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RESEARCH ARTICLE

TWO SCALE DECOMPOSITION BASED MULTI MODEL MEDICAL IMAGE FUSION USING DEEP LEARNING

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Abstract

Medical image fusion is the process of combining information from several imaging modalities to improve the accuracy of diagnoses. In this study, we present an innovative method for multi-modal medical picture fusion that integrates a two-scale decomposition strategy with deep learning. The method breaks down input images into low- and high-frequency parts to keep both big structural elements and little details from diverse types of imaging, such MRI, CT, and PET. Low-frequency components capture the overall shape of the body, whereas high-frequency components save important textures and edges. We use deep convolution neural networks (CNNs) and attention processes to automatically figure out the best way to combine different types of information at each scale. This makes sure that the information is integrated correctly. The treated parts are put together to make the fused image, then post-processing methods are utilize to make the image better. We use the best parts of both scale decomposition and deep learning to make multi-model picture fusion work better by adding more structural detail and reducing noise. The proposed method works better than traditional fusion methods, as shown by experimental findings that show better image quality and more accurate diagnostic information. This method has a lot of potential for use in medicine, where high-quality, multi-modal images are very important for making educated choices.

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Introduction:-

In the last several years, medical image fusion has become an important tool for diagnosing and planning treatment in the medical industry. Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) are all types of medical imaging that give us different but useful information about the body[1-

8]. But no one type of test can provide you all the diagnostic information you need. So, the goal of multi-model medical image fusion is to combine data from several modalities into one image that is more informative and makes it easier fordoctors to understand.Wavelet transforms, PCA, and sparse representation are some of the traditional picture fusion methods that sometimes have problems like losing detail, having bad contrast, or creating artifact. Two-scale image decomposition has been added as a strong per-processing step to deal with these problems. It breaks an image into low-frequency (base) and high-frequency (detail) parts. This breakdown makes it possible to use more specific and focused fusion procedures that keep both the overall structure and the details of the local area [30-31].Image fusion has gotten a lot better at being automated, flexible, and high quality because to the rise of deep learning, particularly Convolution Neural Networks (CNNs). Deep learning models may learn complex representations and fusion rules directly from data,which means less work for people and better performance across different types of images[32].We suggest a two-scale decomposition-based multi-model medical image fusion system that uses deep learning in this work. The method breaks down each source image into base and detail layers. Then, deep learning-based methods are used to combine the two layers while keeping the structure and fine texture information. By putting the fused parts together, the fused image is rebuilt, which makes .it easier to read the diagnostic information [17-29].

The suggested method uses the best parts of both classic picture decomposition and new deep learning to create fused images with a lot of anatomical and pathological information. This will help doctors make better decisions. The primary function of greedy algorithms is to identify the locally optimal atom with the minimal error by computing the inner product of the residual and the atom during each iteration of the algorithm, thereafter estimating the coefficients of the atoms to progressively approximate the original signal. Some classic algorithms are the orthogonal matching pursuit (OMP) [9], the subspace pursuit (SP) [10], and the compressive sampling MP (CoSaMP) [11]. The complexity of this kind of technique is low, however the signal reconstruction quality is not great. To get an approximation of the signal, convex optimization methods turn non-convex issues into convex problems. There are many other types of algorithms, such as the alternate direction method of multipliers (ADMM) [12] and the iterative soft thresh-holding algorithm (ISTA) [13]. Convex optimization methods are a little more complicated than greedy algorithms, but they do a better job at reconstructing signals. Bayesian reconstruction algorithms use statistical prior information about the signal, probabilistic inference, and soft decision-making techniques to guess what the original signal was. This kind of algorithm uses Bayesian inference methods to find the best signal estimate by modeling the distribution of signals and observation noise. When the signal's statistical properties are understood, Bayesian-based sparse reconstruction approaches can give better results. The approximation message passing (AMP) [14], the Bayesian CS algorithm (BCS) [15], and the fast Bayesian matching pursuit algorithm (FBMP) [16] are all examples of algorithms. This kind of method has a better signal reconstruction quality, but it is also more complicated.

