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A Lightweight CNN-Based Approach for CT-MRI Medical Image Fusion Using Average and Maximum Fusion Strategies

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***Abstract* - Medical image fusion plays an important role in enhancing diagnostic accuracy by combining complementary information from different imaging modalities. Computed Tomography (CT) provides detailed information about bone structures, whereas Magnetic Resonance Imaging (MRI) offers superior soft tissue visualization. This study presents a simple convolutional neural network (CNN)-based feature extraction framework for CT-MRI image fusion. The proposed approach extracts feature from CT and MRI images using a shallow CNN architecture and combines them using Average Fusion and Maximum Fusion rules. Experiments were conducted on 24 CT-MRI image pairs obtained from the Harvard Medical Image Fusion Dataset. The fused images were evaluated using Entropy (EN), Structural Similarity Index Measure (SSIM), and Mutual Information (MI). Experimental results demonstrate that the Maximum Fusion strategy achieved higher entropy and mutual information, while Average Fusion obtained a slightly higher SSIM value. The findings indicate that Maximum Fusion preserves more information from source images and provides better overall fusion performance.**

Keywords: Medical Image Fusion, CT-MRI Fusion, CNN, Maximum Fusion, Average Fusion, Entropy, Mutual Information.

I. INTRODUCTION

Medical imaging has become an indispensable tool in modern healthcare systems for disease diagnosis, treatment planning, and clinical decision-making [1]. Various imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT) provide complementary information about anatomical structures and physiological functions [2]. However, a single imaging modality often fails to capture all the information required for accurate diagnosis. Therefore, medical image fusion techniques have gained significant attention in recent years.

CT imaging provides excellent visualization of dense tissues and bone structures with high spatial resolution, whereas MRI offers superior soft tissue contrast and detailed visualization of organs and tissues. Combining information from CT and MRI images into a single fused image can significantly improve diagnostic accuracy and reduce uncertainty during medical interpretation. Image fusion enables clinicians to obtain comprehensive information without simultaneously analyzing multiple images [3].

The traditional techniques for image fusion in medical imaging can be broadly categorized as pixel-level, feature-level, and decision-level fusion techniques. The pixel-level fusion techniques like average approach, PCA, and wavelet transform methods are easy to implement but they are not able to maintain all the structural information present in the source images. In the feature-level image fusion approach, features are extracted from the source images and then combined together, providing enhanced information maintenance [4]. Deep learning methods are relatively new in the field of image fusion due to their ability to automatically learn the representation of an image [5].

Convolutional neural networks (CNNs) have achieved significant success in many image analysis applications including image classification, detection, segmentation, and image fusion. These methods help in extracting discriminative features from the medical images and maintain the important diagnostic information during fusion [6].

In spite of all advancements made in GAN-based, Transformer-based, and attention-based approaches to the fusion of medical images, most of the available solutions require massive datasets, heavy training processes, and high computational cost. These restrictions limit the use of such methods for processing small sets of medical images. Moreover, researchers prefer to work on building complicated

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structures that make implementations difficult. Thus, there is a need to develop a lightweight model of medical image fusion that can preserve diagnostic information efficiently with the help of a limited set of CT-MRI images.

In order to solve this problem, the current research introduces a shallow CNN-based feature extraction algorithm that is applied for CT-MRI image fusion. The extracted features are merged using the average fusion and maximum fusion algorithms. EN, SSIM, and MI metrics are used to evaluate the proposed solutions on the Harvard Medical Image Fusion Dataset.

