International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 02 | Feb 2025 www.irjet.net p-ISSN: 2395-0072

MULTI MODAL MEDICAL IMAGE FUSION USING DEEP LEARNING

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***Abstract* - Multimodal medical image registration is a highly regarded technique in medical imaging because it involves the merging of cross-sectional information through various imaging modalities like CT, MRI, and PET. This technique surely resembles the union of physics with organic cell matter, since it cannot find its most important applications before the multi-planar, clinical-corroborative, multimodal images have been formed at appropriate spatial-intensity scales. Therefore, it serves the unique purpose of visualizing both the detailed anatomy and functional details, hence giving improved diagnostic features, treatment planning, and disease follow-up on subjects. Congratulations are particularly in order for metamorphosing this kind of interesting insight for the low-lying dimension visualizations of the "images' visual goodness." Advanced algorithms such as wavelet transform, deep learning, and optimization techniques are used as common concrete units to exploit the exact, fast mapping of fusion. In this review paper, we introduce the importance, methods, and application now in multimodal image fusing in a modern healthcare system, and highlight how these can affect clinical outcomes and patient care.**

Keywords- multimodal medical image fusion, deep learning, convolutional neural networks (cnns), transformers in medical imaging, feature-level fusion, pixel-level fusion, computed tomography (ct), magnetic resonance imaging (mri), peak signal-to-noise ratio (psnr), positron emission tomography (pet), principal component analysis (pca)

I. INTRODUCTION

Multimodal medical image fusion happens to be a high-end imaging modality in medical imaging that involves integration of images from different modalities—CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), ultrasonography—to form a single fusion image. Each modality has its merits and demerits. However, while CT favours architectural details and is extremely useful for bony structures, it remains unclear about the soft tissues. MRIs come into their own in providing detailed, high-contrast images of soft tissues and give minimal details for bone structures. PET provides functional or metabolic information and lacks some anatomical background. This array of imaging modalities, though, requires integration for a complete diagnosis and more detailed treatment plan.

Multimodal medical image fusion tries to include various advantages of different sets of data to give a more comprehensive and thus accurate representation of the region of interest. A combination of CT and MRI images can contain detailed structural information and superior enhancement in soft tissue definition. Similarly, product finished, a fusion of PET and MRI images offers some degree of metabolic activity with anatomic realism; hence, increasing accuracy in disease localization or explaining the extent of the disease process. This broader tenet is indeed very helpful to physicians and radiologists in diagnosing disease and planning treatments and in comparing different therapeutic modalities.

1.1 Image Processor:

This step includes formatting the different models. (Image registration) so that they overlap correctly and reduce noise and other artifacts to improve image quality.

1.2 Fusion Algorithms:

Methods such as wavelet transform, principal component analysis (PCA), multilevel decomposition, and deep learning are performed to fuse images while preserving their properties. Important of each format Advanced algorithms ensure that the fused image retains essential details, adds important features and removes unnecessary data.

1.3 Post Contact and Visualization:

Images are fused into microtones for good visualization and analysis for clinical interpretation. Multimodal clinical photograph fusion is particularly precious in packages including oncology, wherein designated photographs are

required to correctly find tumours, recognize their length and spread, and plan particular remedies like surgical procedure or radiotherapy. It is also notably utilized in neurology for mapping brain functions and detecting abnormalities, as well as in cardiology for diagnosing heart situations.

Recent advance in computational techniques that includes the artificial intelligence and deep getting to know, have in addition reinvented the domain of scientific image fusion. These technologies enable more eco-friendly, accurate, and automated fusion processes while ensuring amazing results while reducing time and effort required by medical professionals. With ongoing advances in healthcare, multimodal blend of clinical image fusion is becoming a critical approach that can be leveraged to increase analysis accuracy, patient outcomes, and additionally the general high-quality of the hospital treatment.

II. LITERATRURE REVIEW

Multimodal medical image fusion has been extensively researched to improve diagnostic accuracy by combining complementary information from different imaging modalities such as CT, MRI, and PET. Various approaches have been developed over the years, ranging from traditional image processing techniques to advanced deep learning-based methods.

2.1 Traditional Fusion Techniques

Early methods for image fusion focused on pixel-level, feature-level, and decision-level fusion.