Preliminaries:

A.CNN:

In the suggested design of image Compressed Sensing using The flow chart indicates that Deep Learning and Convolutional Neural Networks (CNNs) are particularly important for putting the Base Component of the picture back together. A Convolutional Neural Network (CNN) is a sort of deep learning architecture that is designed specifically for images.It has convolutional, activation, and pooling layers that learn spatial features like edges, textures, and patterns on their own. Conventional compressed sensing approaches rely on repetitive optimization, whereas CNNs provide a direct mapping from compressed data to reconstructed outputs, making recovery faster and more accurate. The main paper, "Image Compressed Sensing: From Deep Learning to Adaptive Learning," says that CNNs use spatial correlations in natural images to keep the overall structure intact while reducing noise. This creates a reliable Fixed Base that is then combined with detail components for better image reconstruction.

Datasets:-

Image fusion is more significant now since combining multi-modal pictures has several benefits. The following data sets were used in this study: MRI - MRA and CT - MRI. There are a lot of details in medical photos: CT (Computerized Tomography) scans can find extremely minor changes in tissue contrast and give information about bones and other dense structures. Using a radio frequency signal and a magnetic field, magnetic resonance imaging (MRI) makes pictures of anatomical structures, disease proximity, and biological capabilities, such as sick soft tissues. Magnetic resonance Angiography (MRA) can quickly find problems with the brain. MRA is a way to take pictures of organs inside the body by recording and saving an electromagnetic wave that the organ makes. MRA is mostly used to find problems in the brain, and its key benefit is that it can tell the difference between healthy and sick tissue. Magnetic resonance can look at both large and small joints in the body. Magnetic resonance imaging can look at organs like the liver, pancreas, spleen, and kidneys to see if there is depression in the stomach. Combining CT-MRI and MRI-MRA [9] makes clinical data better. A single image cannot communicate everything. Multi modal medical image fusion is needed to combine all the necessary data. So, data helps doctors find things that are wrong.

Proposed work:-

This section describes the CNN-based bounded measured Deep learning set method for multimodal medical picture fusion.

System model:-

The suggested (CNN,Deep learning) algorithm system model stages are below:

Take the two images to be fused as image1 and image 2.

Apply 2-Scale decomposition above images. The resultant images are base & detailed images

2-D[Images] = [Base 1, Detail 1]--------(1)

2-D[Images] = [Base 2, Detail 2]--------(2)

Apply CNN on both base images of image 1 and image 2. the resultant image fused base image

Fused base = base 1 + base 2----------(3)

Apply max filter on detailed images of detail 1 & detail 2 two obtain final fused details

Fused deatail = max[detail 1, detail 2]--------(4)

combine equation (3) & equation (4) to generate final fused image

Fused image = Fused base+ Fused detail----------(5)

Apply performance measure [Mean , STD, Avg] on the above image Equation (5) for qualitative analysis

Working:-

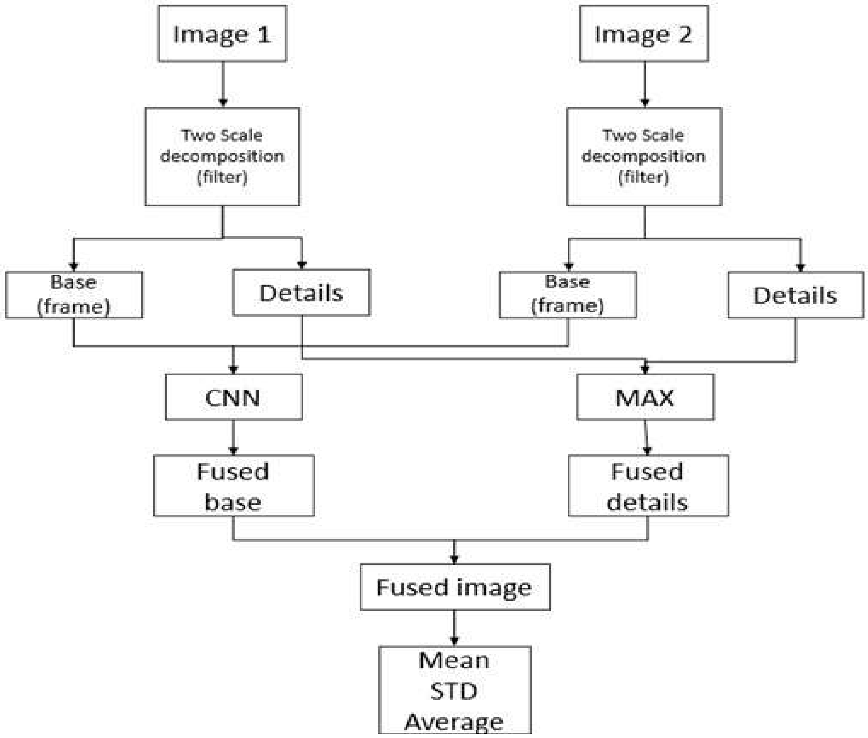
The suggested architecture and framework for the DWT, which is a deep learning algorithm. The fusion algorithm consists of two pairs: deep learning, decomposition with DWT, LF, HF fusion, and finally reconstruction using DWT. The method begins with raw images for deep learning, including CT or MRI scans. After the last phase, a DWT breaks down source images into sub-bands with low and high frequencies. The next phase in the fusion process is to use the average rule for high-frequency sub-bands and the maximum pixel selection rule for low-frequency sub-bands. After the fusion, a reverse DWT is employed to make the final fused picture.

