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Multimodal Medical Image Fusion based on Deep Learning Neural Network for Clinical Treatment Analysis

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Abstract : Multimodal medical image fusion technique is one of the most significant and useful disease investigative techniques by deriving the complementary information from different multimodality medical images. This research paper, proposed an efficient multimodal medical image fusion approach based on deep learning convolutional neural networks (CNN) for fusion process. Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Positran Emission Tomography (PET) are the input multimodality medical images used for the experimental work. In the proposed technique, a siamese convolutional network is adopted to create a weight map which integrates the pixel movement information from two or more multimodality medical images. The medical image fusion process is carried out in a multiscale manner via medical image pyramids to be more reliable with human visual insight. In addition, a local comparison based strategy is applied to adaptively correct the fusion mode for the decomposed coefficients. An experimental result of proposed fusion techniques provides the best fused multimodal medical images of highest quality, shortest processing time and best visualization in both visual quality and objective assessment criteria.
Keywords : Multimodal Medical image fusion, deep learning, siamese convolutional network, CNN, CT, MRI and PET.

1. Introduction

In recent years, the study of pixel level image fusion has lasted for more than 30 years, during which around 1k of related scientific papers have been published. Currently deep learning (DL) has gained many breakthroughs in various computer vision and image processing problems, such as classification, segmentation, super-resolution, etc. In the field of image fusion, the study based on deep learning has also become an active topic in the last three years. A variety of DL-based image fusion methods have been proposed for digital photography (e.g., multi-focus image fusion, multi-exposure image fusion), multi-modality imaging (e.g., medical image fusion, infrared/visible image fusion). Continual development of medical imaging and information processing technologies provides several types of pixel level image fusion using multimodal medical images for clinical disease analysis, multi focus images for digital photography and remote sensing satellite images for concealed weapon detection. Image fusion is the mixture of two or more different images to form a novel image by using certain techniques. It is extracting information from multi-source images and improves the spatial resolution for the original multi-spectral image and preserves the spectral information. Image fusion can be classified into three levels Pixel level fusion, Feature level fusion and Decision level fusion. Pixel-level fusion having a large portion of the remarkable data is protected in the merged image. Feature-level fusion performs on feature-by-feature origin, such as edges, textures. Decision-level fusion refers to make a final merged conclusion. The image fusion decrease quantity of information and hold vital data. It make new output image that is more appropriate for the reasons for human/machine recognition or for further processing tasks. Image fusion is classified into two types' single sensor and multi sensor picture combination consolidating the pictures from a few sensors to shape a composite picture and their individual pictures are converged to acquire an intertwined image Ex: Multi focus and Multi Exposure fusion. Multi sensor image fusions merge the images from several sensors to form a composite image and their individual images are merged to obtain a fused image. Ex: medical imaging, military area. Multimodality medical images categorized into several types which include computed tomography (CT),magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), positron emission tomography (PET), ultra sonography (USG), nuclear magnetic resonance(NMR) spectroscopy, single photon emission computed tomography (SPECT), X-rays, visible, infrared and ultraviolet. MRI, CT, USG and MRA images are the structural therapeutic images which afford lofty resolution images. PET, SPECT and functional MRI (fMRI) images are functional therapeutic images which afford low-spatial resolution images with functional information. Anatomical and functional therapeutic images can be incorporated to obtain more constructive information about the same object. Pixel level image fusion reduces storage cost by storing the single fused image instead of multiple-input images. Multimodal medical image fusion uses the pixel level fusion. Multimodal medical Image fusion increases the effectiveness of image-guided disease analysis, diagnoses and the assessment of medical problems. Image fusion having several applications like medical imaging, biometrics, automatic change detection, machine vision, navigation aid, military applications, remote sensing, digital imaging, aerial and satellite imaging, robot vision, multi focus imaging, microscopic imaging, digital photography and concealed weapon detection. A variety of medical image fusion methods have been proposed. Due to the difference in imaging mechanism, the intensities of different source images at the same location often vary significantly. For this reason, most of these fusion algorithms are introduced in a multi-scale manner to pursue perceptually good results.

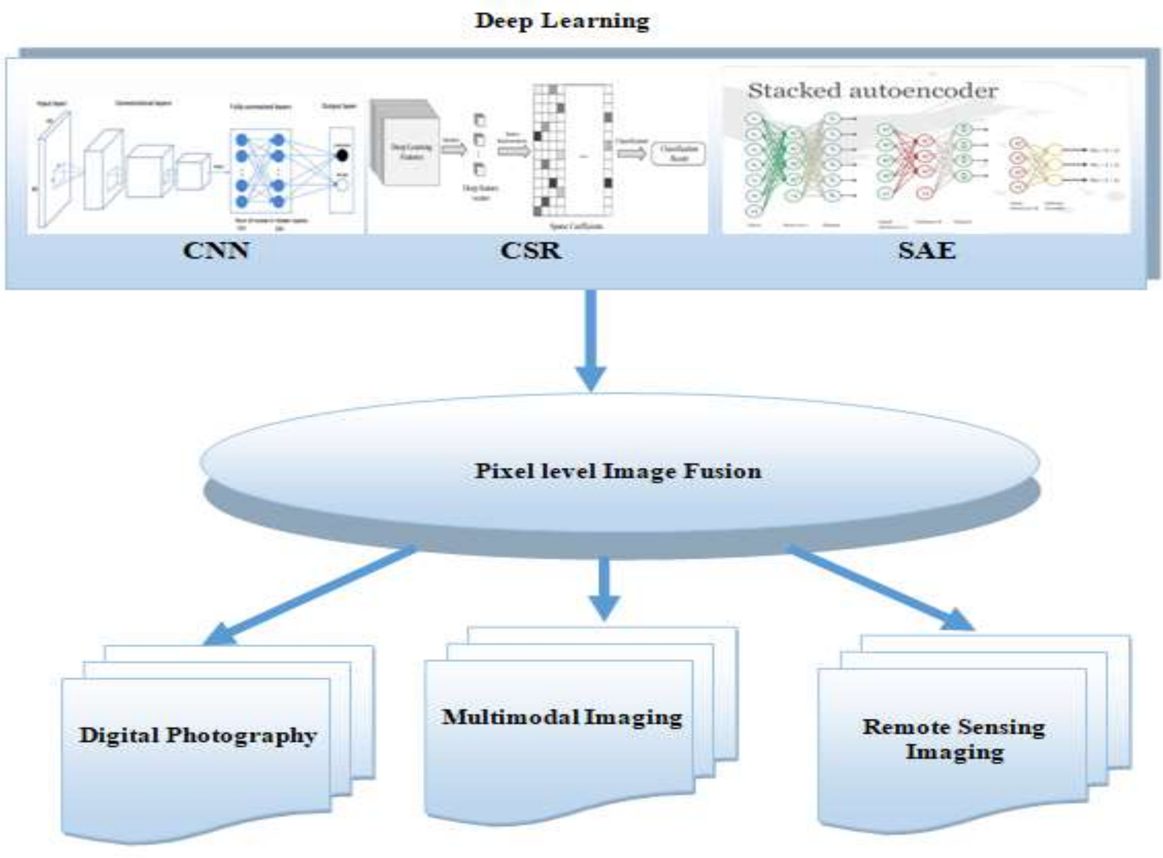


Figure 1: Design of DL based image fusion

3.1 Machine Learning

Machine learning is a subfield of learning representations of data. It is exceptional effective at learning patterns. Machine learning is a field of computer science that gives computers the ability to learn without being explicitly programmed. Most machine learning methods work well because of human-designed representations and input features. ML becomes just optimizing weights to best make a final prediction.

3.2 Deep Learning

Deep learning algorithms attempt to learn (multiple levels of) representation by using a hierarchy of multiple layers. If you provide the system tons of information, it begins to understand it and respond in useful ways. Deep Learning is a set of machine learning algorithms based on multi-layer networks. It is Build features automatically based on training data and combine the feature extraction and classification for different domain. Deep learning (representation learning) seeks to learn rich hierarchical representations (features) automatically through multiple stages of feature learning process.

