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MULTI-MODAL MEDICAL IMAGE FUSION LEVERAGING TRANSFORMER-BASED CROSS-ATTENTION NETWORKS IN CLINICAL APPLICATIONS

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Abstract

Multi-modal medical imaging provides complementary anatomical and functional information essential for accurate diagnosis and treatment planning. However, conventional fusion techniques often fail to retain fine-grained structural and functional details, leading to suboptimal diagnostic quality. Integrating diverse modalities such as MRI, CT, and PET requires an approach capable of capturing complex inter-modal relationships while preserving both spatial structures and functional intensities. Existing convolution-based methods are limited in modeling long-range dependencies, resulting in loss of critical clinical information. This study proposed a transformer-based cross-attention network for multi-modal medical image fusion. Initially, input images underwent preprocessing including normalization, resizing, and noise reduction. Feature representations were extracted via parallel encoder streams for each modality. A cross-attention mechanism then enabled the network to learn modality-specific relationships, highlighting complementary regions while suppressing redundant information. Finally, a fusion module combined the attended features into a single output, followed by reconstruction to generate a high-fidelity fused image. Performance was evaluated using standard metrics including structural similarity index (SSIM), peak signal-to-noise ratio (PSNR), and edge preservation (EP) across multiple datasets. The proposed method consistently outperformed conventional and deep learning-based fusion approaches. Quantitative evaluation showed improvements in structural similarity index (SSIM: 0.94), peak signal-to-noise ratio (PSNR: 39.1 dB), edge preservation (EP: 0.89), mutual information (MI: 1.38), and standard deviation (SD: 47.1) on the ADNI dataset. Qualitative analysis demonstrated enhanced visualization of anatomical and functional features, supporting its potential clinical applicability.

Keywords:

Multi-Modal Fusion, Cross-Attention Transformer, Medical Imaging, MRI, CT, PET

1. INTRODUCTION

Medical imaging has become a cornerstone of modern diagnostic and therapeutic processes, enabling clinicians to visualize anatomical structures and functional processes with unprecedented detail. Multi-modal imaging, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), provides complementary insights that are crucial for accurate diagnosis and treatment planning [1-3]. MRI excels in soft tissue contrast, CT offers high-resolution anatomical details, and PET captures metabolic and functional information. Integrating these modalities can provide a comprehensive understanding of pathological conditions, yet it remains a significant computational challenge due to differences in spatial resolution, intensity distribution, and modality-specific noise characteristics.

Despite the promise of multi-modal imaging, several challenges persist [4-5]. Conventional fusion methods, such as simple averaging, principal component analysis (PCA), and wavelet-based techniques, often fail to preserve both structural and functional details simultaneously. Additionally, existing deep learning approaches primarily rely on convolutional neural networks (CNNs) that excel in local feature extraction but struggle to model long-range dependencies, which are critical for aligning complementary information across modalities. Misalignment or loss of salient features can directly affect the clinical interpretability of fused images, potentially leading to diagnostic inaccuracies.

The core problem lies in developing a fusion framework capable of capturing cross-modal relationships while retaining high-fidelity anatomical and functional information [6]. Multi-modal medical images contain rich but heterogeneous information. The challenge is to design an architecture that not only aligns and integrates features from different sources but also emphasizes clinically significant regions without introducing artifacts or redundancy. Addressing this problem requires a method that combines global context modeling with modality-specific attention mechanisms.

The primary objectives of this study are: (i) to design a transformer-based cross-attention network capable of learning complementary relationships among MRI, CT, and PET modalities; (ii) to preserve both structural and functional details in the fused image; and (iii) to demonstrate improved performance over conventional and deep learning-based fusion techniques through quantitative and qualitative evaluations.

The novelty of this research lies in the integration of transformer-based cross-attention mechanisms for multi-modal medical image fusion. Unlike CNN-based approaches that are limited to local receptive fields, the transformer architecture allows modeling of long-range dependencies, enabling more precise alignment of anatomical and functional structures. The cross-attention mechanism selectively emphasizes salient features from each modality, ensuring that the fused image retains critical diagnostic information while reducing redundancy.

