



Fusion of multi-modality biomedical images using deep neural networks

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Abstract

With the recent advancement in the medical diagnostic tools, multi-modality medical images are extensively utilized as a lifesaving tool. An efficient fusion of medical images can improve the performance of various medical diagnostic tools. But, gathering of all modalities for a given patient is defined as an ill-posed problem as medical images suffer from poor visibility and frequent patient dropout. Therefore, in this paper, an efficient multi-modality image fusion model is proposed to fuse multi-modality medical images. To tune the hyper-parameters of the proposed model, a multi-objective differential evolution is used. The fusion factor and edge strength metrics are utilized to form a multi-objective fitness function. Performance of the proposed model is compared with nine competitive models over fifteen benchmark images. Performance analyses reveal that the proposed model outperforms the competitive fusion models.

Keywords Image fusion · Fusion factor · Computed tomography · Medical images

1 Introduction

Medical imaging are widely accepted in clinical diagnosis, treatment, and assessment of various medical problems. Medical imaging is one of the best ways to see the internal working of human body organs without any surgery. It is a powerful tool to effectively care the patients while treatment and after treatment. The various image modalities are used in medical which provides different types of information about the internal organs of body. The commonly used image modalities are single-photon emission computed tomography (SPECT), positron emission tomography (PET), magnetic resonance imaging (MRI), computerized tomography (CT), ultrasound, X-ray, etc. James and Dasarathy (2014); Kaushik et al. (2021). However, the quality of

acquired images gets affected due to limitation of technology (Du et al. 2016), because every modality has its own benefits and practical limitations. It further affects the interpretation and analysis of medical diagnosis. The quality of images can be enhanced through multi-modal medical image fusion. It combines the images from single or multiple imaging modalities and produces a fused image that provides more comprehensive information about the disease (Daniel et al. 2017). It helps the physicians to make more accurate decisions and to provide better treatment to patients (Kaur et al. 2021; Kaushik et al. 2021). For example, CT image provides better visualization of dense structure like bone, while MRI is used to provide comprehensive information on soft tissue. The fused image of MRI and CT can provide paired information that describe bone and soft tissue simultaneously (see Fig. 1) (Du et al. 2016).

Most of the existing medical image fusion researchers have not considered multi-modality image fusion techniques. Also, the appropriate integration of imaging modalities, processing and extraction of features, and fusion technique for a clinical problem itself is a challenging issue, because improper combination among the images may lead to poor performance. Most of the existing multi-modality image fusion techniques may introduce pseudo-Gibbs and obscure edges. Additionally, the use of deep neural networks can enhance the quality of fused multi-modality images

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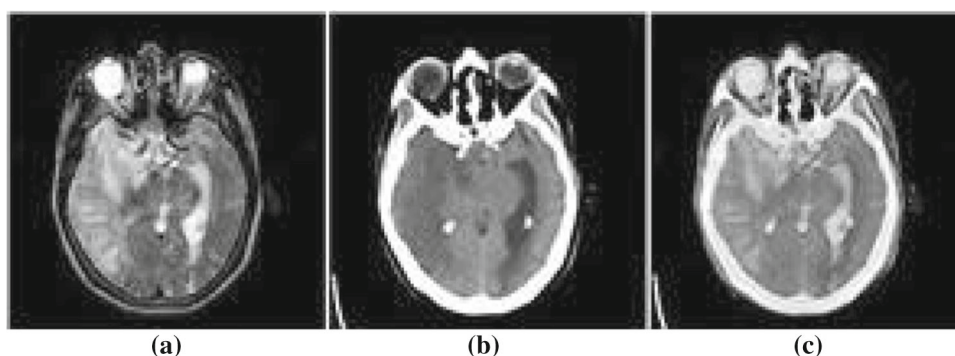
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Fig. 1 Multi-modality image fusion: **a** MRI-T1 image, **b** CT image, **c** fused image



(De Luca 2022; Karthik and Sekhar 2021). But, deep neural networks still suffer from the hyper-parameters tuning issue (Singh et al. 2021; Wani and Khaliq 2021). These issues can be resolved using the metaheuristic techniques such as genetic algorithm (Rezaeipana and Mojarad 2021), ant colony optimization (Liu et al. 2022), differential evolution (Kaur and Singh 2021), etc.

The main contributions of this paper are as:

- An efficient multi-modality image fusion model is proposed that utilizes modality characteristics using the modality-aware model. Also, it exploits the similarity between various modalities by utilizing a layer-wise fusion model.
- Hyper-parameters of the proposed model are tuned by using the multi-objective differential evolution (MDE).
- Multi-objective fitness function is defined by using fusion factor (ρ) and edge strength (e) metrics.
- Performance of the proposed model is compared with nine competitive models over fifteen benchmark images.

The remaining paper is organized as: Existing literature is discussed in Sect. 2. The proposed model is discussed in Sect. 3. Performance analysis is presented in Sect. 4. Section 5 concludes the proposed model.

2 Literature review

Li et al. (2018) used dictionary learning (DL) with low-rank and sparse regularization terms to fuse the medical images to preserve detailed information. Padmavathi et al. (2020) reported the disadvantage of multi-scale decomposition (MSD) methods, i.e., ringing artifacts in image fusion. To alleviate this issue, a total variation (TV) model is used with adaptive weighting method to fuse the medical images. Manchanda and Sharma (2018) fused the images using an improved multi-modal based on fuzzy transform (IMFT). The performance of multi-modal is enhanced using the error

images obtained from fuzzy transform. Ravi and Krishnan (2018) fused the medical images using multi-resolution discrete cosine transform (MDCT).

Prakash et al. (2019) implemented a lifting scheme-based biorthogonal wavelet transform (LBWT) to fuse the multi-modal medical images. In this technique, multiscale fusion scheme is used in the wavelet domain. Hu et al. (2020) proposed an image fusion technique, i.e., GDNST by using Gabor filter, separable dictionary, and non-subsampled contourlet transform (NSCT). Maqsood and Javed (2020) introduced image fusion using sparse representation and two-scale image decomposition (STD). For extracting the edge information, a spatial gradient-based edge detection technique is utilized.