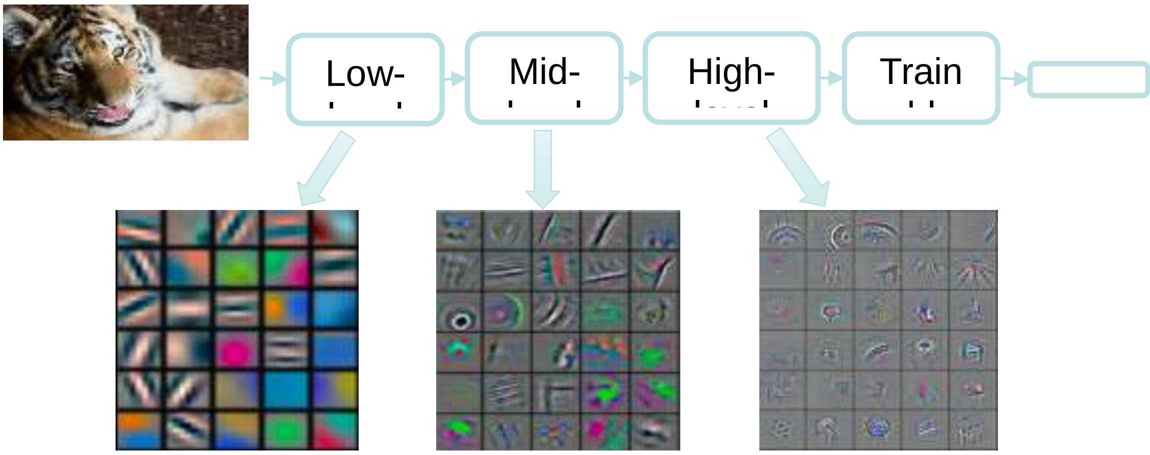


Figure 2: Feature visualization of convolutional net trained on ImageNet

Hierarchy of representations with increasing level of abstraction. Each stage is a kind of trainable nonlinear feature transform

- ❖ Image recognition
  - o Pixel → edge → texton → motif → part → object
- ❖ Text
  - o Character → word → word group → clause → sentence → story

3.2.1 Deep learning classified into three types

(i) Supervised Learning

It is learning with a labeled training set. Example: email *classification* with already labeled emails

- ❖ Convolutional Neural Network
- ❖ Sequence Modelling: RNN and its extensions

(ii) Unsupervised Learning

It is discover patterns in unlabeled data. Example: *cluster* similar documents based on text

- ❖ Autoencoder
- ❖ Stacked Denoising Autoencoder

(iii) Reinforcement Learning

It is learning to act based on feedback/reward. Example: learn to play Go, reward: *win or lose*

- Deep Reinforcement Learning
- Two applications: Playing Atari &AlphaGo

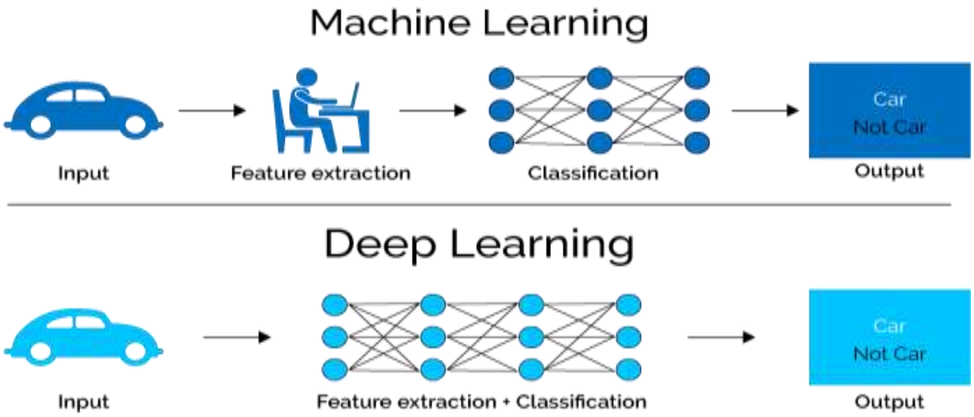


Figure 3: Comparison between machine learning with deep learning

In general, these multi-scales transform (MST)-based fusion methods consist of three steps, namely, decomposition, fusion and reconstruction. Multi-scale transforms which are frequently studied in image fusion include pyramids, wavelets multi-scale geometrical transforms like wavelet, curvelet and shearlet transforms were proposed. In image fusion research, sparse representation is another popular image modelling approach, which has also been successfully applied to fuse multi-modal medical images. One of the most crucial issues in image fusion is calculating a weight map which integrates the pixel activity information from different images. In most existing fusion methods, this target is achieved by two steps known as activity level measurement and weight assignment. In conventional transform domain fusion methods, the absolute value of a decomposed coefficient (or the sum of those values within a small window) is employed to measure its activity, and then a “select-max” or “weighted-average” fusion rule is applied to assign weights to different sources based on the obtained measurement. Clearly, this kind of activity measurement and weight assignment are usually not very robust resulting from many factors like noise, mis-registration and the difference between source pixel intensities. To improve the fusion performance, many complex decomposition approaches and elaborate weight assignment strategies have been recently proposed in the literature. However, it is actually not an easy task to design an ideal activity level measurement or weight assignment strategy which can comprehensively take all the key issues of fusion into account. Moreover, these two steps are designed individually without a strong association by many fusion methods, which may greatly limit the algorithm performance. In this paper, this issue is addressed from another viewpoint to overcome the difficulty in designing robust activity level measurements and weight assignment strategies. Specifically, a convolutional neural network (CNN) is trained to encode a direct mapping from input medical images to the weight map. In this way, the activity level measurement and weight assignment can be jointly achieved in an “optimal” manner via learning network parameters. Considering the different imaging modalities of multi-modal medical images, we adopt a multi-scale approach via image pyramids to make fusion process more consistent with human visual perception. In addition, a local similarity based strategy is applied to adaptively adjust the fusion mode for the decomposed coefficients of input multimodal medicalimages.

The research paper is organized as follows. Sec. 2 describes the literature survey on related works. Sec. 3 discusses the proposed research work method both machine learning and deep learning multimodal medical image fusion techniques. Sec. 4 describes the implemented multimodal medical image fusion experimental results and performance comparative analysis. Finally, Sec. 5 concludes the paper.

2. Related Works

B.Rajalingam, Dr. R.Priya [1] proposed an efficient multimodal therapeutic image fusion approach based on both traditional and hybrid fusion techniques are evaluated using several quality metrics.

B.Rajalingam, Dr. R.Priya [2] Proposed a novel multimodal medicinal image fusion approach based on hybrid fusion techniques. Magnetic resonance imaging, positron emission tomography and single photon emission computed tomography are the input multimodal therapeutic brain images and the curvelet transform with neural network techniques are applied to fuse the multimodal medical image. B.Rajalingam, Dr. R.Priya [3] proposed a novel neuro-fuzzy hybrid multimodal medical image fusion technique to improve the quality of fused multimodality medical image. Yu Liu, Xun Chen, et al [4] proposes the medical image fusion method based on convolutional neural networks (CNNs).Yu Liu, Xun Chen, et al [5] propose the new multi-focus image fusion method based on deep learning approach, aiming to learn a direct mapping between source images and focus map. A deep convolutional neural network (CNN) trained by high-quality image patches and their blurred versions is adopted to encode the mapping. Yu Liu, Xun Chen, et al [6] presents the survey paper on a systematic review of the DL-based pixel-level image fusion literature. Specifically, summarize the main difficulties that exist in conventional image fusion research and discuss the advantages that DL can offer to address each of these problems.DU Chao-ben and GAO She-sheng [7] propose a new all CNN (ACNN)-based multi-focus image fusion method in spatial domain. The main idea is that the max-pooling of CNN is replaced by a convolution layer, the residuals are propagated backwards by gradient descent, and the training parameters of the individual layers of the CNN are updated layer by layer. Satishkumar S. Chavan, Abhishek Mahajan,et al.[8] introduced the technique called Nonsubsampled Rotated Complex Wavelet Transform (NSRCxWT) combining CT and MRI images of the same patient. It is used for the diagnostic purpose and post treatment review of neurocysticercosis. S. Chavan, A. Pawar, et al.[9] innovated a feature based fusion technique Rotated Wavelet Transform and it is used for extraction of edge-related features from both the source modalities. Heba M. El-Hoseny, El-SayedM.El.Rabaie,et al.[10] proposed a hybrid technique that enhance the fused image quality using both traditional and hybrid fusion algorithms(Additive Wavelet Transform and Dual Tree complex wavelet transform. UdhayaSuriya TS, Rangarajan P [11] implemented an innovative image fusion system for the detection of brain tumours by fusing MRI and PET images using Discrete Wavelet Transform. Jingming Yang, YanyanWu, et al.[12] described an Image fusion technique Non-Subsampled Contourlet Transform to decompose the images into lowpass and highpass subbands. C.Karthikeyan, B. Ramadoss[13] proposed the fusion of medical images using dual tree complex wavelet transform and self organizing feature map for better disease diagnosis. Xinzheng Xu, Dong Shana,et al.[14] introduced an adaptive pulse-coupled neural networks, which was optimized by the quantum-behaved particle swarm optimization algorithm to improve the efficiency and quality of QPSO. Three performance evaluation metrics is used. Jyoti Agarwal and Sarabjeet Singh Bedi, et al.[15] innovate the hybrid technique using curvelet and wavelet transform for the medical diagnosis by combining the Computed Tomography image and Magnetic Resonance Imaging.