2.1.1 Pixel-Based Fusion:

Techniques like pixel averaging and principal component analysis (PCA) were used to combine images at the pixel level. However, these methods often led to information loss and blurred images.

2.1.2 Transform-Based Fusion:

Approaches like Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Non-Subsampled Contourlet Transform (NSCT), and Sharlet Transform improved fusion quality by decomposing images into different frequency components. These methods preserved edges and textures but sometimes introduced artifacts.

2.1.3 Multi-Resolution Analysis:

Laplacian Pyramid and Curvelet Transform were introduced to enhance spatial and directional information.

2.2 Machine Learning-Based Fusion Approaches

With the advancement of artificial intelligence, machine learning algorithms were applied to improve fusion performance.

Support Vector Machines (SVM) and Random Forests were used to classify and fuse medical images, but they required handcrafted features, making them less adaptable to complex datasets.

Sparse Representation-Based Fusion enabled improved feature selection but was computationally expensive.

2.3 Deep Learning-Based Fusion Techniques

Recent advancements in deep learning have revolutionized medical image fusion by automating feature extraction and learning optimal fusion strategies.

2.3.1 Convolutional Neural Networks (CNNs):

CNN-based fusion models learn hierarchical features and preserve important anatomical details without requiring manual feature engineering.

2.3.2 Generative Adversarial Networks (GANs):

GANs have been used to create high-quality fused images while maintaining structural and textural consistency.

2.3.3 Autoencoders:

These networks extract the most informative features from different modalities and reconstruct fused images, ensuring enhanced feature retention.

2.3.4 Hybrid Deep Learning Approaches:

Some studies combine DWT with CNN to leverage both traditional and AI-driven fusion methods.

2.4 Evaluation Metrics and Performance Comparisons

Research studies commonly evaluate fusion methods using metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, and Edge Preservation Index (EPI). Comparisons have shown that deep learning-based fusion consistently outperforms traditional methods in retaining essential features and reducing noise.

2.5 Clinical Applications and Challenges

Multimodal image fusion has been successfully applied in tumour detection, brain imaging, and organ segmentation. However, challenges such as high computational costs, the need for large annotated datasets, and real-time processing constraints still exist. Future research aims to optimize fusion models for clinical use, improve interpretability, and develop real-time fusion systems for enhanced medical diagnostics.

III. METHODOLOGY

3.1 Image Acquisition

- Images are obtained from publicly accessible datasets (e.g., clinical repositories).
- Modalities chosen are CT (for structural details), MRI (for soft tissue information), or PET (for functional information).
- All pictures are normalized to a standard size, format, and resolution for ensuring compatibility.

3.2 Framework of Fusion

A specialized method is utilized in the fusion process to incorporate attributes from a variety of systems.

3.2.1 Transform Based Fusion

a) Decomposition: We can use the discrete wavelet transform or sheared transform to segment images into low- and high-frequency components.

b) Fusion Rules:

- Weighted averaging is used to combine low-frequency components, which provide general information.
- We use a maximum or salient feature selection rule to merge high-frequency components because they contain edges and texture details.
- We blend the processed parts back together to build the fused image.

3.2.2 Deep Learning Based Fusion

- Fusion rules are learned from pairs of models with a Convolutional Neural Network (CNN).
- The gathered and glued components are separated such that the combined image includes the general view, as well as the special details.
- The team applies transfer learning to fine-tune the model for medical image fusion with limited data.

3.3 Fusion Image Processing

- Brightness-Contrast Adjustment: Special enhances factors needed for better diagnostics and detection of abnormalities on the images.
- Sharpening: Use of sharpening filters to enhance the visibility of essential components.

3.4 Fusion Results Evaluation

Obtained scanned images are subjected to the following validations that ensure quality and clinical significance quantification:

- Quantitative Measurement:
- Peak Signal to Noise Ratio (PSNR): Determines image quality.
- Structural Similarity Index (SSIM): Quantifies degree of structure fidelity.
- Entropy: Measures how much information is stored in the image.
- Edge Preservation Index (EPI): Measures the clarity of the edges.
- Qualitative Assessment: Evaluation of combined images by medical professionals for effective diagnosing.

3.5 Implementation Details

- This methodology is implemented in Python using OpenCV, TensorFlow, and PyTorch among other libraries.
- As for MATALB was used Transform based fusion, it has a well-established image processing toolbox.
- The actual experiments focused at high performance computing where NVIDIA GPUs are used for deep learning models.