Rajalingam et al. (2019) proposed hybrid fusion algorithm using the combination of NSCT and dual tree contourlet wavelet transform (DTCWT). Polinati and Dhuli (2020) utilized empirical wavelet transform with local energy maxima to fuse the multi-modal images. Singh and Anand (2018) presented an PCN-DRT-based image fusion method based on pulse coupled neural network and discrete ripplelet transform (DRT). Corbat et al. (2020) combined the case-based reasoning and deep learning (CDL) to fuse the images of deformed kidneys. Xu et al. (2020) presented a hybrid optimization technique using the homomorphic filter and wavelet transform to improve the quality of medical images. In this algorithm, shark smell and world cup optimization algorithms are also used for better results. Chen et al. (2020) used rolling guidance filter (RGF) to preserve the structural information of medical images. RGS is used to decompose the image into structural and detail components. Structural component is merged using the Laplacian pyramid-based fusion rule. A sum-modified Laplacian model is applied for the detail component. Liu et al. LIU2018343 preserved the information of multi-modal images using non-subsampled shearlet transform (NSST) with decomposition framework. The fusion of texture and approximate components is done through maximum selection fusion rule and NSST, respectively.

El-Hoseny et al. (2018) presented a technique based on DTCWT and central force optimization (CFO) to fuse the medical images. DT-CWT is used to divide the image into coefficients. Optimum decomposition level is determined by CFO. Du et al. (2020) implemented a three-layer (such as base, detail and intensity layers)-based fusion model for medical images. Jiang et al. (2018) used sparse representation and weighted least squares filter to preserve the information of medical images. Ullah et al. (2020) presented an image fusion technique using novel sum-modified Laplacian (NSML) and local featured fuzzy sets in NSST domain.

Jin et al. (2018) utilized NSST with simplified pulse coupled neural networks (S-PCNNs) to fuse the images. The information of edges is extracted using intersecting cortical models (ICMs). S-PCNNs is used to define the sensitively detailed information of the image. Sheng Guan et al. (2019) implemented an image fusion approach using multi-scale analysis coupling approximate sparse representation. Zong and Qiu (2017) used sparse representation of classified image patches to fuse the medical images. According to patch geometrical direction, an image is decomposed into classified patches. Then, by utilizing the online dictionary learning, corresponding sub-dictionary is trained. Least angle regression technique is applied to each patch to code sparsely. Zhu et al. (2016) proposed a dictionary learning technique for image fusion. A source image is decomposed into patches

using sampling technique. Thereafter, patches are classified using the clustering algorithm into various patch groups that have similar image structure information. K-SVD is then utilized to train every patch group. Wang et al. designed a progressive local filter pruning for efficient image retrieval acceleration. The local geometric properties have been analyzed of every filter and select the one that can be replaced by the neighbors. Finally, progressively prune has been performed on the filter by gradually changing the filter weights. Thus, the representation characteristics of the technique are preserved (Wang et al. 2020).

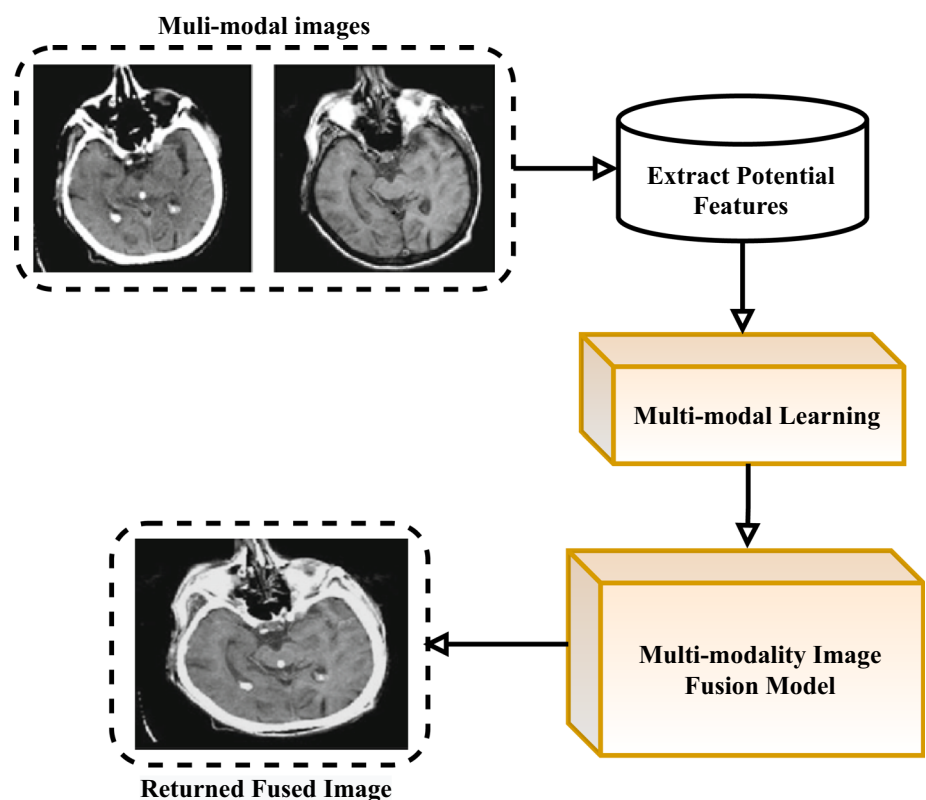
3 Proposed model

This section discusses the proposed image fusion model. Figure 2 shows the diagrammatic flow of the proposed multi-objective image fusion model.

3.1 Multi-modal learning

To train multi-modal model, required details and similarities from various modalities are required to improve the learning rate. Therefore, it becomes important to exploit the similarities between various modalities and also obtain the modality-aware details to conserve their characteristics.

Fig. 2 Diagrammatic flow of the proposed MDE-based fusion model



Initially, a modality-aware model is designed for every modality (e.g., u_a). Therefore, the high-level features, i.e., h_{u_a} , for a th modality are defined as:

$$H_{u_a} = F_{\Theta_a^{\text{en}}}(u_a) \quad (1)$$

Here, Θ_a^{en} defines the attributes of model. To develop a high-level definition, an autoencoder (Xia et al. 2019) to build the actual image by considering the trained high-level features. An autoencoder is a kind of neural network utilized to learn significant data coding in an unsupervised fashion (Karim et al. 2019). It can learn an encoding for a set of data by building the model to reduce the training loss. The loss function for reconstruction is defined as Zhou et al. (2020):

$$l^{\text{rep}} = \sum_a \|u_a - \hat{u}_a\|_1 \quad (2)$$

Here, $\hat{u}_a = F_{\Theta_a^{\text{de}}}(u_a)$ shows the reevaluated image of u_a . Θ_a^{de} represents the respective attributes of the model. The ℓ_1 -norm is also utilized to evaluate the error between the input and the obtained images. The obtained loss contains side output to provide modality-aware model that builds a discrimination definition for every individual modality. (For more details please see Zhou et al. 2020.)

