fusion 11 (2) (2010) 85–94.

[6] Y. Yang, A novel DWT based multi-focus image fusion method, ProcediaEngineering 24 (1) (2011) 177–181.

[7] B. Yu, B. Jia, L. Ding, Z. Cai, Q. Wu, Hybrid dual-tree complex wavelettransform and support vector machine for digital multi-focus image fusion,Neurocomputing 182 (2016) 1–9.

[8] S. Yang, M. Wang, L. Jiao, R. Wu, Z. Wang, Image fusion based on a newcontourlet packet, Information Fusion 11 (2) (2010) 78–84.
[9] F. Nencini, A. Garzelli, S. Baronti, L. Alparone, Remote sensing image fusionusing the curvelet transform, Information Fusion 8 (2) (2007) 143–156.
[10] H. Li, H. Qiu, Z. Yu, Y. Zhang, Infrared and visible image fusion scheme basedon NSCT and low-level visual features, Infrared Physics and Technology 76(2016) 174–184.
[11] B. Yang, S. Li, Multifocus image fusion and restoration with sparserepresentation, IEEE Transactions on Instrumentation and Measurement 59(4) (2010) 884–892.
[12] H. Liu, Y. Yu, F. Sun, J. Gu, Visualtactile fusion for object recognition, IEEETransaction on Automation Science and Engineering 14 (2) (2017) 996–1008.
[13] J. Cao, J. Hao, X. Lai, C.M. Vong, M. Luo, Ensemble extreme learning machineand sparse representation classification, Journal of The Franklin Institute 353(17) (2016) 4526–4541.
[14] J. Yang, Z. Wang, Z. Lin, S. Cohen, T.S. Huang, Coupled dictionary training forimage super-resolution, IEEE Transaction on Image Processing 21 (8) (2012)3467–3478.
[15] H. Liu, Y. Liu, F. Sun, Robust exemplar extraction using structured sparsecoding, IEEE Transaction on Neural Network and Learning System 26 (8)(2015) 1816–1821.
[16] H. Liu, D. Guo, F. Sun, Object recognition using tactile measurements: kernelsparse coding methods, IEEE Transaction on Instrument and Measurement 65(3) (2016) 656–665.
[17] Z. Zhu, Y. Chai, H. Yin, Y. Li, Z. Liu, A novel dictionary learning approach formulti-modality medical image fusion, Neurocomputing 214 (2016) 471–482.
[18] B. Yang, S. Li, Multifocus image fusion and restoration with sparserepresentation, IEEE Transaction on Instrument and Measurement 59 (4)(2010) 884–892.
[19] S. Li, H. Yin, L. Fang, Group-sparse representation with dictionary learning formedical image denoising and fusion, IEEE Transaction on BiomedicalEngineering 59 (12) (2012) 3450–3459.
[20] N. Mitianoudis, T. Stathaki, Pixel-based and region-based image fusionschemes using ICA bases, Information Fusion 8 (2) (2007) 131–142.
[21] M. Nejati, S. Samavi, S. Shirani, Multi-focus image fusion usingdictionary-based sparse representation, Information Fusion 25 (2015) 72–84.
[22] H. Yin, Y. Li, Y. Chai, Z. Liu, Z. Zhu, A novel sparse representation-basedmulti-focus image fusion approach, Neurocomputing 216 (2016) 216–229.
[23] H. Yin, S. Li, Multimodal image fusion with joint sparsity model, OpticalEngineering 50 (6) (2011) 067007.
[24] S. Li, B. Yang, J. Hu, Performance comparison of different multi-resolutiontransforms for image fusion, Information Fusion 12 (2) (2011) 74–84.
[25] Y. Liu, S. Liu, Z. Wang, A general framework for image fusion based onmulti-scale transform and sparse representation, Information Fusion 24(2015) 147–164.
[26] M. Kim, D.K. Han, H. Ko, Joint patch clustering-based dictionary learning formultimodal image fusion, Information Fusion 27 (2016) 198–214.
[27] W. Wang, L. Jiao, S. Yang, Fusion of multispectral and panchromatic imagesvia sparse representation and local auto regressive model, Information Fusion20 (2014) 73–87.[
[28] S. Poddar, S. Tewary, D. Sharma, V. Karar, A. Ghosh, S.K. Pal, Non-parametricmodified histogram equalisation for contrast enhancement, IET ImageProcessing 7 (2013) 641–652.
[29] J.J. Mathew, A.P. James, Spatial stimuli gradient sketch model, IEEE SignalProcessing Letters 22 (2015) 1336–1339.
[30] B. Wohlberg, Efficient algorithms for convolutional sparse representation,IEEETranscation on Image Processing 25 (1) (2016) 215–301.
[31] V.S. Petrovi, C.S. Xydeas, Sensor noise effects on signal-level image fusionperformance, Information Fusion 4 (2003) 167–183.

[32] M. Hossny, S. Nahavandi, D. Vreighton, Comments on information measure forperformance of image fusion, Electronics Letters 44 (18) (2008) 1066–1067.
[33] M.B.A. Haghighat, A. Aghagolzadeh, H. Seyedarabi, A non-reference imagefusion metric based on mutual information of image features, Computers andElectrical Engineering 37 (2011) 744–756.
[34] Y. Han, Y. Cai, Y. Cao, X. Xu, A new image fusion performance metric based onvisual information fidelity, Information Fusion 14 (2) (2013) 127–135.
[35] J. Du, W. Li, B. Xiao, Union laplacian pyramid with multiple features formedical image fusion, Neurocomputing 194 (19) (2016) 326–339.
[36] S. Li, X. Kang, J. Hu, Image fusion with guided filtering, IEEE Transactions onImage Processing 22 (7) (2013) 2864–2875.
[37] M. Yin, X. Liu, Y. Liu, X. Chen, Medical Image Fusion With Parameter-AdaptivePulse Coupled-Neural Network in NonsubsampledShearletTransformDomain, IEEE Transactions on Instrumentation and Measurement 68 (1)(2019) 49–64.
[38] Y. Liu, X. Chen, R.K. Ward, Z.J. Wang, Medical Image Fusion via ConvolutionalSparsity Based Morphological Component Analysis, IEEE Signal ProcessingLetters 26 (3) (2019) 485–489.