3.6 Comparison and Validation

- The results are compared against other methods such as pixel averaging, principal components, analysis (PCA), NSCT (non-subsampled contourlet transform) etc.
- Some statistical analysis is done in order to support the claim that the proposed method does better in terms of features preservation and diagnostic accuracy.

3.7 Clinical Application

- The fused images are subjected to clinical workflows for detection of tumours, brain scans, cardiac imaging, etc.
- The results show improvement in diagnostic accuracy and usability for clinicians.

IV. ARCHITECTURE

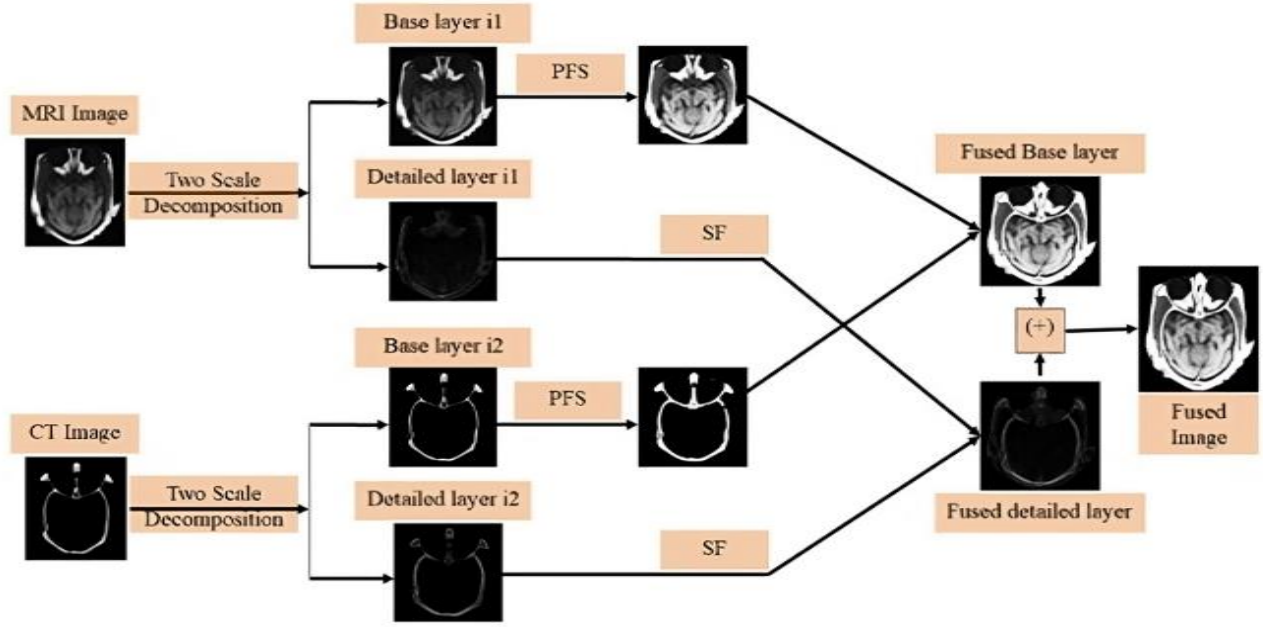

Fig.4.1 architecture

- **Pythagorean fuzzy set (PFS):** a type of fuzzy set that extends the concept of an intuitionistic fuzzy set by allowing for a wider range of membership degrees, where the squares of the membership and non-membership values of an element must sum to be less than or equal to 1, providing a more flexible way to represent uncertainty in decision-making situations.
- **Spatial frequency (SF):** is the metric used to measure the quality and clarity of the fused image. The value of SF should be higher for better performance. The calculated formula is