3. Proposed Research Work

3.1 Convolutional network layer for medical image fusion

Convolutional Neural Networks is extension of traditional Multi-layer Perceptron, based on three ideas: Local receive fields, Shared weights, Spatial / temporal sub-sampling. Input can have very high dimension. Using a fully-connected neural network would need a large amount of parameters. Inspired by the neuro physiological experiments conducted by CNNs are a special type of neural network whose hidden units are only connected to local receptive field. The number of parameters needed by CNNs is much smaller. Three stages of a Convolutional layer

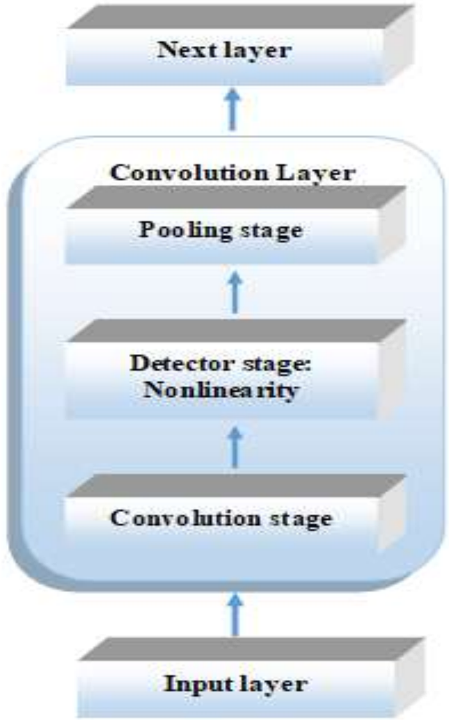


Figure 4: Convolution Layer Terminology

(i) Convolution stage
(ii) Nonlinearity: A nonlinear transform such as rectified linear or tanh
(iii) Pooling: output a summary statistics of local input, such as max pooling and average pooling

3.1.1 Convolution Operation in CNN

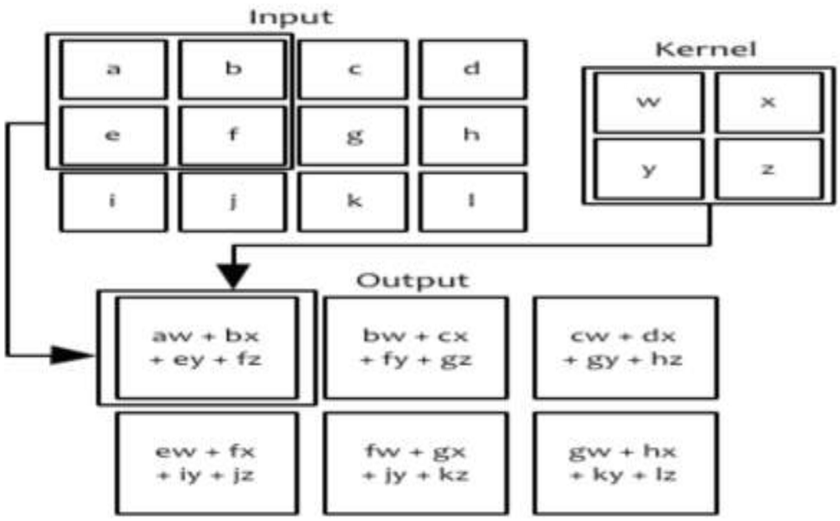
Input: an image (2-D array) x

Convolution kernel/operator (2-D array of learnable parameters): w

Feature map (2-D array of processed data): s

Convolution operation in 2-D domains:

$$C[i,j] = (X * W)[i,j] = \sum_{m=-M}^{M} \sum_{n=-N}^{N} X[i+m, j+n]W[m,n] \quad (1)$$



3.1.2 Multiple Convolutions

Usually there are multiple feature maps, one for each convolution operator.

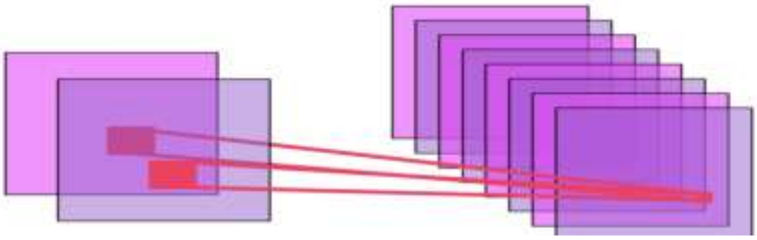
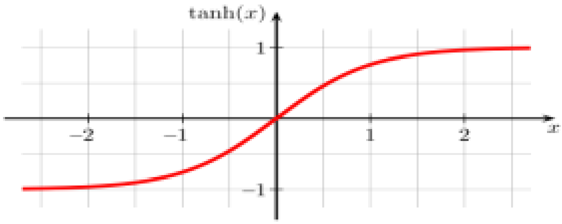
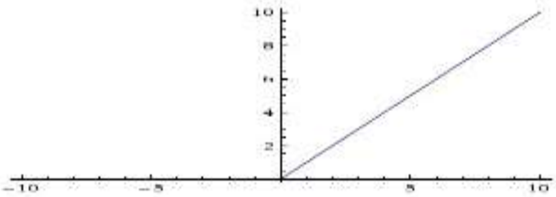


Figure 5: Multiple Convolutions

3.1.3 Non-linearity

Tanh(x) **ReLU**





$$\boldsymbol{tanh}(\boldsymbol{X}) = \frac{\boldsymbol{e}^{\boldsymbol{X}} - \boldsymbol{e}^{-\boldsymbol{X}}}{\boldsymbol{e}^{\boldsymbol{X}} - \boldsymbol{e}^{-\boldsymbol{X}}} \boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{max}(\boldsymbol{0}, \boldsymbol{x})$$

3.1.4 Common pooling operations

- ❖ Max pooling: reports the maximum output within a rectangular neighborhood.
- ❖ Average pooling: reports the average output of a rectangular neighborhood (possibly weighted by the distance from the central pixel).

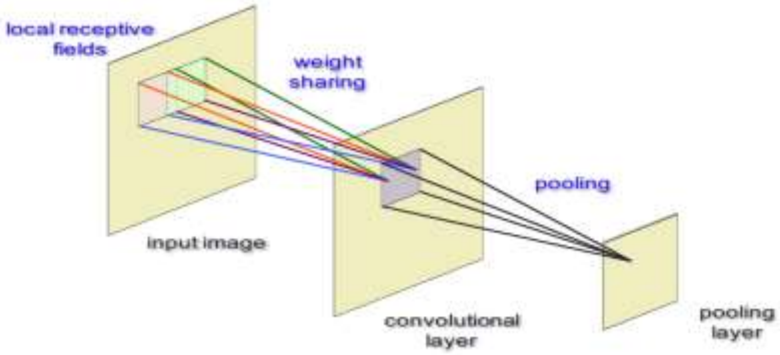


Figure 6: Convolution pooling operations

3.1 5 Uses of deep learning

- ❖ Manually designed features are often over-specified, incomplete and take a long time to design and validate
- ❖ Learned Features are easy to adapt, fast to learn
- ❖ Deep learning provides a very flexible, (almost?) universal, learnable framework for representing world, visual and linguistic information.