3.2 Multi-modality image fusion model

A layer-wise multi-model image fusion model is designed, to evaluate the similarity among multi-level definitions from various layers such as high-level and shallow layers, and to minimize the diversity of various modalities. The utilized multi-modality image fusion model evaluates the similarities between various modalities by considering low- and high-level characteristics. (For more information please see Zhou et al. 2020.)

Three different fusion approaches are utilized in this paper. A convolutional layer is utilized to dynamically weight these fusion approaches. The output $\mu_{m-1}^{(a)} \in \mathbb{R}^{C_{\text{els}} \times W_{\text{th}} \times H_{\text{th}}}$ for $(m-1)^{\text{th}}$ is pooling layer of a th modality. Here, C_{els} defines characteristic channels. W_{th} and H_{th} define height and width of the characteristics maps. Thereafter, fusion approaches are applied on inputs $\mu_{m-1}^{(a)}$ ($a = 1, 2$) to compute:

$$\begin{cases} v_+ = \mu_{m-1}^{(1)} + \mu_{m-1}^{(2)}; \\ v_{\times} = \mu_{m-1}^{(1)} \times \mu_{m-1}^{(2)}; \\ v_m = \text{Max}(\mu_{m-1}^{(1)}, \mu_{m-1}^{(2)}) \end{cases} \quad (3)$$

Here, Max, $\times$ and $+$ define element-wise maximization, product and summation operations, respectively. Thereafter, fusion approaches are integrated as:

$$v_{\text{concat}} = [v_+; v_{\times}; v_m] \in \mathbb{R}^{3C_{\text{els}} \times W_{\text{th}} \times H_{\text{th}}} \quad (4)$$

F_{concat} is evaluated and merged to the first convolutional layer. The output of first convolutional layer is then fused with the succeeding outcome v_{m-1} of $(m-1)^{\text{th}}$ module and assigned to the next convolutional layer. In the end, an output v_m of m th module is computed. If $m = 1$, then it is assumed that there exists no succeeding output v_{m-1} ; therefore, we add an output of the first layer to second layer. The size and numbers of filters are obtained by using the proposed MDE along with other hyper-parameters. In the proposed model *ReLU* activation function is utilized. The remaining section discusses the parameters optimization of the proposed model.

3.3 Problem formulation

The proposed model has various hyper-parameters. These hyper-parameters are size of filters, numbers of filters, epochs, learning rate, λ_1 and λ_2 . The tuning of these parameters on hit and trail basis may reduce the efficiency of the proposed model. Thus, a meta-heuristic algorithm is required to optimize the initial parameters of the proposed model. Figure 2 shows the proposed MDE-based fusion model.

3.4 Multi-objective fitness function

The performance metrics, i.e., fusion factor (ρ) and edge strength (e), are utilized to define the multi-objective fitness ($f(t)$) function as:

$$f(t) = \begin{cases} \text{Maximize } (\rho) \\ \text{Maximize } (e) \end{cases} \quad (5)$$

In this case, the concept of a single solution that concurrently optimizes all objectives disappears in favor of the model of compromise solutions. Therefore, MDE is utilized as an optimal Pareto group for the proposed model, demonstrating the significant trade-off between fusion factor and edge strength metrics.

3.5 Multi-objective differential evolution

The proposed multi-objective multi-modality image fusion model is discussed given below.

Step I: Initialization Initially, the values of control attributes of differential evolution such as Ψ , c_r and B_{group} are defined. The random solutions are obtained as $\eta_{\delta}^0 = \eta_{\text{in}} + r_d \cdot (\eta_M - \eta_{\text{in}})$ ($\delta = 1, 2, \dots, \varphi$). P_1^0 shows initial population which contains all φ initial solutions. Define $t = 0$ and the value of φ . Allocate $t_s = 0.2 * \varphi$ (see Fan et al. (2017) Fan and Yan 2018; Singh et al. 2022 for more information). A mutation operation pool (Q') with $\varphi/2$ operations is obtained from $\mathcal{D}/r_d/1$ and $\mathcal{D}/b_s/1$ models, respectively.