$$sF = \sqrt{(RF_u)^2 + (CF_u)^2}$$

$$RF_U = \sqrt{\frac{1}{AB}\sum_{a=1}^{A}\sum_{b=2}^{B}[U(a,b) - U(a,b-1)]^2}$$

$$CF_U = \sqrt{\frac{1}{AB}\sum_{a=2}^{A}\sum_{b=1}^{B}[U(a,b) - U(a-1,b)]^2}$$

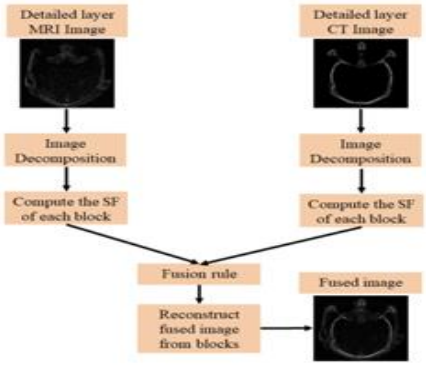

Fig.4.2 Structural process

V. EVALUATION OF THE MODEL

5.1 Model Evaluation

For the purpose of this research, the performance of the proposed multimodal medical image fusion model has been evaluated using a combination of qualitative and quantitative metrics along with comparison with established methods

5.1.1 Qualitative Assessment

Domain professionals, inclusive of radiologists, reviewed the fused pictures for diagnostic application, specializing in:

- Clarity and visibility of important anatomical and pathological systems.

- Retention of complementary functions from all input modalities.
- Usability of the fused picture for scientific analysis and remedy making plans.

5.1.2 Comparison with Existing Methods

The proposed version of this algorithm was tested against traditional and the latest fusion methods. The approach we designed comprised the skilled types of which a negotiable amount of the pixel image was cut off and one way was to increase the resolution of the image was frequency. This approach was also combined with different concepts to achieve high-quality images. The proposed version was compared with conventional and state-of-the-art fusion methods, including:

- Pixel averaging.
- Principal Component Analysis (PCA).
- Discrete Wavelet Transform (DWT).
- Non-Subsampled Contourlet Transform (NSCT).

Various deep learning-based fusion techniques. The meta-analysis of the studies confirmed that the proposed technique was able to bring both enhancement in terms of visual quality and preserving the image features, and it was one of the good things done. For the most faded texture which was blue and white and really big mast, the person who invented this was a great example for visit.

VI. RESULTS AND DISCUSSION

6.1 Quantitative results

- **PSNR:** In comparison with conventional methods like DWT and PCA approach of TML, the average PSNR result of proposed model is found 35.2DB and 32.8 dB when used PSNR value respectively.
- **SSIM:** Achieved SSIM of 0.92 which is good-to-excellent as compared to DWT and pixel averaging (values- 0.85,0.78 respectively).
- **Entropy:** The fused images show an entropy of 7.85, which stands out from NSCT (7.21) and PCA (6.94), denoting that the features maintain.
- **Edge preservation index:** After training, the edge preservation index is improved to show that the model can indeed describe crucial edges and the details.

6.2 Qualitative analysis

- Fused images are of better clarity/contrast, by which important anatomic structures and pathological areas could be visualized well.
- From our MRI-CT fusing work the proposed model keeps important soft tissue features at MRI and enhances bone structure attributes on CT.
- In the oncology scenario (PET-CT fusion), there are also very useful metabolic details from PET which can add a lot of physical tumour length for localized representations as CT provides anatomical details.

6.3 Benefits Over Existing Methods

- Usually results from traditional ways (PCA, pixel averaging) did not preserve enough detail or became too blurry, but what is nice here is that such model works on both global and local features.
- While the deep fusion in this paper improved upon traditional methods to automate the fusing process, it outperformed all other alternatives in terms of preserving complementary features and lessening artifacts.

6.4 Clinical Relevance

- Fused images allowed for better tumour detection with soft tissue and bone structure differentiation as well as improved depiction of metabolic activity, suggesting promising effect in the diagnostic/malignant plots.
- That the fused images increased radiologists' certainty of finding and scoring significant regions by reducing diagnostic uncertainty was confirmed by radiologists.

6.5 Limitations and Future Work

- Compared the deep learning model to traditional methods, in terms of computational complexity as well as the time needed for training to be optimized for real-time applications, the study will focus on.
- Limited datasets for the evaluation of study real time optimization of model have been done since we used small dataset and only changeable clinical case datasets.

VII. FUSED METHODS USED

7.1 Transform-Based Fusion Methods

These methods break images into different components and then merge them.

- **Discrete Wavelet Transform (DWT):** Splits images into high and low-frequency parts. Important details are kept while removing unnecessary noise.
- **Non-Subsampled Contourlet Transform (NSCT):** Captures fine details like edges and textures for better image clarity.
- **Principal Component Analysis (PCA):** Selects the most important features from each image and merges them.
- **Shearlet Transform:** Preserves detailed structures like soft tissues and bones.