- Can learn both unsupervised and supervised
- Effective end-to-end joint system learning
- Utilize large amounts of training data

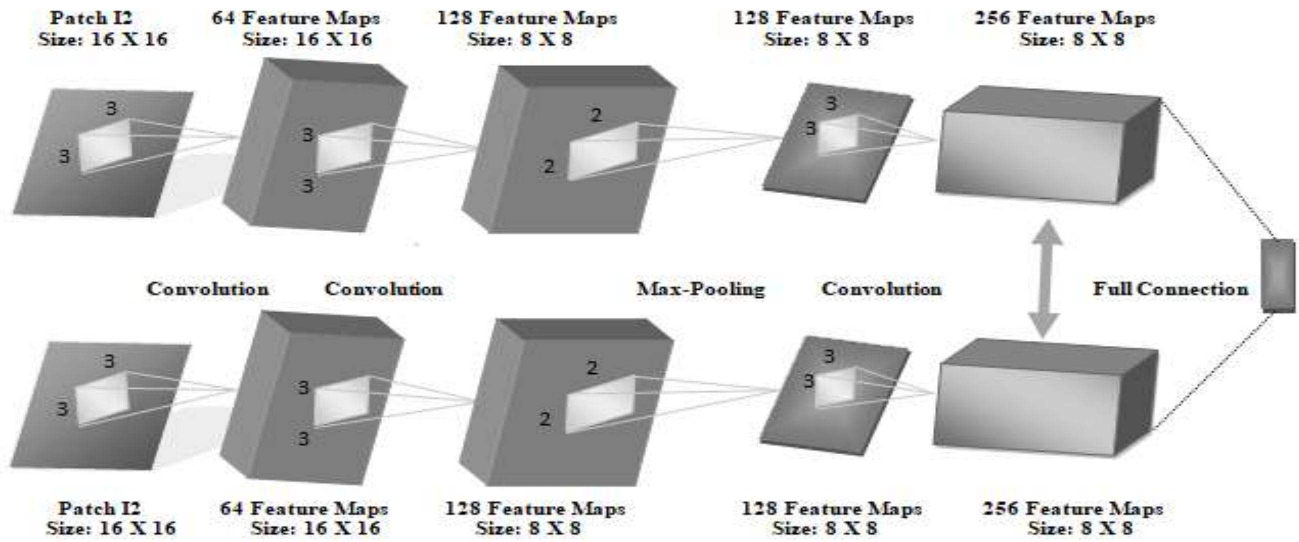


Figure 7: Siamese network architecture for training the input data

The proposed medical image fusion algorithm uses the convolutional neural network showed in figure 7. It is a siamese network in which the weightsof the two twigs are constrained to the same. Each divisionconsists of three convolutional layers and one max-poolinglayer, which is the same as the network used. Toreduce the memory consumption as well as increase thecomputational efficiency, we adopt a much slighter modelin this work by removing a fully-connected layer from thenetwork. The 512 feature maps after concatenationare directly connected to a 2-dimensional vector. It can becalculated that the slight mode only takes up about 1.66 MBof physical memory in single precision, which is significantlyless than the 33.6 MB model employed. Finally, this 2-dimensional vector is fed to a 2-way softmax layer, which produces a probability distribution over twoclasses. The two classes correspond two kinds of normalizedweight assignment results, namely, “first patch 1 and secondpatch 0” and “first patch 0 and second patch 1”, respectively.The probability of each class indicates the possibility of eachweight assignment. In this situation, also considering that thesum of two output probabilities is 1, the probability of eachclass just indicates the weight assigned to its correspondinginput patch.The network is trained by high-quality image patches andtheir blurred versions using the approach. In thetraining process, the spatial size of the input patch is set to16 × 16 according to the analysis. The creation oftraining examples are based on multi-scale Gaussian filteringand random sampling. The softmax loss function is employedas the optimization objective and we adopt the stochasticgradient descent (SGD) algorithm to minimize it. The trainingprocess is operated on the popular deep learning frameworkCaffe. The network has a fully-connected layer that have fixeddimensions (pre-defined) on input and output data, the inputof the network must have a fixed size to ensure that the inputdata of a fully-connected layer is fixed. In image fusion, tohandle input medical images of arbitrary size, one can divide theimages into overlapping patches and input each patch pairinto the network, but it will introduce a large number ofrepeated calculations. To solve this problem, we first convertthe fully-connected layer into a equivalent convolutional layercontaining two kernels of size 8 × 8 × 512. After theconversion, the network can process input medical images of arbitrarysize as a whole to generate a dense prediction map, in whicheach prediction (a 2-dimensional vector) contains the relativeclarity information of a source patch pair at the correspondinglocation. As there are only two dimensions in each predictionand their sum is normalized to 1, the output can be simplifiedas the weight of the first (or second) input. Finally, to obtaina weight map with the same size of input multimodality medical images, assignthe value as the weights of all the pixels within the patchlocation and average the overlapped pixels.

3.2Multimodal Medical Image Fusion Techniques based on deep learning

Multimodality medical image fusion based on machine learning techniques lacks the ability to get high-quality images. So, there is a need to use deep learning fusion techniques to achieve this objective. These deep learning convolution models provide better characterization of input medical images, better handling of curved shapes and higher quality for fused details. The overall advantages of the deep learning techniques are improving the visual quality of the images, and decreasing image artifacts and noise. Each image size is 256*256 dimensions. Figure 8 illustrates the overall Structure of the proposed multimodal medical image fusion algorithm.

3.2.1 Procedural steps for medical image fusion

The fusion method can beprécis as the following four steps.

Stage 1: Generate the weight map using CNN model

Select the two input multimodality medical images X and Y to the two branches of the convolutional network. Generate the weight map using CNN layer.

Stage 2: Decompose the multimodality medical images into pyramids

Perform the decomposition operation on each input multimodality medical image into a Laplacian pyramid. Pyramids of the X and Y denote the $L\{X\}^s$ and $L\{B\}^s$ respectively, where s indicates the decomposition stage. The Gaussian pyramid $G\{WG\}$ decompose the weight map WG. The total decomposition stages of each pyramid is set to the maximum achievable value $\lfloor \log_2 \min(M,N) \rfloor$, where $M \times N$ is the spatial size of input medical images and flooring operation represent the $\lfloor \cdot \rfloor$

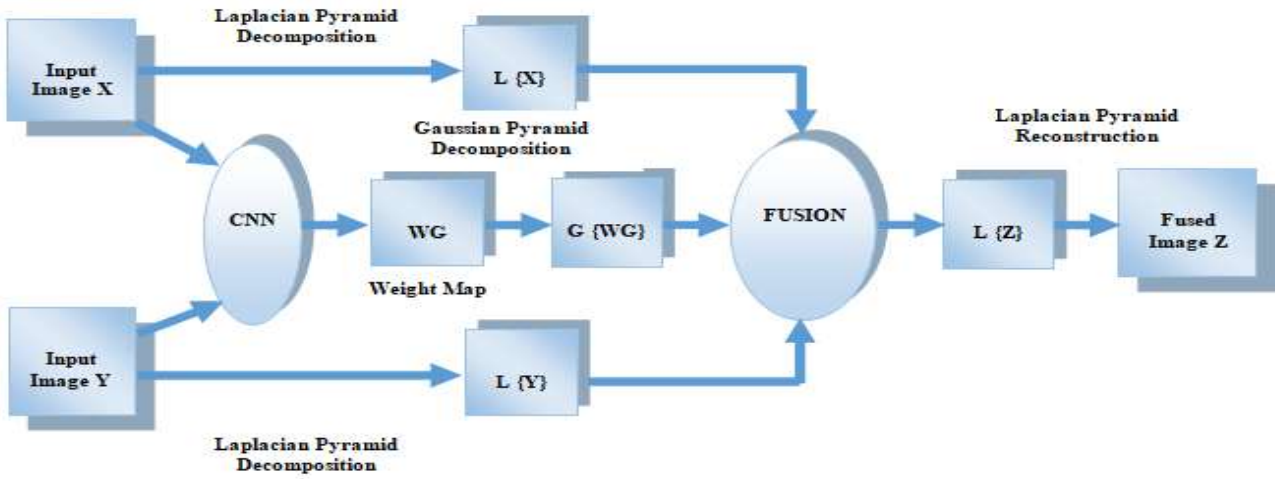


Figure 8: Overall Structure of the Proposed Multimodal Medical Image Fusion Algorithm