II. RELATED WORK

The combination of complementary information from different medical imaging modalities in one image is considered in medical image fusion, which has been gaining increasing attention owing to its potential benefits. Earlier research by James and Dasarathy (2014) [7] and Li *et al.* (2017) [8] provided a systematic review of traditional image fusion algorithms and the advantages of using feature-based algorithms in contrast to pixel-wise ones. Deep learning-based image fusion techniques have gained popularity recently, as their applicability and efficiency were confirmed by Liu *et al.* (2017) [9], who showed the possibility of applying CNN to achieve better structural consistency and informative value. Furthermore, Ma *et al.* (2019) [10] presented a novel deep learning-based approach named FusionGAN for more effective medical images fusion that utilized generative adversarial networks (GAN). Moreover, Zhou *et al.* (2023) [11] gave a review of the latest achievements in deep learning-based fusion techniques and stated the effectiveness of CNN-based feature extraction framework usage. Safari *et al.* (2023 [12] proposed MedFusionGAN for CT-MRI fusion, whereas Huang *et al.* (2023) [13] suggested an attention-based disentangled representation network for multimodal feature preservation. Nisha and Siva Rani (2023) [14] used both CNN and Bi-LSTM approaches for image fusion. While Liang (2024) [15] presented a deep neural network architecture for multimodal image fusion in 2024, Gu *et al.* (2024) [16], and Wang *et al.* (2024) [17] presented advanced CNN- and transformer-based multimodal fusion models, which gave very impressive results on medical image datasets. However, while these techniques present a number of significant advancements, most of them use extensive data and heavy computation, making the need arise for more lightweight fusion architectures.

III. DATASET DESCRIPTION

The experiments have been performed on CT-MRI image pairs that are taken from the famous benchmark database called Harvard Medical Image Fusion Database [18]. This particular dataset contains 24 CT images and 24 MRI images corresponding to each other, hence, resulting in 24 image pairs altogether. All of the images in this dataset are brain images containing complementary anatomical information, where the CT images contain information about the bone structure while MRI images contain information about the soft tissue. Before performing any kind of fusion procedure, all images are pre-processed and resized to 256 × 256-pixel resolution. The purpose of this dataset is to test the efficacy of the CNN fusion approach through average fusion and maximum fusion approaches.

IV. METHODOLOGY

The framework that has been proposed (see figure 1) includes the following steps:

Step 1: Image Acquisition

Images from CT and MRI are acquired using the Harvard database.

Step 2: Preprocessing

- Image resizing to 256 × 256 pixels
- Intensity normalization
- Conversion to grayscale format

Step 3: CNN-Based Feature Extraction

A shallow CNN architecture with two convolutional layers is used:

- Conv2D (16 filters, 3×3 kernel)
- Conv2D (32 filters, 3×3 kernel)

Feature representations are extracted from both CT and MRI images through the CNN.

Step 4: Feature Fusion

Two fusion strategies are investigated:

Average Fusion

Feature maps are fused using:

$$F = \frac{F_{CT} + F_{MRI}}{2}$$

Maximum Fusion

Feature maps are fused using:

$$F = \max(F_{CT}, F_{MRI})$$

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Step 5: Image Reconstruction

The fused features maps are then averaged on the channel-wise level and normalized to generate the fused image.

Step 6: Performance Evaluation

The fused images are evaluated using:

- Entropy (EN)
- Structural Similarity Index Measure (SSIM)
- Mutual Information (MI)