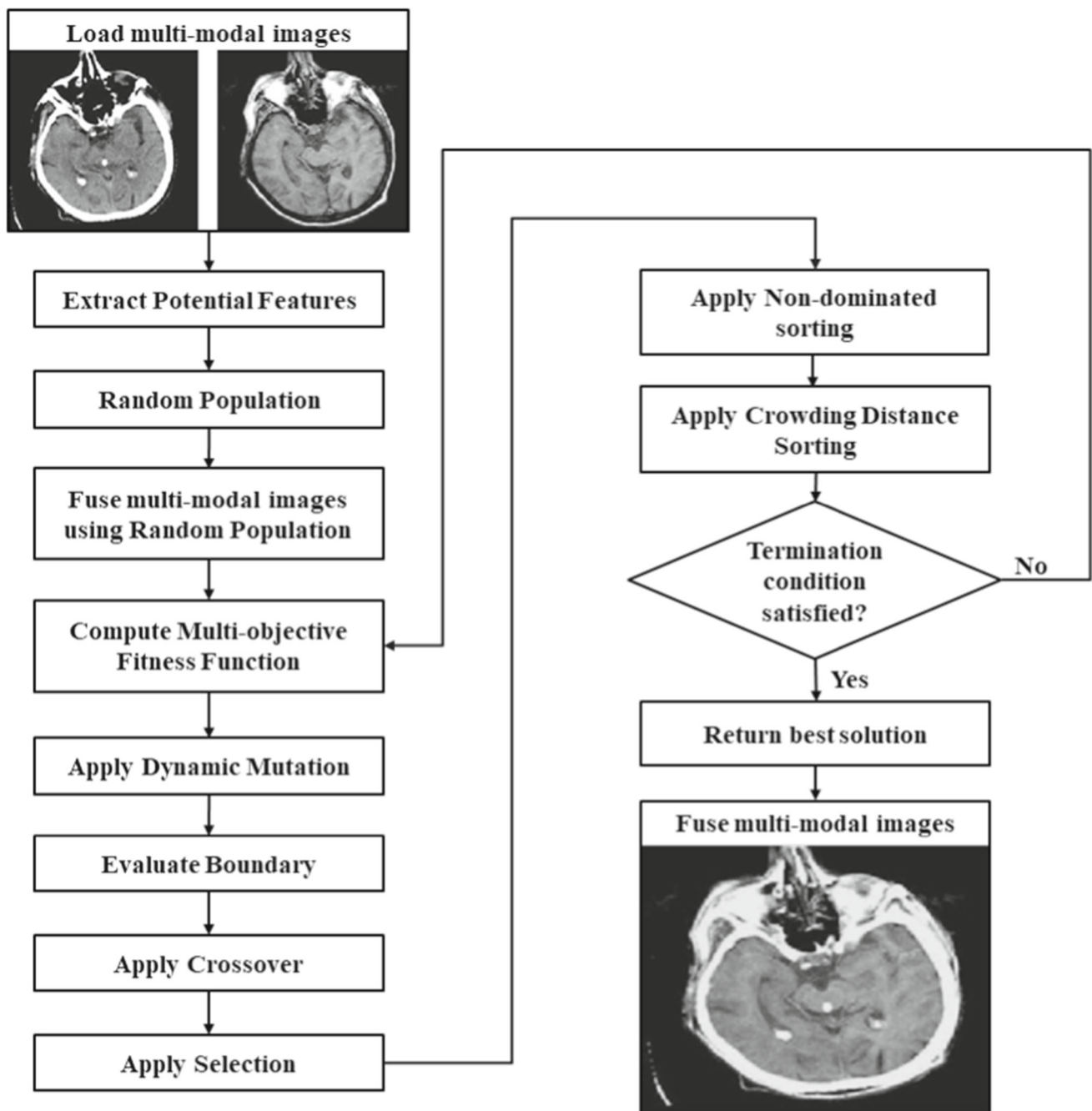


Fig. 3 Diagrammatic flow of the proposed MDE-based fusion model

Step II: Evolution

A. Mutation: For every solution η_{δ}^t , if $t < t_s$, then $\mathcal{D}/r_d/1$ is utilized to obtain solutions; otherwise, a randomly elected mutation operation from Q^t is used to obtain a vector γ_{δ}^t and will be recomputed from Q^t . Also, the best solution in mutation model $\mathcal{D}/b_s/1$ is randomly elected from φ , which is evaluated at $t - 1$ th iteration.

B. Crossover: A trial vector α_{δ}^t can be computed by using the two points crossover

Step III: Selection Selection can be achieved as:

1. If $\eta_{\delta}^t > \alpha_{\delta}^t$, then η_{δ}^t is stored in P_1^t .
2. If $\alpha_{\delta}^t > \eta_{\delta}^t$, then η_{δ}^t is replaced by α_{δ}^t in P_1^t .
3. If η_{δ}^t and α_{δ}^t has no dominated relationship among them, α_{δ}^t is then utilized in P_1^t .

Step IV: Selection Crowding distance sorting (C_d) (Li et al. 2008) is utilized to select solutions. It is a solution which

can be computed by considering the mean distance of its two sibling solutions. Actual C_d can be computed by aggregating all C_d values. Consider φ to aggregate in P_1^t using C_d values.

Step V $t = t + 1$

Step VI Repeat steps II to V until $t = \varphi$.

4 Experiments and results

This section discusses the experimental setup and results. The performance of the proposed medical image fusion model is evaluated by considering benchmark medical images dataset (Ullah et al. 2020). A group of 5 set of source images are shown in Fig. 4. It shows that there are two source input images with some modalities in each image. Our objective is to fuse a given set of images into a single multi-modality image. The comparisons are drawn between the proposed and nine competitive image fusion models. These nine competitive image fusion techniques are as MDCT, TV, IMFT, LBWT, GDNST, STD, PCN-DRT, CDL and CFO. We have implemented all the image fusion techniques on MATLAB 2018a. The parameters setting of the existing image fusion are taken as reported in their respective papers.

4.1 Visual analyses

Figure 5 demonstrates the visual analyses among the proposed model and the existing image fusion models. It is observed that the proposed model achieves better modalities images as compared to the competitive image fusion models. Also, the fused images obtained from the proposed fusion show that the proposed model does not suffer from various issues such as noise, halo and gradient reversal artifacts, edge and texture distortion, etc. Thus, visual analyses indicate that the proposed model achieves remarkably good results than the competitive image fusion models.

4.2 Quantitative analysis

Various performance metrics are used to compare the proposed model with the competitive fusion models. These metrics are standard deviation, entropy, fusion symmetry, fusion factor, and edge strength. (For more details please see Prakash et al. 2019.)

The fused image generally comes up with good standard deviation values. Figure 6 depicts the performance analyses of the proposed multi-modality image fusion model with the existing image fusion models in terms of standard deviation. It is found that the proposed model achieves better standard deviation values than the existing multi-modality image fusion models. An average improvement in terms of standard deviation over the existing proposed model models is 1.3827%.

