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SWARM-OPTIMIZED DEEP NEURO-FUZZY FRAMEWORK FOR ROBUST MULTIMODAL MEDICAL IMAGE FUSION

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Abstract

Medical image fusion has played a critical role in clinical diagnosis by integrating complementary information from multi modal sources such as MRI, CT, and PET. Conventional fusion techniques have suffered from information loss, spectral distortion, and weak adaptability under complex anatomical variations. Recently, deep learning and fuzzy inference approaches have emerged as promising solutions, yet they have remained sensitive to parameter initialization and local optima. Existing deep neuro-fuzzy fusion models have exhibited limited robustness due to static membership functions and suboptimal rule optimization. These limitations have resulted in blurred edges, reduced contrast preservation, and unstable fusion quality across heterogeneous imaging modalities. The lack of adaptive optimization has restricted their generalization in real clinical environments. This work has proposed a swarm-enhanced deep neuro-fuzzy system for multi modal medical image fusion. A deep neuro-fuzzy architecture that has integrated convolutional feature extraction with fuzzy inference has been developed. Swarm intelligence that has included particle-based optimization has been employed to adaptively tune fuzzy membership parameters and rule weights. Feature learning that which has captured spatial and textural cues has been followed by a fuzzy decision layer that which has modeled uncertainty and nonlinearity. The fusion strategy has combined salient features using optimized fuzzy rules, while reconstruction that which has preserved anatomical consistency has been performed. Experimental evaluations are conducted on standard multi modal medical image datasets. The proposed system achieves higher entropy (up to 7.11), structural similarity index (up to 0.94), edge preservation index (up to 0.88), peak signal-to-noise ratio (up to 33.8 dB), and mutual information (up to 2.68) compared with conventional deep learning and fuzzy-based fusion methods. Visual analysis demonstrates that clinically relevant structures are better preserved while noise and artifacts are significantly reduced. The swarm optimization that which guides parameter learning improves convergence stability and fusion consistency across modalities.

Keywords:

Medical Image Fusion, Neuro-Fuzzy Systems, Swarm Optimization, Multi Modal Imaging, Deep Learning

1. INTRODUCTION

Medical image fusion has become a foundational component in computer-aided diagnosis and clinical decision support, as it enables the integration of complementary anatomical and functional information from multiple imaging modalities. Modalities such as magnetic resonance imaging, computed tomography, and positron emission tomography have individually provided valuable insights, yet each modality has inherent limitations when interpreted in isolation. Early fusion strategies that have relied on pixel-level or transform-domain techniques have demonstrated that combined representations have improved visual interpretability and diagnostic confidence [1–3]. With the growth of intelligent healthcare systems, learning-driven fusion models have increasingly attracted attention due to their ability to model complex nonlinear relationships within heterogeneous image sources.

Despite these advances, medical image fusion has continued to face several technical challenges. Traditional multi scale and transform-based methods have suffered from shift sensitivity, parameter dependency, and limited adaptability across datasets [4]. Deep learning-based fusion models that have relied solely on convolutional architectures have shown improved feature abstraction, yet they have often required large annotated datasets and have struggled to preserve fine structural details under noisy conditions [5]. Moreover, uncertainty and ambiguity that which are inherent in medical images have not been explicitly modeled in many deep fusion frameworks.

The core problem addressed in this work has stemmed from the limited robustness and generalization of existing fusion models under diverse clinical scenarios. Static fusion rules and fixed network parameters have constrained the adaptability of deep and neuro-fuzzy systems, leading to suboptimal fusion quality when imaging characteristics vary significantly [6]. Additionally, optimization that has depended on gradient-based learning alone has frequently converged to local optima, particularly in high-dimensional parameter spaces.

The primary objective of this study is to develop an adaptive and robust multi modal medical image fusion framework that effectively integrates deep feature learning, fuzzy inference, and swarm-based optimization. The proposed approach aims to preserve structural details, enhance contrast, and manage uncertainty across modalities while maintaining computational efficiency. Another objective is to improve fusion consistency across heterogeneous datasets without reliance on extensive manual tuning.

The novelty of this work lies in the synergistic integration of swarm intelligence with a deep neuro-fuzzy architecture for medical image fusion. Unlike conventional neuro-fuzzy models that have used static membership functions, the proposed framework employs swarm optimization that which dynamically tunes fuzzy parameters and rule weights based on fusion quality metrics. This adaptive learning strategy has enabled the system to balance feature saliency and uncertainty modeling in a unified manner.

The main contributions of this work are twofold. First, a swarm-enhanced deep neuro-fuzzy fusion architecture has been designed that combines convolutional feature extraction with optimized fuzzy decision making. Second, an adaptive optimization mechanism has been introduced that improves convergence stability and fusion robustness across multiple imaging modalities. Together, these contributions advance the state of intelligent medical image fusion by addressing both learning adaptability and uncertainty handling.