Experimentation and results:-

The experimentation image stage involved a systematic evaluation of diverse image fusion techniques applied to various pairs of medical images, specifically MRI images, CT T1-MR images, and MRA images. The goal was to see how well each method worked to keep the structure intact, improve contrast, and keep diagnostic details. Four fusion methods—Average, PCA, DWT, and the proposed approach termed Our Work—were employed under homogenized prepossessingcircumstances, specifically grayscale transformation, resolution standardization, and intensity standardization. Quantitative measurements of all fused outputs were taken in terms of Mean, Standard Deviation (STD), and Average Gradient (AG) to check for statistical consistency and edge sharpness.

The results indicated that "Our Work" was selected as the best across all metrics and image kinds, exhibiting a higher mean intensity value in publications, improved standard deviation, and excellent gradient responses. This shows that it keeps characteristics better and makes things clearer, which are both important for clinical interpretation. To further support performance analysis, comparative bar graphs were used. Each group of metrics had four analysis bars: Average (blue), PCA (orange), DWT (gray), and Our Work (yellow). These bars showed consistency and interpret-ability in visual representation to make sure that the graphs were consistent and easy to understand. The suggested method demonstrated significant superiority through both numerical indicators and visual analysis, indicating its potential application in real-world medical imaging. The comprehensive assessment of this study systematically confirms the robustness, adaptability, and diagnostic relevance of the developed fusion technique.