The contributions of this study is: We developed a novel transformer-based cross-attention framework for multi-modal medical image fusion that significantly enhances structural and functional feature retention.

2. RELATED WORKS

Multi-modal medical image fusion has been widely explored in recent years, with approaches ranging from traditional signal processing techniques to advanced deep learning architectures [7-15]. Early fusion methods primarily relied on spatial or frequency domain techniques, such as PCA, discrete wavelet transform (DWT), and Laplacian pyramid methods, which aimed to integrate complementary information by combining coefficients

or averaging intensity values [7-9]. While these approaches were computationally efficient and easy to implement, they often resulted in blurred edges, loss of fine details, and insufficient representation of functional information.

To overcome these limitations, researchers shifted toward CNN-based fusion methods. CNNs demonstrated superior ability to extract hierarchical features and integrate multi-modal information through end-to-end learning [10-12]. Methods such as autoencoder-based fusion and residual learning models were employed to preserve structural details while enhancing feature representation. However, these CNN-based models primarily captured local correlations and struggled with long-range dependencies, which are critical for aligning modalities with significant structural differences.

Recent studies introduced attention mechanisms to address the shortcomings of CNNs. Channel-wise and spatial attention modules were incorporated into fusion networks to emphasize important features from each modality [13]. These models improved edge preservation and contrast in fused images, but they still faced challenges in capturing global contextual relationships, which are essential for accurately integrating MRI, CT, and PET images.

More recently, transformer-based architectures emerged as a promising solution for multi-modal fusion due to their ability to model global dependencies and selectively attend to relevant features [14-15]. Transformers employ self-attention mechanisms to weigh contributions from different spatial regions, enabling better alignment of anatomical and functional structures across modalities. Studies demonstrated that transformer-based fusion outperformed conventional CNN methods in retaining both structural and functional information, providing clearer visualization for clinical applications.

3. PROPOSED METHOD

The method applied transformer-based cross-attention to learn complementary information across modalities. Each modality was processed through a dedicated encoder to extract hierarchical features. Cross-attention layers aligned features, emphasizing important structural and functional cues from each modality. A fusion block merged the attended features, which were then reconstructed into a high-quality fused image, ensuring the retention of critical anatomical and functional details.

1. Preprocess input images (normalize, resize, denoise).
2. Encode each modality separately using a dedicated encoder.
3. Apply cross-attention between modality feature maps to learn inter-modal relationships.
4. Fuse attended features using a weighted summation or concatenation strategy.
5. Reconstruct fused feature maps into final image.
6. Evaluate performance using SSIM, PSNR, EP metrics.

3.1 PREPROCESSING/FEATURE EXTRACTION

The first step involves preparing the multi-modal images for effective feature extraction. Preprocessing ensures uniformity in size, intensity normalization, and noise reduction. MRI, CT, and PET images often differ in resolution and intensity scales, which can introduce alignment and fusion challenges.

- **Resizing:** All input images are resized to a uniform spatial resolution (e.g., 256×256) to maintain alignment across modalities.
- **Normalization:** Intensity values are normalized to a 0–1 range to prevent scale dominance of one modality over another.
- **Noise Reduction:** Gaussian filtering and histogram equalization are applied to reduce modality-specific noise while enhancing contrast.

The normalization is defined as:

$$I_{\text{norm}}(x,y) = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}}$$

Table.1. Preprocessing Output (Intensities)

Modality	Original Range	Normalized Range
MRI	0–4095	0–1
CT	-1024–3071	0–1
PET	0–255	0–1

The Table.1 shows the preprocessing results of MRI, CT, and PET images, indicating uniform normalization and noise reduction across modalities. Preprocessing ensures that all subsequent feature extraction and fusion steps operate on standardized input data, reducing misalignment and intensity bias.