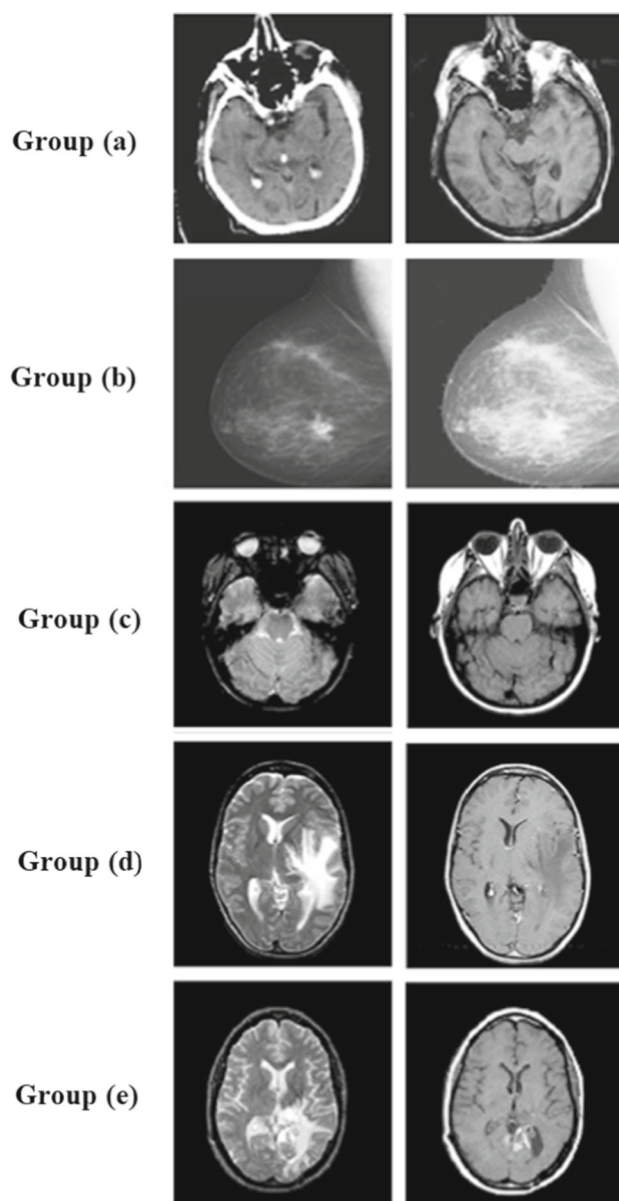


Fig. 4 Five sets of source input images. Each set will be used to obtain a single fused image. Similarly, we have selected 10 more set of images for evaluation purpose. Thus, in total 15 images are taken for experimental analysis

A fusion model is said to be efficient, if it provides good entropy values. Figure 7 shows comparative analyses in terms of entropy among the proposed and the competitive models. It is shown that the proposed model achieves remarkable more entropy values than competitive image fusion models. An average enhancement in case of the proposed image fusion model in terms of entropy is found to be 1.2616%.

A mutual information measure is utilized to evaluate the preserved information in the fused image. Generally, a fused image has more mutual information; therefore, it is desirable to be maximum. Figure 8 depicts the mutual information

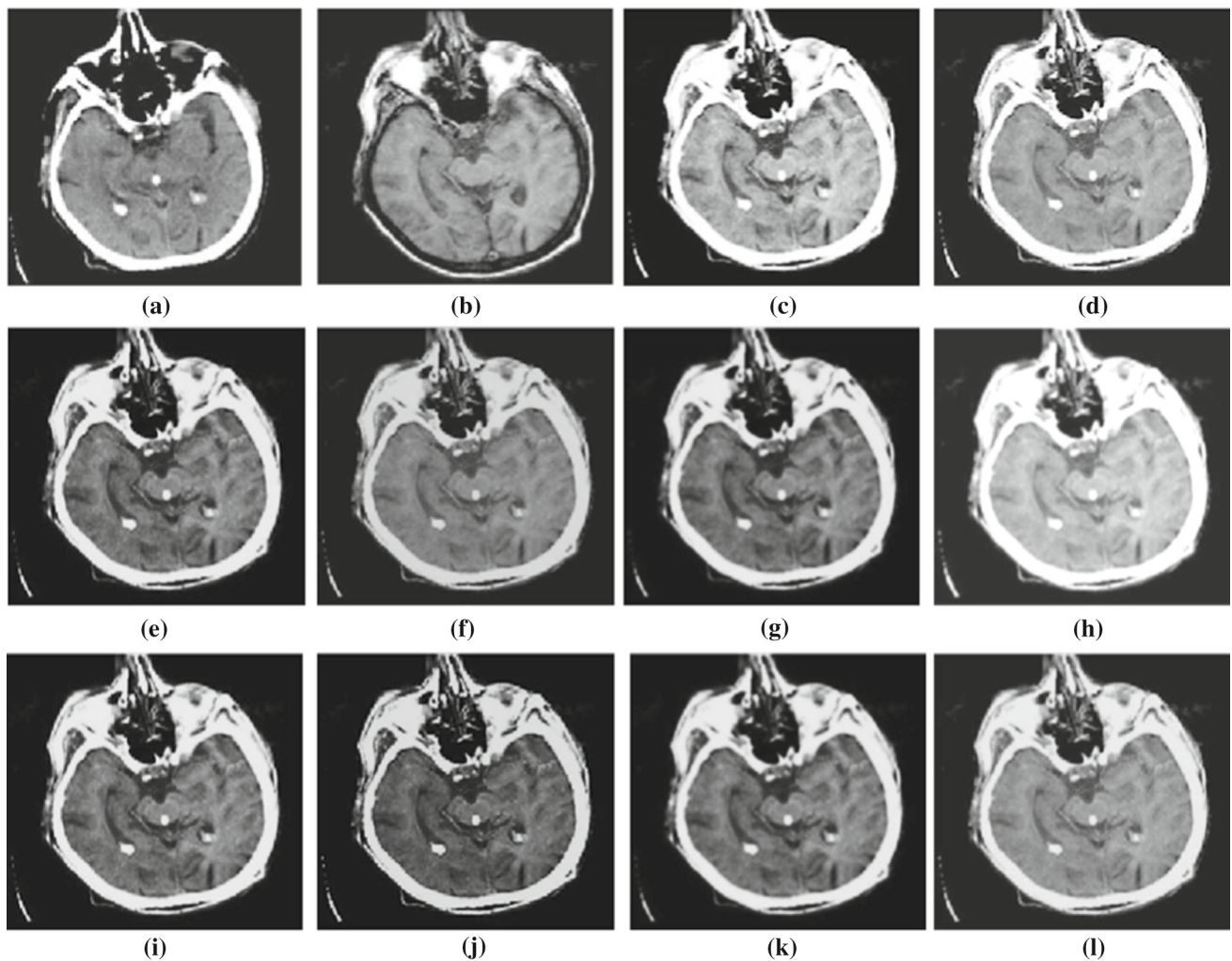


Fig. 5 Multi-modality image fusion visual analysis for group 1 source images: **a** CT image, **b** MRI-T1 image, **c** MDCT, **d** TV, **e** IMFT, **f** LBWT, **g** GDNSCT, **h** STD, **i** PCN-DRT, **j** CDL, **k** CFO and **l** proposed model

analyses between the existing and the proposed fusion models. It is evaluated that the average enhancement in terms of mutual information is 1.2756%.

Fusion factor is another standard measure to evaluate the performance of the image fusion models. Figure 9 depicts fusion factor analyses between the competitive and the proposed model models. It is computed that the average enhancement in terms of fusion factor in case of proposed model over the competitive models is 1.2947%. Therefore, the proposed model model achieves significantly better fused images.

The fusion symmetry is another metric used to compute the degree of symmetry of information between two images.