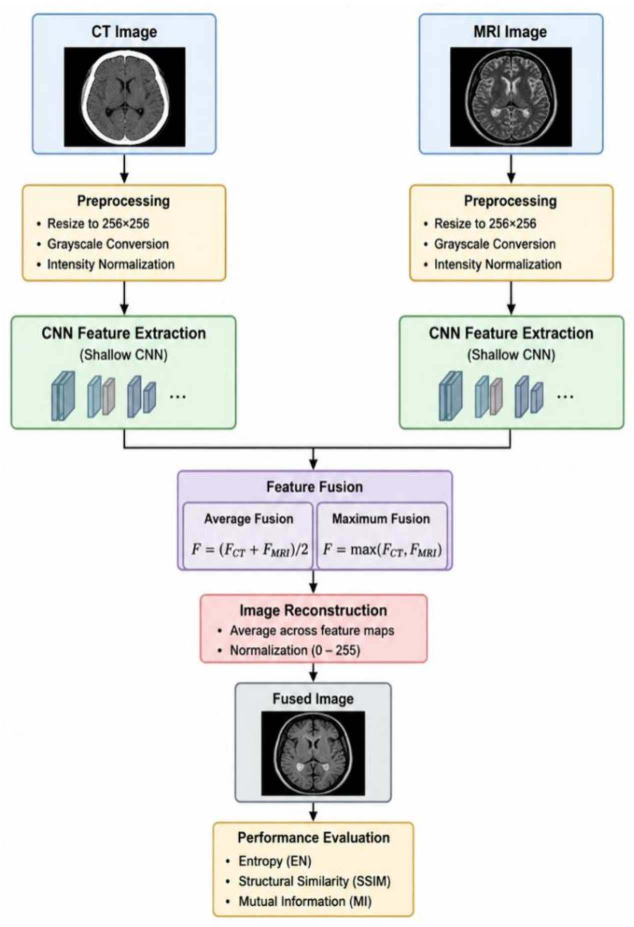

Figure 1: Flow Chart of Proposed System

V. EXPERIMENTAL RESULTS AND DISCUSSION

Table 1 provides quantitative comparison results for Average Fusion and Maximum Fusion, while Fig. 2 and 3 of show graphical illustration of the respective fusion methods.

Table 1: Performance Comparison

Method	Entropy	SSIM	MI
Average Fusion	4.7916	0.6618	0.9030
Maximum Fusion	4.8500	0.6425	0.9614

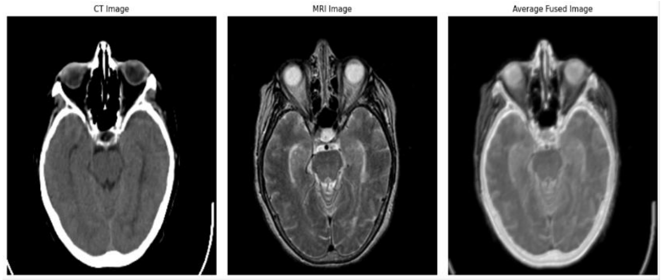

Figure 2: CT, MRI, Average Fusion Images

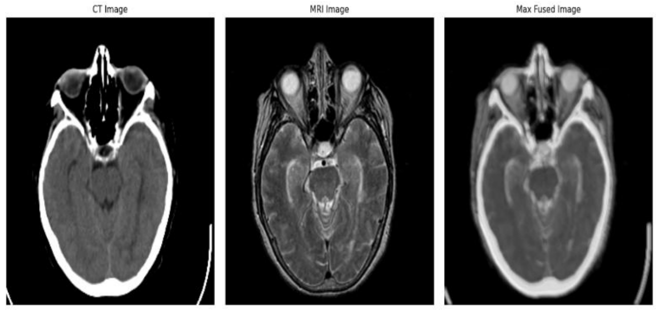

Figure 3: CT, MRI, Maximum Fusion Images

The results obtained show that the two fusion methods were able to fuse information from both the CT and MRI modalities. The Average Fusion method yielded the highest SSIM with a value of 0.6618, which shows better structural integrity. The Maximum Fusion method provided higher values for entropy and mutual information (4.8500 and 0.9614 respectively). It can be seen that the Maximum Fusion method retains more complementary information from CT and MRI modalities than the Average Fusion method.

VI. APPLICATIONS OF THE PROPOSED SYSTEM

This proposed framework involving CNN for medical image fusion of CT and MRI is widely applicable in the field of medical diagnostics and planning as well as clinical decision making. By combining the useful features of CT and MRI images, this technique helps achieve better visualization of both bone structure and soft tissues. This helps improve the identification and localization of abnormalities such as brain tumors and neurological diseases. The fused images can help surgeons plan for surgery by providing complete anatomical details, which will ensure accuracy and reduce the risks associated with the procedures. The proposed technique can also be used in computer aided diagnostics (CAD) systems to enhance their performance. The fused output images can also help in monitoring the progress of the disease and effects of any treatments. Due to its light weight CNN based system and low computational needs, the proposed framework can be used effectively in healthcare institutions with fewer computing capabilities.