The second step involves extracting meaningful hierarchical features from each modality independently. Each modality passes through a dedicated encoder network, typically composed of convolutional layers followed by transformer blocks. This step captures both local texture information and long-range dependencies within each modality.

- **Convolutional Encoding:** Initial convolutional layers extract low-level features such as edges, contours, and texture.
- **Transformer Blocks:** Self-attention mechanisms capture global dependencies, ensuring that spatial relationships within each modality are modeled accurately.
- **Feature Map Output:** For each modality, a feature tensor $F_m \in \mathrm{R}^{C\times H\times W}$ is produced, where C is the number of channels, and H, W are spatial dimensions.

The Feature Extraction via Self-Attention:

$$F_m^{'} = \text{Softmax}\left(\frac{Q_m K_m^T}{\sqrt{d_k}}\right) V_m$$

where Q_m, K_m, V_m are the query, key, and value matrices derived from modality m, and d_k is the dimensionality of the key vectors.

Table.2. Feature Map Summary (Values for a 4×4 Patch)

Modality	Channel 1	Channel 2	Channel 3
MRI	0.12	0.35	0.45
CT	0.88	0.76	0.60
PET	0.22	0.50	0.78

The Table.2 illustrates feature values for a 4×4 patch across modalities, showing how distinctive characteristics are preserved per channel. Feature extraction ensures that both modality-specific and modality-independent information is preserved, providing a rich representation for cross-modal alignment.

3.2 CROSS-ATTENTION FUSION

The core innovation of the proposed method is the cross-attention fusion module. This step aligns features across modalities, emphasizing complementary information while suppressing redundant or irrelevant features. Cross-attention allows the network to selectively attend to regions in one modality guided by features from another.

- **Query-Key-Value Mapping:** Features from a primary modality act as queries, while secondary modality features act as keys and values.
- **Attention Score Calculation:** The relevance of each feature vector is computed using the scaled dot-product attention mechanism.
- **Weighted Fusion:** The attended features are combined via a weighted summation, producing a fused feature tensor that captures complementary information.

The Cross-Attention:

$$F_{\text{fused}} = \text{Softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right)V_j + F_i$$

where F_i is the feature map of the reference modality, F_j is the secondary modality feature map, and F_{fused} is the resulting fused feature map.

Table.3. Cross-Attention Scores (4×4 Patch)

Query Pixel	Key Pixel	Attention Score
(1,1) MRI	(1,1) CT	0.85
(2,2) MRI	(2,2) PET	0.65
(3,3) CT	(3,3) PET	0.42
(4,4) MRI	(4,4) CT	0.91

The Table.3 demonstrates attention scores computed between modalities, highlighting areas where complementary information is emphasized.

The cross-attention mechanism ensures that the fused features preserve both anatomical and functional integrity, addressing the limitations of CNN-only fusion approaches.

The final step reconstructs the fused image from the fused feature tensor. A decoder network, often mirroring the encoder architecture, generates the high-resolution output image. Reconstruction aims to translate the learned feature representations back into the spatial domain while maintaining fidelity to the original modalities.

- **Upsampling Layers:** Transpose convolutions or interpolation layers restore spatial dimensions.
- **Feature Aggregation:** Skip connections from encoders help retain fine-grained details.
- **Output Generation:** The reconstructed image is normalized to maintain clinical interpretability.

The reconstruction via decoder:

$$I_{\text{fused}}(x,y) = \sigma\left(\sum_{c=1}^{C} W_c \cdot F_{\text{fused}}^{c}(x,y) + b\right)$$

where * denotes convolution, W_c is the kernel for channel c, F_{fused}^{c} is the fused feature map, b is bias, and σ is an activation function ensuring the output remains within valid intensity bounds.

Table.4. Reconstructed Image Metrics

Modality Pair	SSIM	PSNR (dB)	Edge Preservation
MRI + CT	0.92	38.5	0.89
MRI + PET	0.88	36.2	0.85
CT + PET	0.90	37.1	0.87

The Table.4 reports quantitative metrics for the reconstructed fused images, illustrating the effectiveness of the proposed method. The reconstruction process ensures that the final image is visually and clinically meaningful, retaining salient structures and highlighting functional regions. The combination of transformer-based attention and dedicated decoders ensures minimal information loss, making the method suitable for diagnostic and treatment planning applications.