Figure 10 depicts the fusion symmetry analyses among the proposed and competitive models. It is computed that an average enhancement of the proposed model in terms of fusion symmetry over competitive models is 1.2183%.

Edge strength computed the edge preservation degree and a fused image should have maximum edge strength values (Xydeas and Petrovic 2000). Figure 11 depicts the edge strength analyses among the competitive and the proposed models. It is found that the proposed model can efficiently preserve more edges than the competitive models. An average enhancement in terms of edge strength in case of the proposed multi-modality image fusion model over others is 1.2137%.

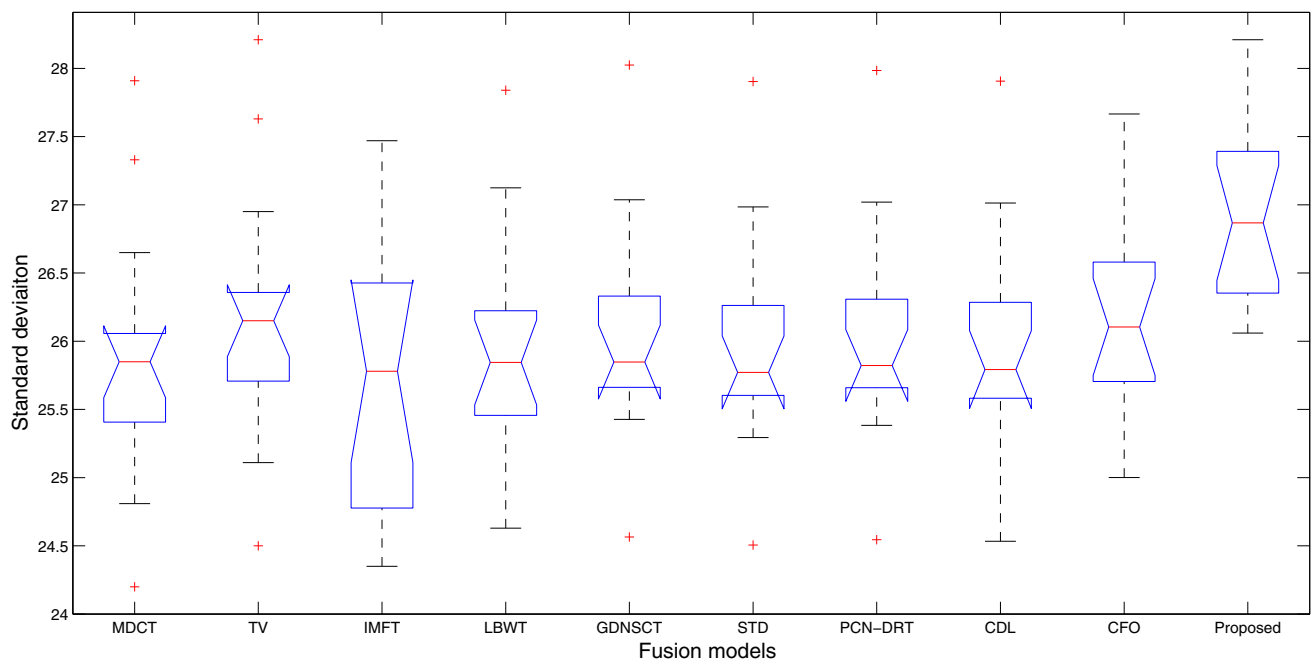


Fig. 6 Standard deviation analysis of the proposed model

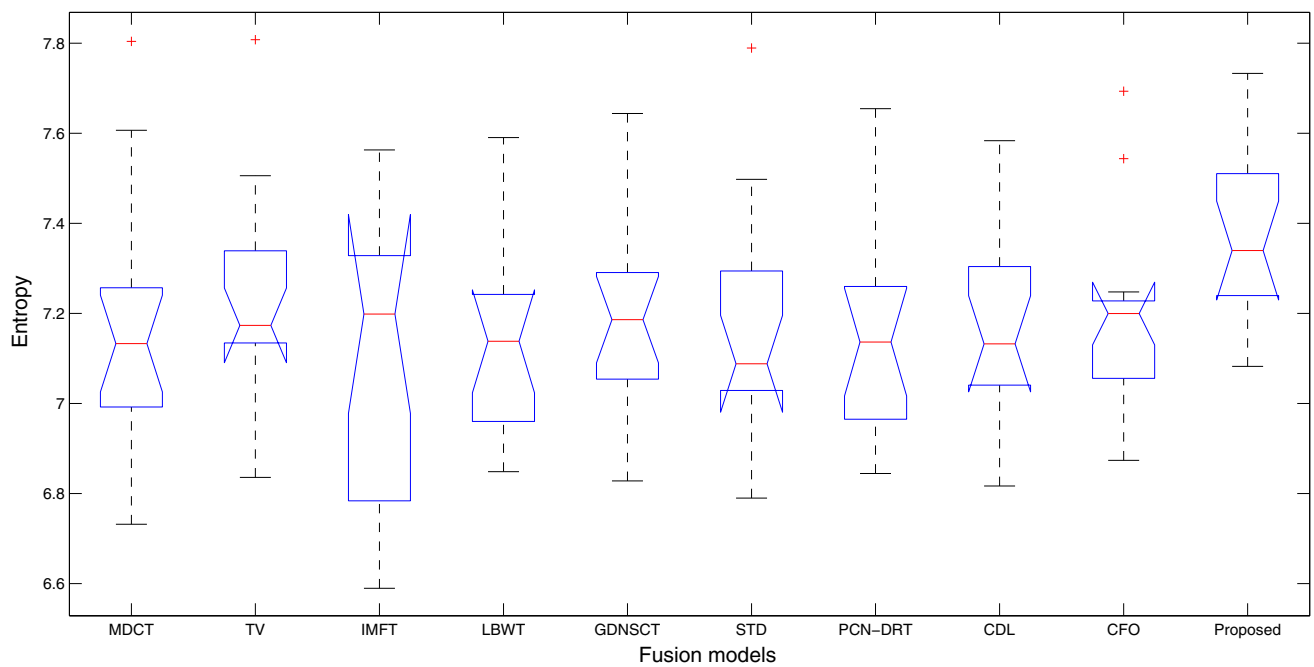


Fig. 7 Entropy analysis of the proposed model

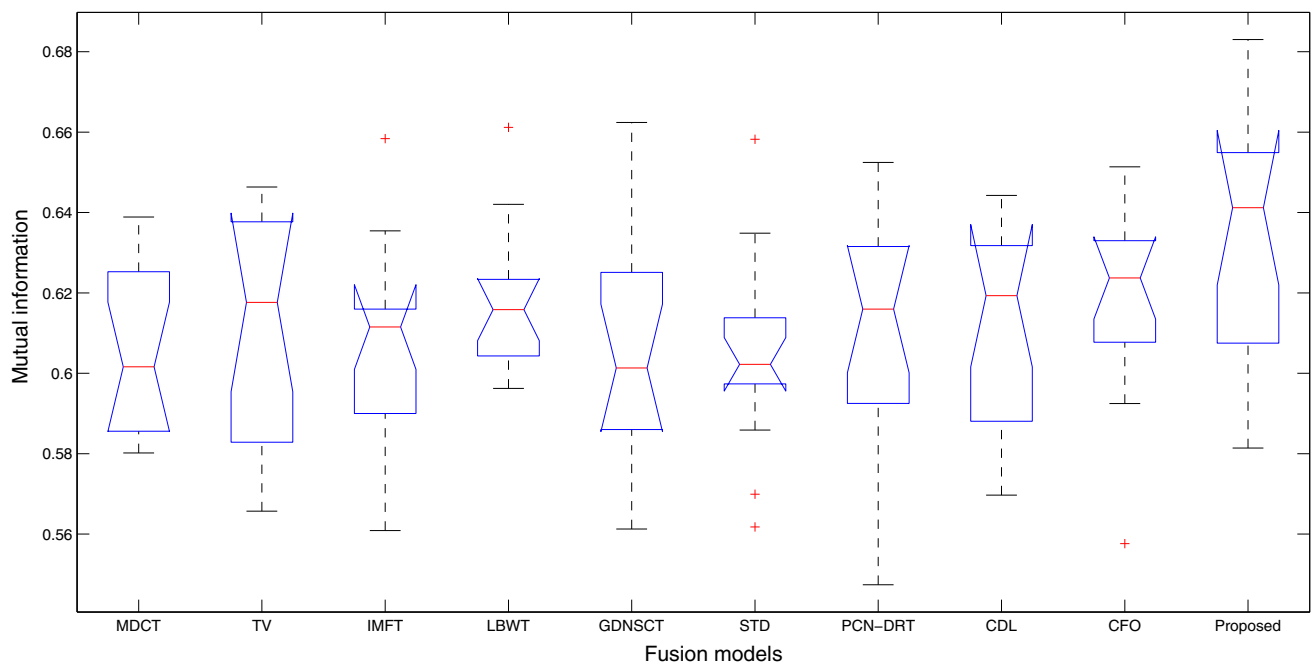


Fig. 8 Mutual information analysis of the proposed model

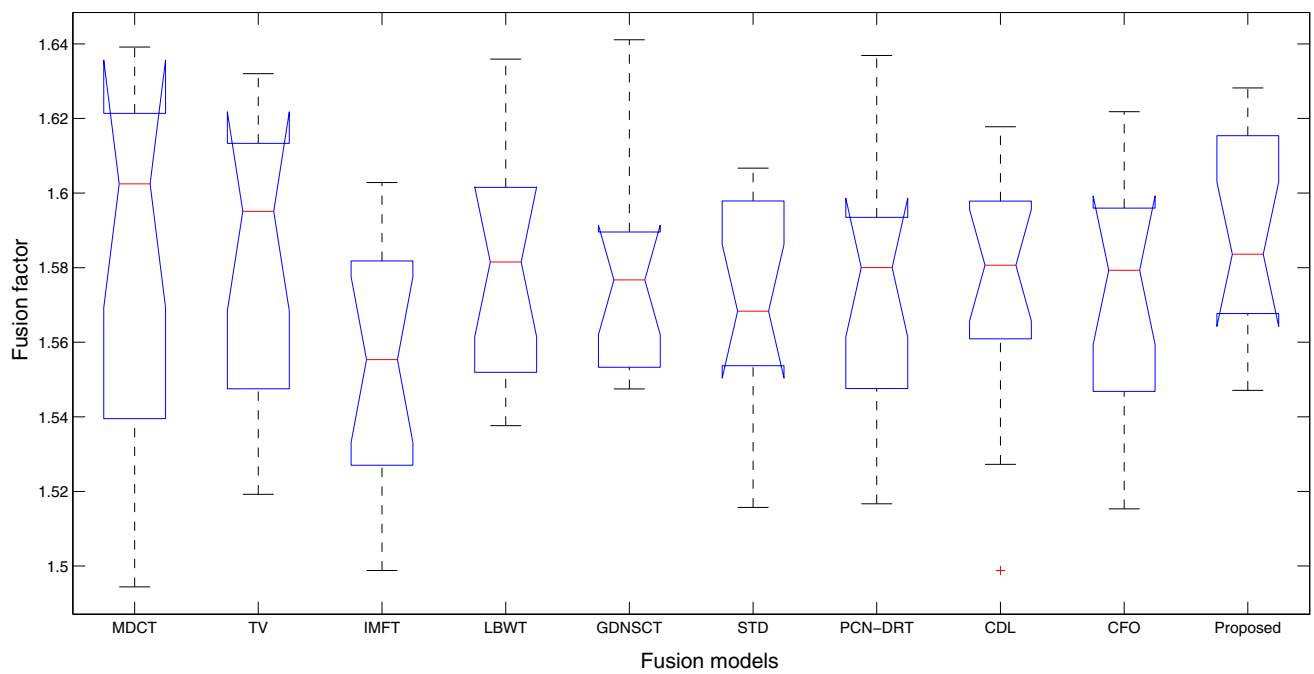