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VII. CONCLUSION

The proposed research paper is centered around the implementation of an image fusion scheme using CNN in CT-MRI medical imaging using the methods of Average Fusion and Maximum Fusion. In this experiment, 24 images of CT-MRI were obtained from the Harvard Medical Image Database. From the results obtained in the quantitative analysis, it was seen that Maximum Fusion technique provides higher values of entropy and mutual information and the Average Fusion technique provided higher values of structural similarity index. It can thus be concluded that Maximum Fusion Technique provides better information preservation capabilities

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REFERENCES

[1] Gu, X., Wang, L., Deng, Z., Cao, Y., Huang, X., & Zhu, Y. M. (2024). Adaptive spatial and frequency experts fusion network for medical image fusion. *Biomedical Signal Processing and Control*, 96, 106478.

[2] El-Sayed, F., El-Shafai, W., & Elsayed Taha, T. (2021). Efficient fusion of medical images based on CNN. *Menoufia Journal of Electronic Engineering Research*, 30(2), 79-83.

[3] Thenmoezhi, N., Perumal, B., & Lakshmi, A. (2025). Efficient image fusion using multi scale decomposition and absolute maximum fusion rule for MRI and CT brain images. *International Journal of System Assurance Engineering and Management*, 16(10), 3250-3262.

[4] Shalini, S., & Indira, K. P. (2024, November). Multimodal medical image fusion for the detection of amnesia using daubechies wavelet transform and compared with average and choose max fusion rule. *In AIP Conference Proceedings* (Vol. 3193, No. 1, p. 020109). AIP Publishing LLC.

[5] Faragallah, O. S., El-Hoseny, H., El-Shafai, W., Abd El-Rahman, W., El-Sayed, H. S., El-Rabaie, E. S. M., ... &Geweid, G. G. (2020). A comprehensive survey analysis for present solutions of medical image fusion and future directions. *IEEE Access*, 9, 11358-11371.

[6] Trivedi, G. J., & Sanghvi, R. (2022). Medical image fusion using CNN with automated pooling. *Indian Journal of Science and Technology*, 15(42), 2267-2274.

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

[8] Li, S., Kang, X., & Fang, L. (2017). Pixel-level image fusion: A survey of the state of the art. *Information Fusion*, 33, 100–112.

[9] Liu, Y., Chen, X., Peng, H., & Wang, Z. (2017). Multi-focus image fusion with a deep convolutional neural network. *Information Fusion*, 36, 191–207.

[10] Ma, J., Yu, W., Liang, P., Li, C., & Jiang, J. (2019). FusionGAN: A generative adversarial network for infrared and visible image fusion. *Information Fusion*, 48, 11–26.

[11] Zhou, T., Cheng, Q., Lu, H., Li, Q., Zhang, X., & Qiu, S. (2023). Deep learning methods for medical image fusion: A review. *Computers in Biology and Medicine*, 160, 106959.

[12] Safari, M., Fatemi, A., & Archambault, L. (2023). MedFusionGAN: Multimodal medical image fusion using an unsupervised deep generative adversarial network. *BMC Medical Imaging*, 23(1), 203.

[13] Huang, W., Zhang, H., Cheng, Y., & Quan, X. (2023). DRCM: A disentangled representation network based on coordinate and multimodal attention for medical image fusion. *Frontiers in Physiology*, 14, 1241370.

[14] Nisha, A. S., & Siva Rani, T. S. (2023). Novel hybrid CNN with Bi-LSTM multi-focus image fusion method based on modified tetrolet transform in MRI and CT images. *Journal of Intelligent & Fuzzy Systems*, 45(4).

[15] Liang, N. (2024). Medical image fusion with deep neural networks. *Scientific Reports*, 14, 7972.

[16] Gu, X., Xia, Y., & Zhang, J. (2024). Multimodal medical image fusion based on interval gradients and convolutional neural networks. *BMC Medical Imaging*, 24, 232.

[17] Wang, W., He, J., Liu, H., & Yuan, W. (2024). MDC-RHT: Multi-modal medical image fusion via multi-dimensional dynamic convolution and residual hybrid transformer. *Sensors*, 24(13), 4056.

[18] [Vidoni, E. D. (2012). The Whole Brain Atlas. *Journal of Neurologic Physical Therapy*, 36(2), 108.

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