Stage 3: Fusing the Coefficients of the input medical images

For every decomposition stage s,evaluate the local energymap of $L\{X\}^s$ and $L\{Y\}^s$, respectively.

$$C_X^s(a,b) = \sum_m \sum_n L\{X\}^s(a+m,b+n)^2 \quad (2)$$

$$C_Y^s(a,b) = \sum_m \sum_n L\{Y\}^s(a+m,b+n)^2 \quad (3)$$

$$L\{Z\}^s(a,b) = \begin{cases} G\{WG\}^s(a,b).L\{X\}^s(a,b) + \left(1 - G\{WG\}^s(a,b)\right).L\{Y\}^s(a,b), \text{if } K^s(a,b) \geq t \\ L\{X\}^s(a,b), \text{if } K^s(a,b) < t \text{ and } C_X^s(a,b) \geq C_Y^s(a,b) \\ L\{Y\}^s(a,b), \text{if } K^s(a,b) < t \text{ and } C_X^s(a,b) < C_Y^s(a,b) \end{cases} \quad (4)$$

The similarity measure used for fusion mode determination iscalculated asthe range of this measure is [-1 1] and a value closer to 1indicates a higher similarity. A threshold t is set to determinethe fusion mode to be used. If $(x,\ y) \geq t$, the “weightedaverage”fusion mode based on the weight map. The fusion strategy can be summarized as a whole shown in

$$K^s(a,b) = \frac{2\sum_m \sum_n L\{X\}^s(a+m,b+n)L\{Y\}^s(a+m,b+n)}{C_X^s(a,b) + C_Y^s(a,b)} \qquad (5)$$

$$L\{Z\}^s(a,b) = G\{WG\}^s(a,b).L\{X\}^s(a,b) + \left(1 - G\{WG\}^s(a,b)\right).L\{Y\}^s(a,b) \quad (6)$$

$$L\{Z\}^s(a,b) = \begin{cases} L\{X\}^s(a,b), \text{if } C_X^s(a,b) \geq C_Y^s(a,b) \\ L\{Y\}^s(a,b), \text{if } C_X^s(a,b) < C_Y^s(a,b) \end{cases} \qquad (7)$$

Stage 4: Reconstruct the medical image using Laplacian pyramid

Reconstruct the merged medical image Z from the Laplacian pyramid

4. Experimental Results and Discussions

The implementations are based on nine sets of input medical images and the proposed deep learning technique is compared with existing different type’s existing machine learning algorithm. The implementation is executed in MATLAB R2015b on windows 7 laptop with Intel Core I5 Processor, 4.0 GB RAM and 500 GB Hard Disk. The processed multimodality medical input images are gathered from harvard medical school [16] and radiopedia.org [17]medical image online database. The size of the image is 256 × 256 for execution process.In the experimentation, five objective fusion metrics which are commonly used in multimodal medical image fusion are implementing to make quantitative and qualitative evaluations.Average Gradient (AG), Standard Deviation (SD),Xydeas and Petrovic Metric ($Q^{AB/F}$), Mutual Information (MI) and Processing Time (PT)[1],[2],[3]. A high score indicates a superior performance for first four metrics and least time is best for final metrics. The proposed multimodal medical image fusion method is compared with other five recently proposed medical image fusion methods, which are the Discrete wavelet transform, discrete cosine transform, curvelet transform, pulse coupled neural network and the guided filtering (GF). The parameters of these five methods are all set to the default values reported in the related publications. In the proposed fusion method, the parameter of threshold t is experimentally set to 0.6 by comparing the visual experience and objective performance using different settings.

4.1 Dataset 1

The MRI and PET are the input images as shown in Figure-9a, b respectively. Figure-9h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-9c, d, e, f and g respectively.

4.2 Dataset 2

The CT and MRI are the input images as shown in Figure-10a, b respectively. Figure-10h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-10c, d, e, f and g respectively.

4.3 Dataset 3

The CT and MRI are the input images as shown in Figure-11a, b respectively. Figure-11h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-11c, d, e, f and g respectively.

4.4 Dataset 4

The MRI and PET are the input images as shown in Figure-12a, b respectively. Figure-12h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-12c, d, e, f and g respectively.

4.5 Dataset 5

The MRI and PET are the input images as shown in Figure-13a, b respectively. Figure-13h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-13c, d, e, f and g respectively.

4.6 Dataset 6

The MRI and PET are the input images as shown in Figure-14a, b respectively. Figure-14h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-14c, d, e, f and g respectively.

4.7 Dataset 7

he MRI and PET are the input images as shown in Figure-15a, b respectively. Figure-15h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-15c, d, e, f and g respectively.

4.8 Dataset 8

The MRI and PET are the input images as shown in Figure-16a, b respectively. Figure-16h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-16c, d, e, f and g respectively.

4.9 Dataset 9

The MRI and PET are the input images as shown in Figure-17a, b respectively. Figure-17h is the fused final output image of the proposed technique. The Existing techniques are DWT, DCT, CVT, GF and PCNN outputs as shown in Figure-17c, d, e, f and g respectively.