Fig. 9 Fusion factor analysis of the proposed model

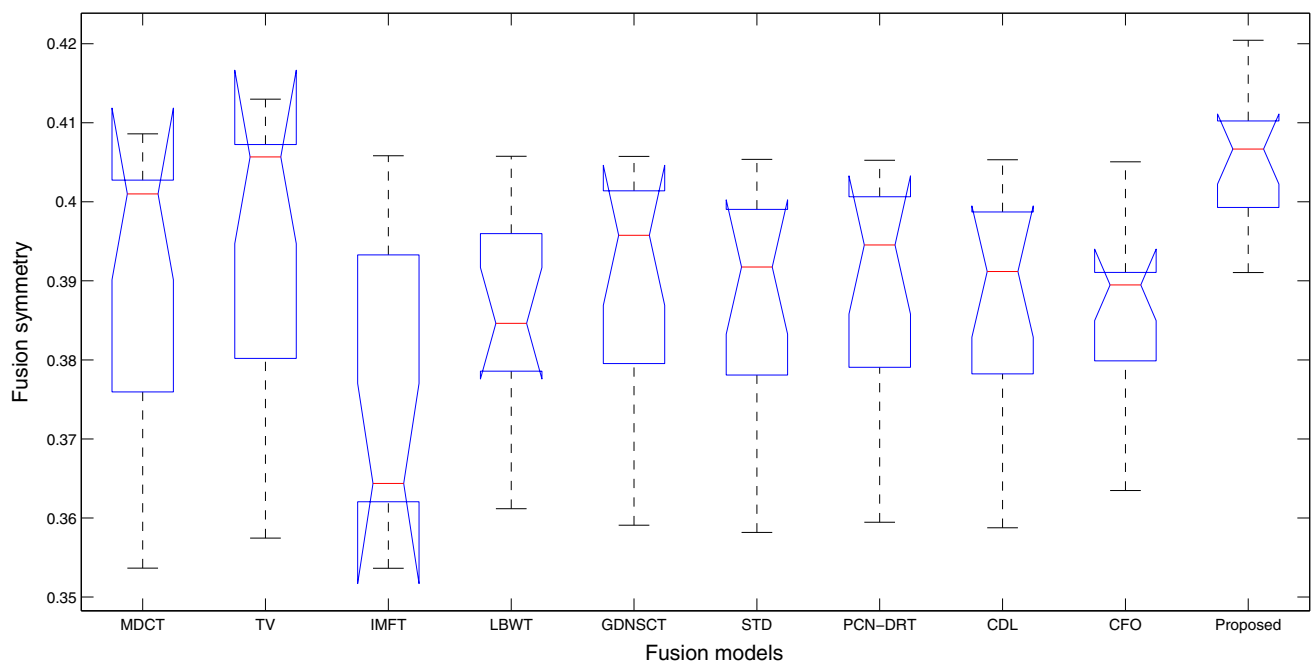


Fig. 10 Fusion symmetry analysis of the proposed model

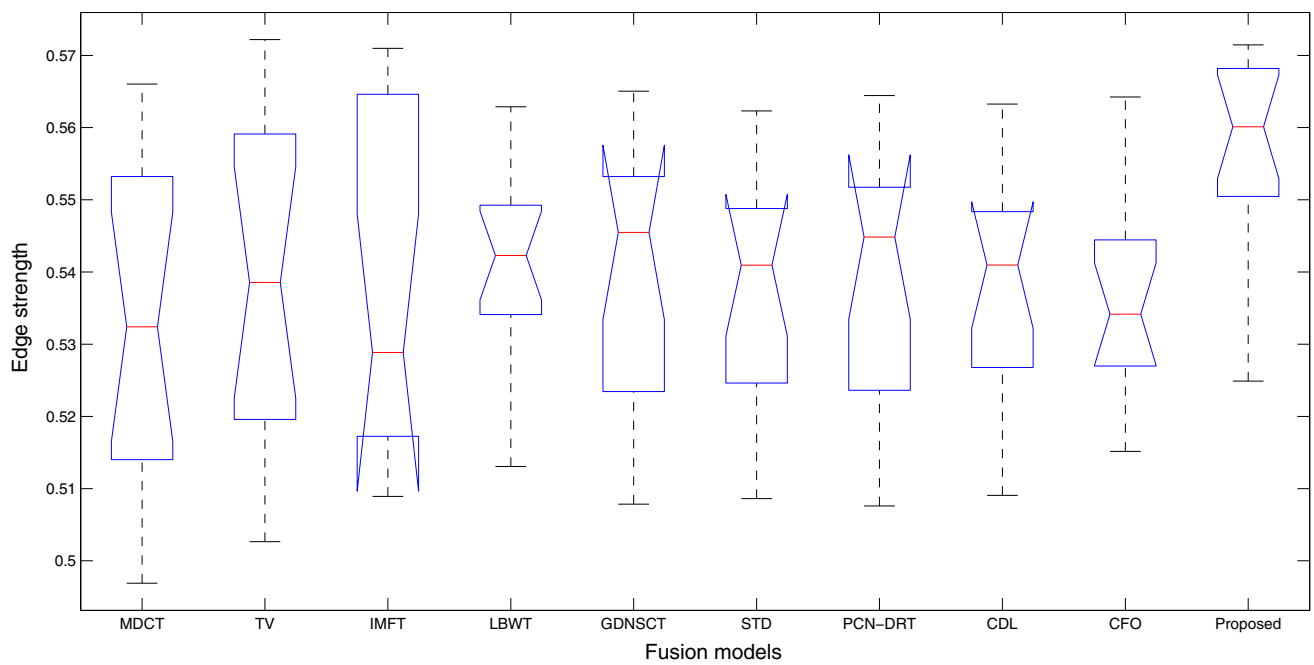


Fig. 11 Edge strength analysis of the proposed model

5 Conclusion

An efficient medical image fusion framework was designed and implemented for multi-modal medical images. The modality-level features within every modality were considered along with their respective inter-modalities similarities. A layer-wise fusion approach was implemented to combine various modalities within various characteristic layers. However, the proposed multi-modality image fusion model suffers from hyper-parameters tuning issue. A MDE was utilized to optimize the initial parameters of the proposed model. Fusion factor and edge strength metrics were used to design a multi-objective fitness function. Both quantitative and qualitative analyses were drawn to evaluate the significant improvement of the proposed technique than the nine competitive fusion models over fifteen benchmark images. The proposed model has achieved average improvement in terms of standard deviation, entropy, mutual information, fusion factor, fusion symmetry and edge strength over the existing proposed model models as 1.3827%, 1.2616%, 1.2756%, 1.2947%, 1.2183% and 1.2137%, respectively.

In near future, the proposed model can be extended by using the concept of deep federated learning models as deep federated learning models can train a more generalized model by sharing the network weights with other organizations without sharing the data itself. Additionally, instead of using the existing metaheuristic technique a novel technique can be designed to automate the hyper-parameters of the proposed model.

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Data Availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare no conflict of interest regarding the publication of this paper.

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