4. RESULTS AND DISCUSSION

The proposed transformer-based cross-attention fusion network was implemented using the Python programming language with the PyTorch deep learning framework. All experiments were conducted on a workstation equipped with an Intel Core i9-12900K CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU. The experiments were carried out over 100 epochs to ensure sufficient convergence of the network. During training, the Adam optimizer was employed with a learning rate of 0.0001, and the batch size was set to 8 to balance computational efficiency and memory constraints.

To enhance generalization, data augmentation techniques such as random rotations, flips, and scaling were applied to the training set. Each modality underwent preprocessing, normalization, and resizing to 256×256 pixels before being input to the encoder networks. Cross-validation was performed to ensure the robustness of the results, and early stopping criteria were applied based on validation loss to prevent overfitting.

4.1 EXPERIMENTAL PARAMETERS

The key hyperparameters and Results and Discussion are summarized in Table.1. These values were selected based on preliminary trials and literature benchmarks to optimize network performance while maintaining computational feasibility.

Table.5. Experimental Setup and Parameter Values

Parameter	Value/Setting
Epochs	100
Batch Size	8

Learning Rate	0.0001
Optimizer	Adam
Input Image Size	256 × 256
Data Augmentation	Rotation, Flip, Scaling
Encoder Layers	4 convolutional + 2 transformer
Decoder Layers	4 transposed convolution layers
Loss Function	Weighted combination of SSIM + MSE

The Table.5 summarizes the experimental setup and parameter values used for training and evaluating the proposed fusion network.

4.2 PERFORMANCE METRICS

The evaluation of the fused images was conducted using five standard performance metrics:

- **Structural Similarity Index (SSIM):** SSIM quantifies the structural similarity between the fused image and reference images. It ranges from 0 to 1, with higher values indicating better preservation of structural details.

$$\mathrm{SSIM}(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$$

- **Peak Signal-to-Noise Ratio (PSNR):** PSNR measures the fidelity of the fused image relative to the original images in terms of intensity, expressed in decibels. Higher PSNR indicates less distortion.

$$\mathrm{PSNR}=10\cdot\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right)$$

- **Edge Preservation (EP):** EP evaluates how well edges and fine details are retained in the fused image. It is computed by comparing gradient maps of the fused image and source images.
- **Mutual Information (MI):** MI measures the amount of information the fused image shares with each source modality, reflecting the retention of complementary information.
- **Standard Deviation (SD):** SD assesses the contrast and intensity distribution of the fused image. Higher values indicate better differentiation of tissue structures.

4.3 DATASET DESCRIPTION

The experimental evaluation was conducted on publicly available multi-modal medical imaging datasets, comprising MRI, CT, and PET images. The dataset includes both structural and functional images from patients with diverse pathologies to validate the robustness of the proposed method.

Table.6. Dataset Description

Dataset	Modality Types	Number of Samples	Image Size
ADNI	MRI, PET	500	256×256
TCIA	CT, MRI	400	256×256
Custom PET-CT	PET, CT	200	256×256

The Table.6 summarizes the datasets used for evaluation, including modality types, counts, and image resolution. These datasets were divided into training (70%), validation (15%), and testing (15%) sets to evaluate generalization and performance consistency across unseen samples. Three existing methods were selected from the related works to serve as baselines: CNN-based Autoencoder Fusion [10], Attention-Guided Fusion [13] and Transformer-Based Single Attention Fusion [15].

5. COMPARATIVE PERFORMANCE ANALYSIS

The proposed transformer-based cross-attention fusion network was evaluated against three existing methods: CNN-based autoencoder fusion [10], attention-guided fusion [13], and transformer-based single attention fusion [15]. Each method was tested over 100 iterations, sampled at steps of 20, to compare performance across five metrics: SSIM, PSNR, Edge Preservation (EP), Mutual Information (MI), and Standard Deviation (SD). values are presented in the tables below.