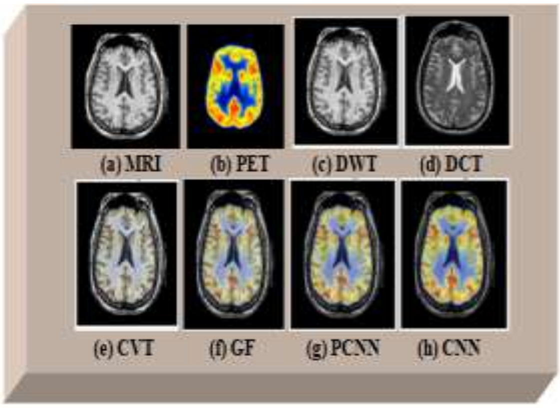


Figure 9: Experimental Results Dataset 1

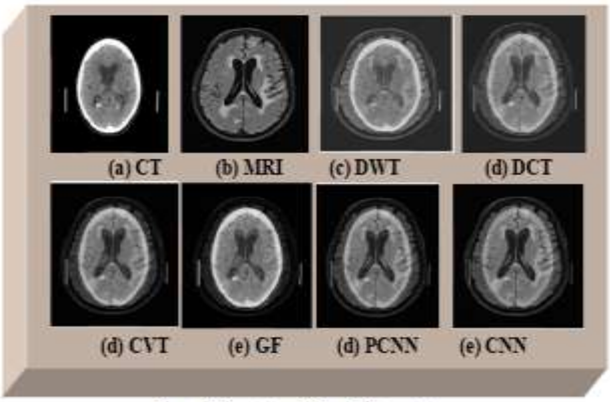


Figure 10: Experimental Results Dataset 2

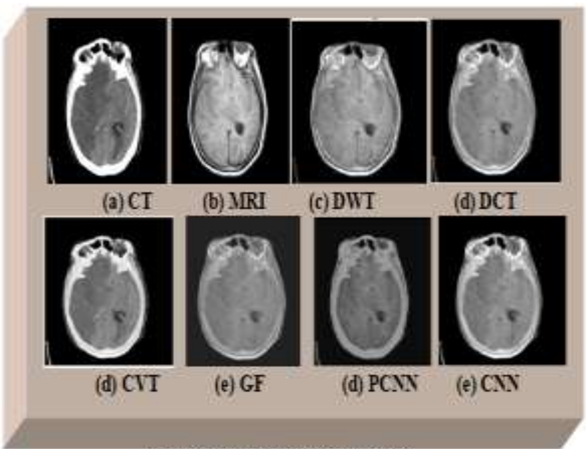


Figure 11: Experimental Results Dataset 3

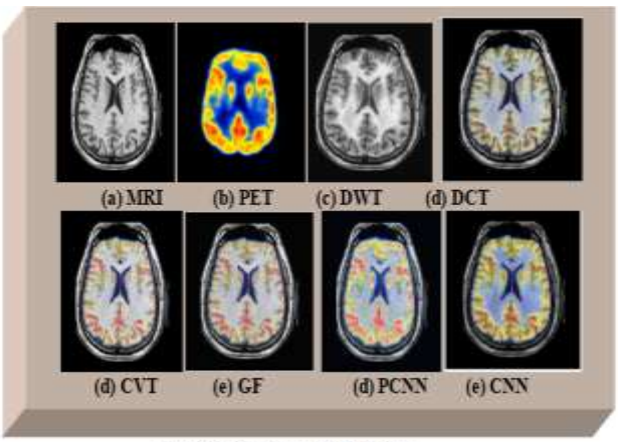


Figure 12: Experimental Results Dataset 4

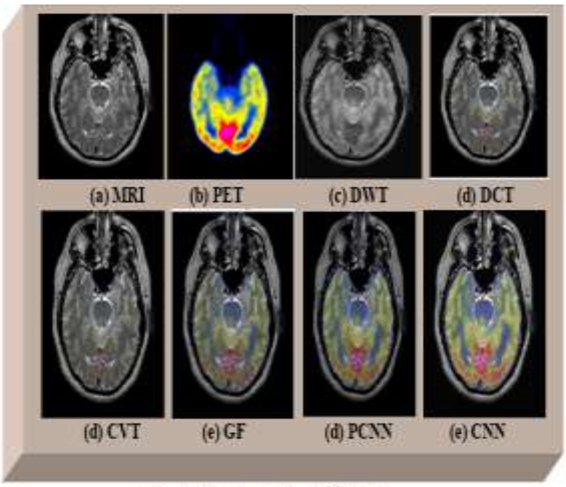


Figure 13: Experimental Results Dataset 5

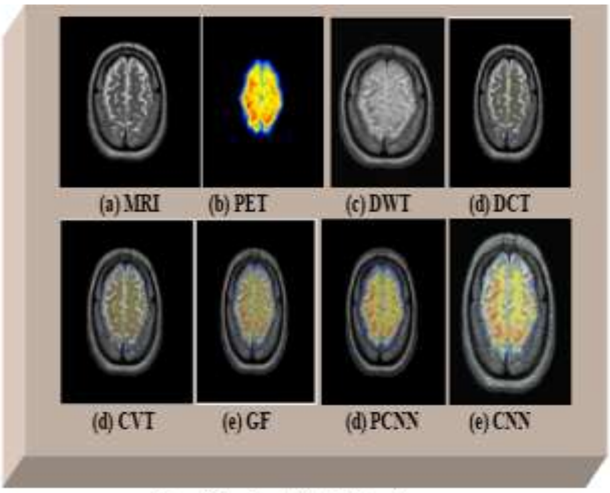


Figure 14: Experimental Results Dataset 6

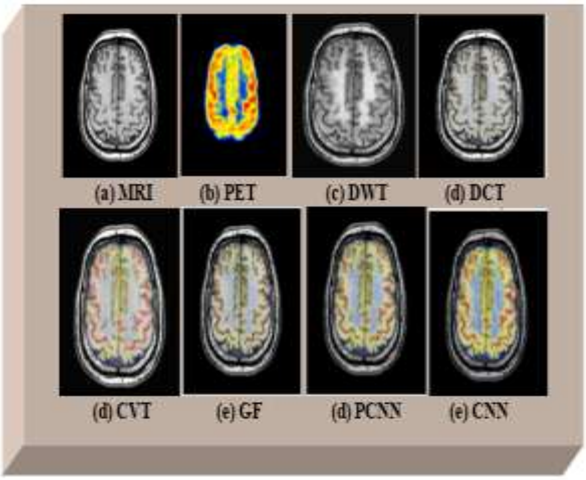


Figure 15: Experimental Results Dataset 7

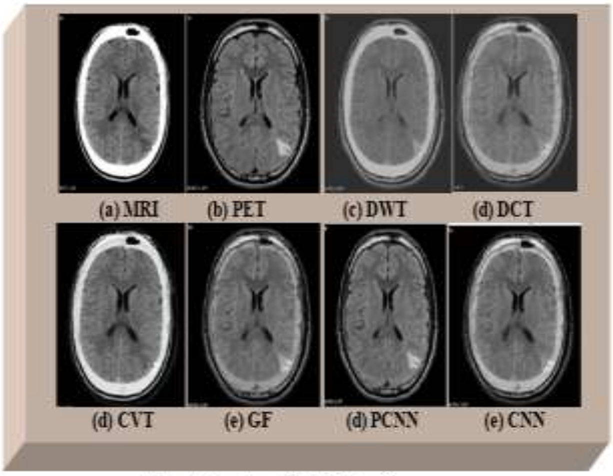


Figure 16: Experimental Results Dataset 8

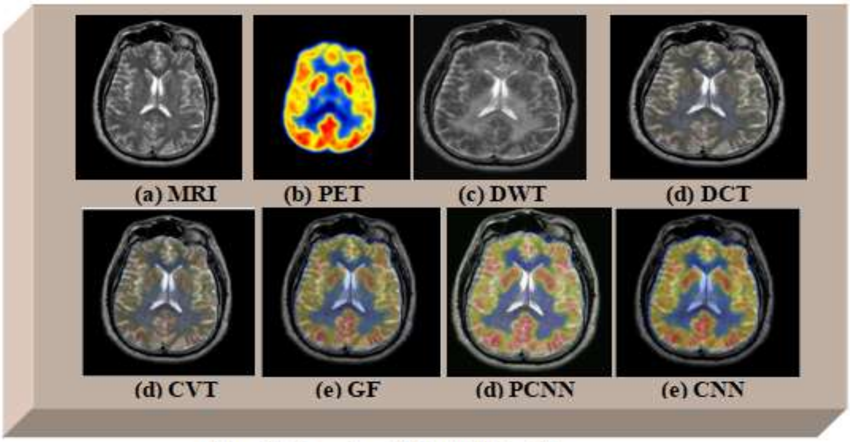
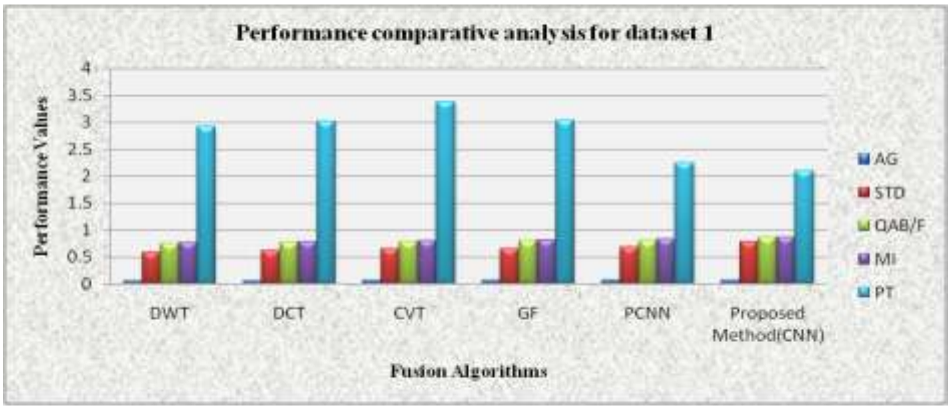


Figure 17: Experimental Results Dataset 9

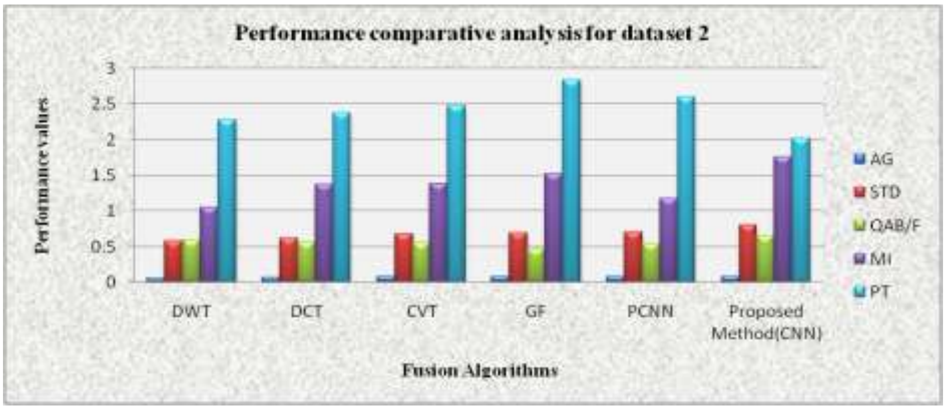
Table1: Performance Metrics values obtained from different multimodal medical image fusion techniques