Block Diagram



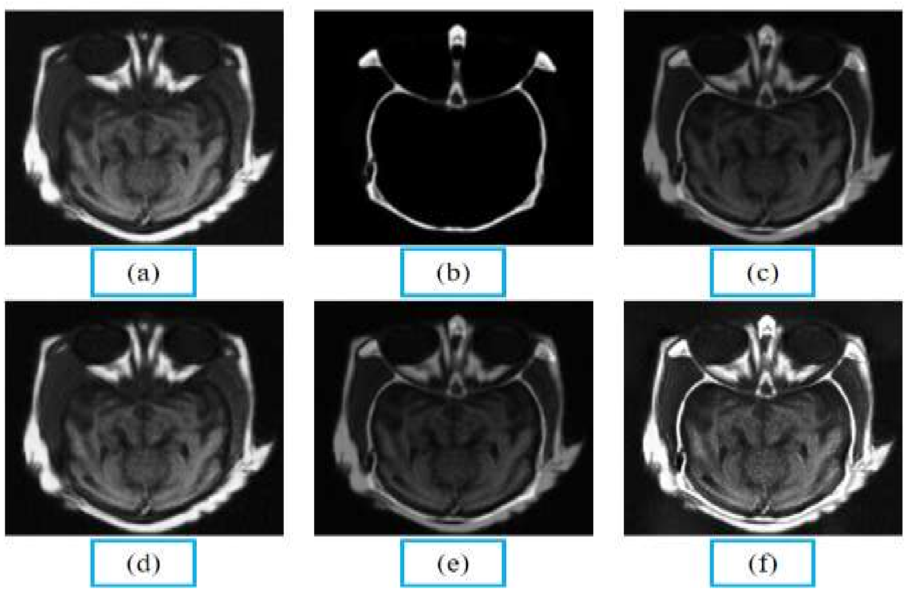


Fig. 1. Schematic diagram of proposed method using DWT,PCA,Deep learning

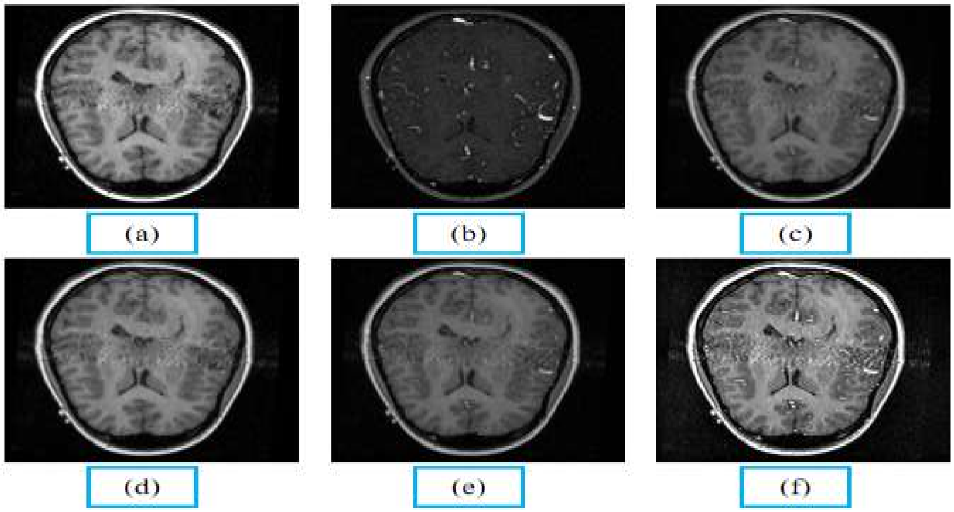


Fig. 2. Subjective analysis of Fusion results. (a) MRI image (b) CT image/ MRA image, (c) The average approach, (d) the PCA method, and (e) the DWT method and (f) Final Result

TABLE 1.Objective fusion performance

Fusion methods	Medical image pairs					
	MRI-CT			T1-MR - MRA		
	Mean	STD	AG	Mean	STD	AG
Average	32.673	34.9506	3.8980	45.5719	45.4870	6.4314
PCA	52.7361	54.0957	5.3965	56.5364	57.7863	7.6807
DWT	32.6739	34.9506	3.8980	45.5719	45.4870	6.4314
PROPOSED ALGORITHM	**67.0665**	69.9335	11.0708	71.0874	78.8184	9.2021
Final Result	**60.6864**	**61.2166**	**7.0651**	**67.6129**	**68.2391**	**9.2021**

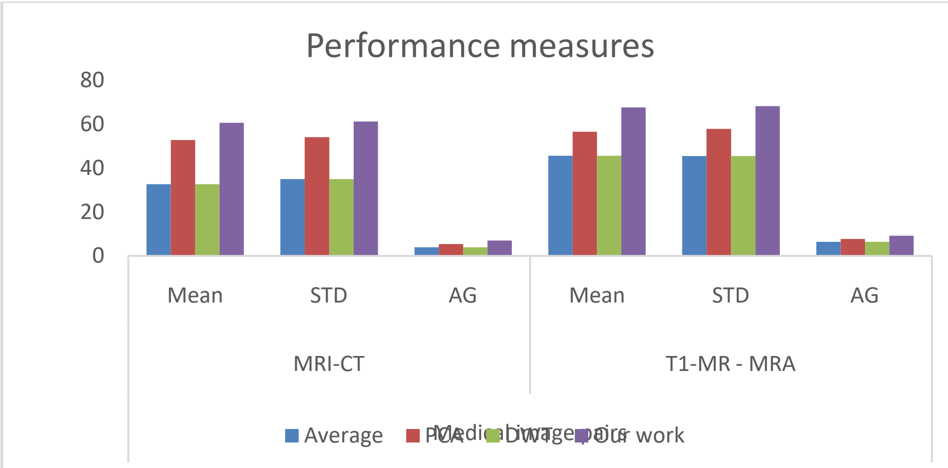


Fig. 3. Graphical analysis of Fusion results.

Conclusion:-

In the project, we suggested a two-scale decomposition-based mechanism to implement the multi-model fusion of medical images through deep learning. The pictures were initially separated into base and detail, which retained the global structures as well as fine details. The base components were fused, and the detail components were fused with a Convolutional Neural Network (CNN) and Max operation respectively, making sure not to lose the critical information of the two images. Mean, Standard Deviation (STD), and Average Gradient (AG) were used to compare the fused image and the results indicated that our method was better than the traditional ones such as PCA and DWT. This technique proved to be much better in maintaining both structural and textual structures as well as improving the clarity and usefulness of medical images in diagnosing medical needs. This is due to the fact that the This method can be extended to various imaging modalities because it uses deep learning, which is a powerful tool in the analysis of medical images and their usage in clinical settings in the future.

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