Table.7. Structural Similarity Index (SSIM) Comparison

Iteration	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
20	0.84	0.87	0.89	0.91
40	0.85	0.88	0.90	0.92
60	0.85	0.88	0.91	0.93
80	0.86	0.89	0.91	0.94
100	0.86	0.90	0.92	0.95

The Table.7 shows SSIM performance across iterations, indicating improved structural fidelity with the proposed method.

Table.8. Peak Signal-to-Noise Ratio (PSNR) Comparison (dB)

Iteration	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
20	35.2	36.5	37.0	38.2
40	35.4	36.8	37.4	38.6
60	35.6	36.9	37.6	38.8
80	35.8	37.1	37.8	39.0
100	36.0	37.3	38.0	39.2

The Table.8 presents PSNR results, showing the proposed method reduces reconstruction error while preserving intensity fidelity.

Table.9. Edge Preservation (EP) Comparison

Iteration	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
20	0.78	0.81	0.83	0.87
40	0.79	0.82	0.84	0.88
60	0.79	0.83	0.85	0.89

80	0.80	0.83	0.85	0.90
100	0.80	0.84	0.86	0.91

The Table.9 demonstrates superior edge preservation by the proposed method across iterations, capturing fine structural details.

Table.10. Mutual Information (MI) Comparison

Iteration	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
20	1.12	1.21	1.27	1.34
40	1.14	1.23	1.29	1.36
60	1.15	1.24	1.31	1.38
80	1.16	1.25	1.32	1.39
100	1.17	1.26	1.33	1.41

The Table.10 indicates that the proposed method retains higher mutual information, integrating complementary modality features effectively.

Table.11. Standard Deviation (SD) Comparison

Iteration	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
20	42.5	44.1	45.3	47.0
40	42.8	44.4	45.6	47.3
60	43.0	44.6	45.8	47.5
80	43.2	44.8	46.0	47.8
100	43.5	45.0	46.2	48.0

The Table.11 shows SD values, indicating better contrast and intensity differentiation in the fused images produced by the proposed approach.

5.1.1 Discussion of Results:

The comparative analysis reveals a consistent performance advantage of the proposed transformer-based cross-attention fusion method across all five metrics. For SSIM (Table.7), the proposed approach achieved values of 0.95 at 100 iterations, exceeding the transformer single attention method (0.92) and attention-guided fusion (0.90). This improvement highlights the network's ability to maintain structural fidelity by leveraging cross-modal dependencies rather than relying solely on self-attention or local feature extraction.

In terms of PSNR (Table.8), the proposed method attained 39.2 dB at 100 iterations, reflecting a reduction in reconstruction errors compared to CNN autoencoder (36.0 dB) and transformer single attention (38.0 dB). The higher PSNR indicates that the proposed fusion preserves intensity information effectively, ensuring that both anatomical and functional signals remain distinguishable.

Edge preservation (Table.9) further demonstrates the superiority of the proposed approach. By modeling inter-modal attention, the network retained finer structural edges, reaching 0.91 at iteration 100, whereas attention-guided fusion achieved 0.84. This suggests that cross-attention mechanisms more accurately emphasize diagnostically relevant regions, a crucial factor in clinical image analysis.

Mutual information (Table.10) was highest for the proposed method, reaching 1.41 at iteration 100, compared to 1.33 for transformer single attention. This metric confirms that complementary features from multiple modalities were effectively integrated, reflecting the method's ability to enhance overall information content.

5.2 COMPARATIVE PERFORMANCE ACROSS DATASETS

The proposed transformer-based cross-attention fusion network was evaluated on three datasets: ADNI (MRI + PET), TCIA (CT + MRI), and PET-CT. The performance of the proposed method was compared against three existing methods: CNN-based autoencoder fusion [10], attention-guided fusion [13], and transformer-based single attention fusion [15].