Method	Metrics	DWT	DCT	CVT	GF	PCNN	Proposed Method(CNN)
Dataset 1	**AG**	0.0653	0.0647	0.0691	0.0701	0.0729	**0.0844**
	STD	0.5850	0.6217	0.6484	0.6586	0.6868	**0.7782**
	$Q^{AB/F}$	0.7491	0.7618	0.7811	0.7965	0.8015	**0.8662**
	MI	0.7641	0.7891	0.7937	0.8134	0.8276	**0.8735**
	PT	2.917sec	3.012 sec	3.382sec	3.032 sec	2.253 sec	**2.094 sec**
Dataset 2	**AG**	0.0627	0.0692	0.0795	0.0828	0.0848	**0.0822**
	STD	0.5791	0.6182	0.6785	0.6972	0.7023	**0.8031**
	$Q^{AB/F}$	0.5925	0.5639	0.5498	0.4698	0.5386	**0.6524**
	MI	1.0482	1.3724	1.3815	1.5212	1.1733	**1.7621**
	PT	2.276 sec	2.381 sec	2.482 sec	2.832 sec	2.597sec	**2.014 sec**
Dataset 3	**AG**	0.0718	0.0782	0.0801	0.0821	0.0851	**0.0886**
	STD	0.875	0.874	0.889	0.871	0.901	**0.954**
	$Q^{AB/F}$	0.701	0.6916	0.6871	0.6916	0.6981	**0.7172**
	MI	1.1841	1.195	1.271	1.316	1.417	**1.516**
	PT	2.511 sec	3.127 sec	3.216 sec	3.517 sec	2.612 sec	**2.051 sec**
Dataset 4	**AG**	0.0638	0.0751	0.06917	0.0785	0.0812	**0.0893**
	STD	0.782	0.724	0.691	0.748	0.785	**0.8023**
	$Q^{AB/F}$	0.5374	0.5629	0.5672	0.5821	0.5374	**0.6012**
	MI	1.072	1.192	1.269	1.372	1.372	**1.5721**
	PT	3.638 sec	2.493 sec	3.103sec	3.391 sec	2.532 sec	**3.012sec**
Dataset 5	**AG**	0.0716	0.0731	0.0765	0.0783	0.0803	**0.0835**
	STD	0.6822	0.6944	0.7013	0.7183	0.7262	**0.7514**
	$Q^{AB/F}$	0.6510	0.6815	0.6916	0.7016	0.6984	**0.7327**
	MI	0.9861	0.9915	1.016	1.162	1.217	**1.374**
	PT	2.217sec	2.315 sec	2.517sec	2.816sec	2.165 sec	**2.016 sec**
Dataset 6	**AG**	0.0727	0.0792	0.0799	0.0801	0.0815	**0.0831**
	STD	0.6151	0.6262	0.6410	0.6851	0.7161	**0.7915**
	$Q^{AB/F}$	0.6150	0.5916	0.6271	0.5998	0.6017	**0.6251**
	MI	1.2512	1.2161	1.3711	1.2716	1.5211	**1.6821**
	PT	2.612 sec	2.326 sec	2.016 sec	2.521 sec	2.032sec	**1.962 sec**
Dataset 7	**AG**	0.0638	0.0751	0.0778	0.0785	0.0842	**0.08945**
	STD	0.782	0.724	0.697	0.798	0.793	**0.8023**
	$Q^{AB/F}$	0.5319	0.5629	0.5721	0.5723	0.5612	**0.5872**
	MI	1.034	1.178	0.9987	1.381	1.8816	**1.2451**
	PT	3.869 sec	2.393 sec	2.579 sec	3.263 sec	2.572 sec	**2.127 sec**
Dataset 8	**AG**	0.0757	0.0797	0.0791	0.0801	0.0829	**0.0874**
	STD	0.6350	0.6517	0.6684	0.6986	0.7068	**0.7231**
	$Q^{AB/F}$	0.6481	0.6824	0.6915	0.7163	0.7317	**0.7517**
	MI	0.7172	0.7261	0.7416	0.7816	0.7916	**0.8026**
	PT	2.751sec	3.065 sec	3.271sec	3.086 sec	2.871 sec	**2.172 sec**
Dataset 9	**AG**	0.0779	0.0758	0.0846	0.0841	0.0813	**0.0893**
	STD	0.935	0.963	0.987	0.927	0.938	**0.998**
	$Q^{AB/F}$	0.6718	0.6471	0.6921	0.6724	0.6619	**0.7832**
	MI	1.1691	1.0162	1.5821	1.3216	1.5271	**1.4351**
	PT	2.472 sec	3.372 sec	3.182 sec	3.582 sec	2.672 sec	**2.274 sec**

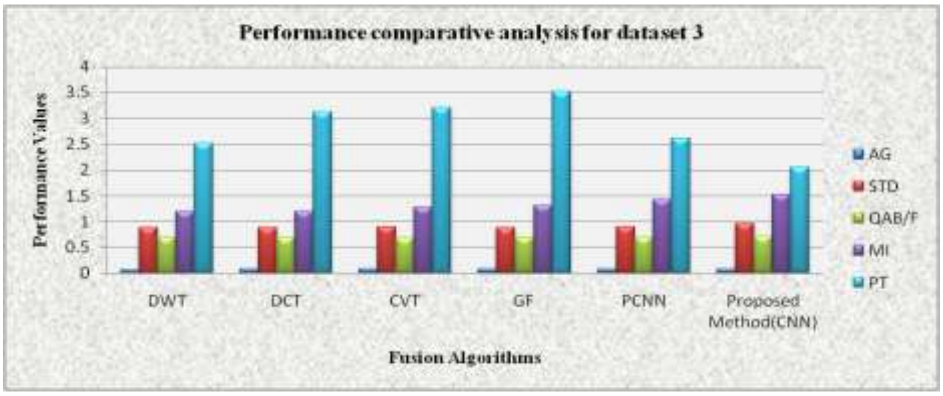
(A)


Performance comparative analysis for dataset 1
Performance Values
4
3.5
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

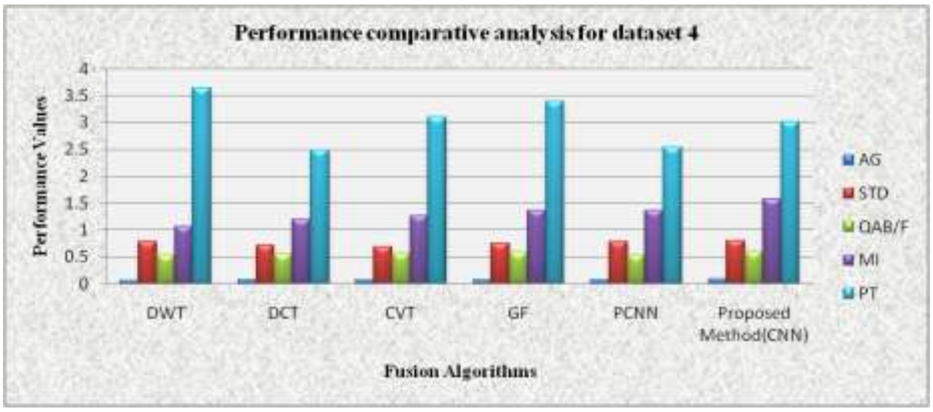
(B)


Performance comparative analysis for dataset 2
Performance values
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

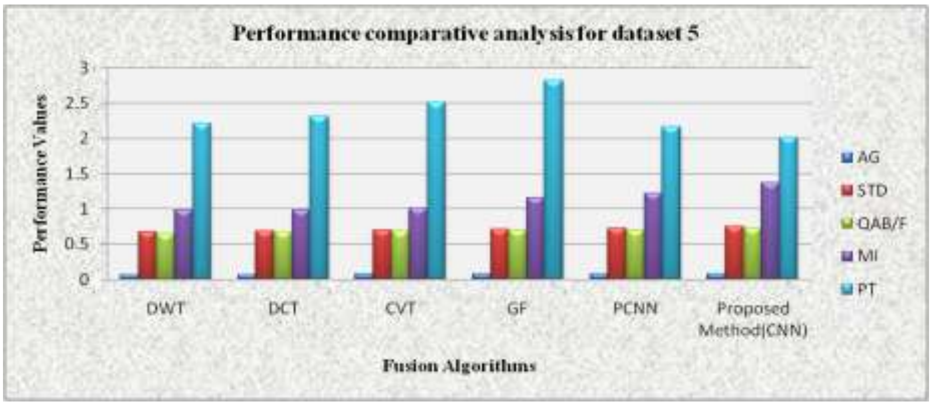
(C)