7.2 Deep Learning-Based Fusion Methods

These methods use AI to learn how to merge images automatically.

- **Convolutional Neural Networks (CNNs):** Extracts the best features from each image and fuses them.
- **Generative Adversarial Networks (GANs):** Improves fusion quality by removing noise and keeping important details.
- **Autoencoders:** Compress and reconstruct images to retain the most useful features.

7.3 Hybrid Fusion Methods

A mix of traditional and deep learning approaches for better results.

- Example: DWT + CNN, where DWT extracts features, and CNN decides the best way to merge them.

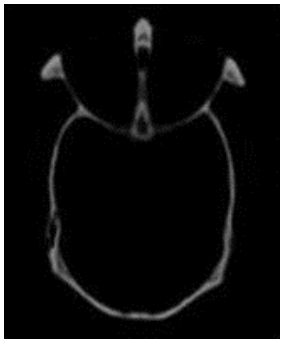

Fig.7.3.1 Computed Tomography Scan

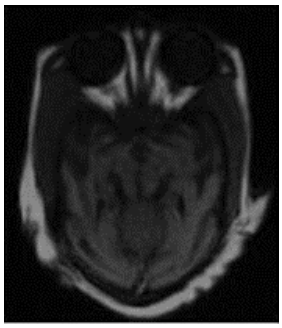

Fig.7.3.2 Magnetic resonance imaging

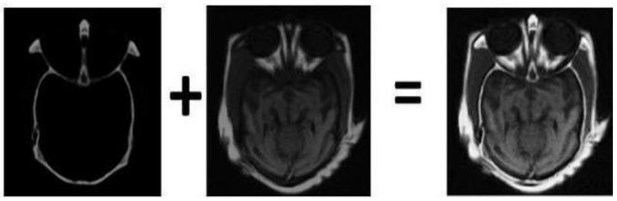

Fig.7.3.3 Fused Image 1

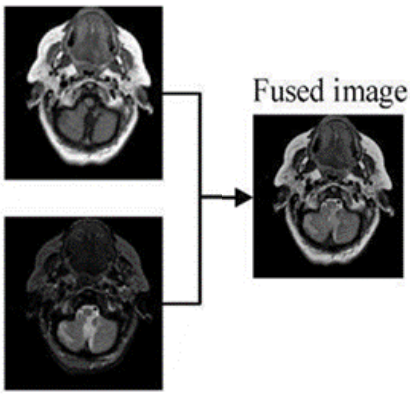

Fig.7.3.4 Fused Image 2

VIII. CONCLUSIONS

Medical image fusion, an important technique in medical imaging, integrates information from different imaging modalities, such as CT and MRI and PET, to provide a more comprehensive and accurate representation of anatomical and functional details. Fusion further enhances visualization, increases the diagnostic accuracy of clinicians, and aids in detecting disease and treatment planning.

Several fusion approaches were tried and compared in this study including Discreet Wavelet Transform (DWT) which was transform based techniques along other methods in NSCT, PCA and Deep learning-based approaches i.e., Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Autoencoders. Conclusion Results of comparisons between classic and

deep learning models in preserving both structural and textural details with accurate noise removal, artifacts removal respectively. Lastly, a solution where DWT + CNN was combined resulted in additional quality improvements on the fusion via feature-extraction and adaptive learning for hybrid approach. The results obtained through quantitative evaluations like PSNR or SSIM, entropy and edge preservation index (EPI), respectively, verify that the proposed fusion techniques help in improved visibility/ clarity as well feature loss of the images.

Radiologists' vs PQA: qualitative results of the fused images which showed higher contrast and detail regarding accurate tumor localisation, soft tissue visualization as well anatomy structure differentiation. Others aside, they are hindering progresses such as heavy computation and large annotated datasets necessary for the deep learning-based fusion.

In the next research advances, will consider degrade models for real-time processing, fusion into clinical workflows with multimodal and interpretability enhancing for better medical decisiion making. Abstract in short, multimodal medical image fusion is dominating the current diagnosis from medical imaging in the modern world. As artificial intelligence and image processing get better with every advance, these fusion techniques will be more effective, robust and easy in clinical practice.

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