Table.12. Structural Similarity Index (SSIM) Comparison Across Datasets

Dataset	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
ADNI	0.84	0.87	0.89	0.94
TCIA	0.81	0.85	0.87	0.91
PET-CT	0.83	0.86	0.88	0.93

The Table.12 shows that the proposed method achieves higher SSIM values across all datasets, indicating superior structural preservation.

Table.13. Peak Signal-to-Noise Ratio (PSNR) Comparison Across Datasets (dB)

Dataset	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
ADNI	35.2	36.5	37.0	39.1
TCIA	34.5	35.8	36.4	38.3
PET-CT	34.9	36.2	36.8	38.7

The Table.13 highlights improved PSNR with the proposed method, reflecting reduced reconstruction error and better intensity fidelity.

Table.14. Edge Preservation (EP) Comparison Across Datasets

Dataset	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
ADNI	0.78	0.81	0.83	0.89
TCIA	0.75	0.79	0.81	0.86
PET-CT	0.77	0.80	0.82	0.88

The Table.14 demonstrates that the proposed network preserves edges more effectively, enhancing structural details.

Table.15. Mutual Information (MI) Comparison Across Datasets

Dataset	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
ADNI	1.12	1.21	1.27	1.38
TCIA	1.08	1.17	1.23	1.34
PET-CT	1.10	1.19	1.25	1.36

The Table.15 shows higher mutual information for the proposed method, confirming effective integration of complementary features across modalities.

Table.16. Standard Deviation (SD) Comparison Across Datasets

Dataset	CNN AE	Attention-Guided Fusion	Transformer Single Attention	Proposed Cross-Attention
ADNI	42.5	44.1	45.3	47.1
TCIA	41.8	43.5	44.7	46.5
PET-CT	42.0	43.7	45.0	46.8

The Table.16 indicates that the proposed approach maintains higher SD, suggesting better contrast and intensity distribution.

5.2.1 Discussion of Results

The comparative analysis across three datasets demonstrates that the proposed transformer-based cross-attention fusion method consistently outperforms existing approaches. For SSIM (Table.12), the proposed method achieved 0.94 on the ADNI dataset, outperforming the CNN autoencoder (0.84) and attention-guided fusion (0.87), indicating superior preservation of structural integrity. Similarly, PSNR values (Table.13) reached 39.1 dB for ADNI, which reflects improved reconstruction fidelity compared to 37.0 dB with transformer single attention.

Edge preservation (Table.14) shows a clear advantage of the proposed method, with EP values of 0.89 for ADNI, demonstrating that fine anatomical details are retained more effectively than in previous approaches. Mutual information (Table.15) also increased substantially, reaching 1.38 for ADNI, confirming that the cross-attention mechanism captures complementary features from different modalities more effectively than existing methods. Standard deviation (Table.16) indicates improved contrast in fused images, facilitating better visualization of subtle structures across all datasets.

Quantitatively, the proposed method consistently demonstrates 3–10% improvements in SSIM and EP, 2–3 dB gains in PSNR, and approximately 0.1–0.2 increments in MI and SD relative to transformer-based single attention fusion. These numerical improvements highlight the robustness of the network across diverse imaging datasets and modality combinations.

6. CONCLUSION

This study introduced a transformer-based cross-attention network for multi-modal medical image fusion, integrating complementary information from MRI, CT, and PET images. Experimental results across three datasets demonstrated that the proposed method outperforms conventional CNN-based autoencoder, attention-guided fusion, and transformer single attention methods across all performance metrics, including SSIM, PSNR, edge preservation, mutual information, and standard deviation.

The cross-attention mechanism enabled selective highlighting of relevant regions from each modality, ensuring retention of fine structural details and functional information. Quantitative results showed improvements of up to 10% in SSIM and EP, 3 dB in PSNR, and noticeable gains in MI and SD, confirming the robustness and generalizability of the approach. The method converged efficiently over 100 epochs and maintained consistent performance across diverse datasets, making it suitable.for clinical applications.

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