Performance comparative analysis for dataset 3
Performance Values
4
3.5
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

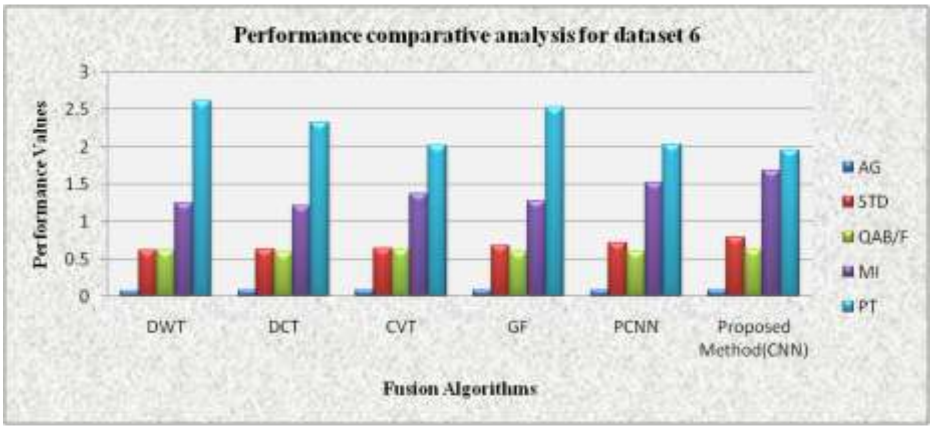
(D)


Performance comparative analysis for dataset 4
Performance Values
4
3.5
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

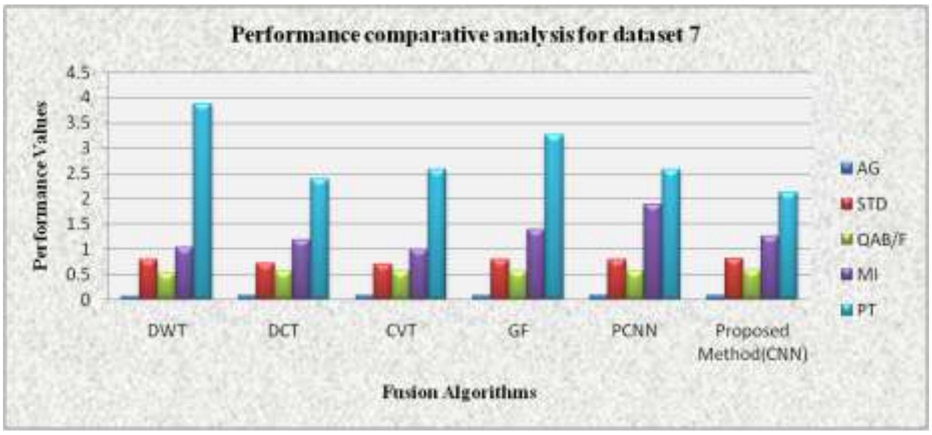
(E)


Performance comparative analysis for dataset 5
Performance Values
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

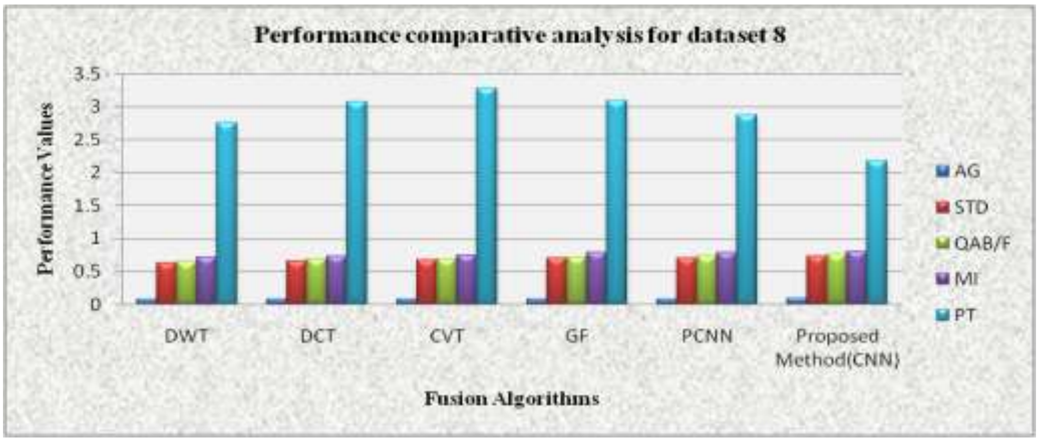
(F)


Performance comparative analysis for dataset 6
Performance Values
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

(G)


Performance comparative analysis for dataset 7
Performance Values
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
DWT
DCT
CVT
GF
PCNN
Proposed Method(CNN)
Fusion Algorithms
AG
STD
QAB/F
MI
PT

(H)



(I)

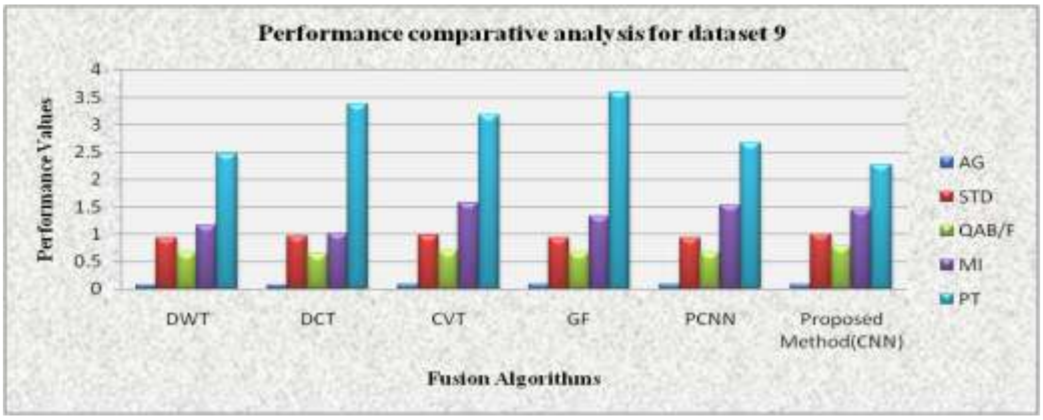


Figure 18(A-I): Comparative analysis for experimented medical images performance metrics

The Table 1 demonstrates the performance metrics of the traditional machine learning fusion algorithms and proposed deep learning fusion algorithm on the dataset 1 to 9. To evaluate the performance of the proposed image fusion approach CT, MRI and PET image are selected as the input medical images. It can be seen that because of different imaging standards, the input images with various modalities contain integral data. The performance metrics are compared with the traditional methods like Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Curvelet Transform, Guided Filtering and Pulse Coupled Neural Network (PCNN) to the KNN deep learning algorithm. The evaluations of performance metrics for deep learning techniques results are better than other existing techniques. By means of objective criteria analysis, the proposed algorithm not only preserves edge information but also improves the spatial detail information. Therefore, the proposed method of multimodal medical image fusion is an effective method in both subjective and objective evaluation criterion. The experimental results are shown in Figure 9 to 17.Note that the better performance value in each column of Table 1 is shown in bold. The graphs for all the values of Table 1 are shown in the Figure 18 (A – I). From the Table 1 and Figure 18 (A-I), it is clear the proposed technique outperform the existing techniques for all the performance metrics.

5. Conclusion

In this paper, a multimodal medical image fusion method based on convolutional neural networks is proposed. Implemented siamese network to generate a direct mapping from input multimodal medical images into a weight map which contains the integrated pixel activity information. The main novelty of this approach is it can jointly implement activity level measurement and weight assignment via network learning, which can overcome the difficulty of artificial design. To achieve perceptually good results, some popular techniques in medical image fusion is proposed. All these advantages the proposed method is a good choice for several applications such as medical disease analysis for an accurate treatment. Experimental results demonstrate thatthe compared with other existing techniques the proposed technique gives the better processing performance and results in both subjective and objective evaluation criteria. In addition to the proposed algorithm itself, another contribution of this research work is that it exhibits the great potential of some deep learning techniques for medical image fusion, which will be further examined in the future.

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