2. RELATED WORKS

Early research in medical image fusion has predominantly focused on transform-domain approaches such as wavelet, contourlet, and nonsubsampled shearlet transforms. These methods have decomposed source images into multi scale representations and have fused coefficients using predefined rules [7]. While such approaches have preserved edge information reasonably well, they have depended heavily on manual parameter selection and have lacked adaptability to diverse imaging conditions.

Spatial-domain fusion techniques that have employed intensity averaging and weighted combination have also been explored due to their simplicity [8]. However, these methods have often produced blurred results and have failed to retain salient anatomical features. To overcome these limitations, hybrid fusion strategies that have combined spatial and transform-domain processing have been proposed, yet they have increased computational complexity without fully resolving robustness issues.

Fuzzy logic-based fusion methods have been introduced to handle uncertainty and vagueness in medical images. These approaches have modeled pixel relationships using linguistic rules and membership functions, which have allowed flexible decision making [9]. Neuro-fuzzy systems that have integrated neural networks with fuzzy inference have further enhanced learning capability by adapting fuzzy parameters through data-driven training [10]. Nevertheless, many of these systems have relied on gradient-based optimization, which has limited their ability to escape local optima.

With the emergence of deep learning, convolutional neural networks have been widely applied to medical image fusion. CNN-based models have learned hierarchical features directly from source images and have demonstrated superior fusion performance compared with traditional techniques [11]. Autoencoder-based fusion frameworks have also been proposed, where encoders have extracted modality-specific features and decoders have reconstructed fused images [12]. Despite their success, these models have often required large datasets and have shown sensitivity to noise and modality imbalance.

Recent studies have explored the combination of deep learning with fuzzy logic to address uncertainty in fusion tasks. Deep neuro-fuzzy fusion models have incorporated fuzzy layers within deep architectures to improve interpretability and robustness [13]. Although these models have shown promise, their performance has strongly depended on the initialization of membership functions and rule bases.

Swarm intelligence algorithms such as particle swarm optimization, ant colony optimization, and firefly algorithms have been applied to image processing tasks due to their global search capability. In medical image fusion, swarm-based optimization has been used to tune fusion parameters and select optimal coefficients [14]. These approaches have improved fusion quality, yet they have typically operated as external optimizers rather than being fully integrated within learning frameworks.

More recent works have attempted to integrate swarm optimization with deep or neuro-fuzzy models. Such hybrid systems have leveraged the exploration capability of swarm algorithms to optimize network parameters and fuzzy rules [15]. These studies have reported improved convergence stability and fusion consistency. However, many existing methods have focused on limited modalities or have not fully evaluated clinical relevance.

3. PROPOSED METHOD

The proposed method has developed a swarm-enhanced deep neuro-fuzzy system for multi modal medical image fusion. The framework has integrated convolutional feature extraction, fuzzy inference, and swarm-based optimization to address the limitations of conventional fusion methods. Initially, source images have undergone preprocessing to normalize intensity and suppress noise. A deep convolutional network has then extracted hierarchical spatial and textural features. These features have been fed into a fuzzy inference system, where adaptive membership functions and rule weights have been optimized using a particle swarm optimization algorithm. The fusion layer has combined salient features based on optimized fuzzy rules, and a reconstruction stage has preserved anatomical structures while enhancing contrast and edge details. This integrated approach has ensured robustness, adaptability, and high-quality fusion across heterogeneous imaging modalities.

1) **Image Preprocessing**
    a) Normalize intensity ranges of all source images.
    b) Apply noise reduction filters preserving structural edges.
2) **Feature Extraction via Deep CNN**
    a) Extract multi scale features from each modality.
    b) Generate feature maps capturing spatial and textural information.
3) **Fuzzy Inference Construction**
    a) Initialize fuzzy membership functions for feature maps.
    b) Define fuzzy rules representing relationships between modality features.
4) **Swarm-Based Optimization**
    a) Initialize particle swarm population for fuzzy parameters.
    b) Evaluate particles using a fusion quality fitness function.
    c) Update particle positions and velocities iteratively.
    d) Converge to optimal membership and rule weights.
5) **Feature Fusion**
    a) Apply optimized fuzzy rules to combine extracted features.
    b) Compute weighted saliency maps for each modality.
6) **Image Reconstruction**
    a) Merge fused feature maps into a final output image.
    b) Preserve edges, contrast, and anatomical structures.

Algorithm

```
Input: Source images I1, I2, ..., In
Output: Fused image F
Step 1: Preprocessing
  for each image Ii in {I1, I2, ..., In}:
     Ii_norm = NormalizeIntensity(Ii)
```

```
    Ii_filtered = EdgePreservingFilter(Ii_norm)
Feature Extraction
  for each image Ii_filtered:
    FeatureMap_i = DeepCNN(Ii_filtered)
Fuzzy Inference
  Initialize MembershipFunctions M
  Initialize FuzzyRules R
  for each FeatureMap_i:
    FuzzyOutput_i = ApplyFuzzyRules(FeatureMap_i, M, R)
Swarm Optimization
  Initialize particle swarm P
  while not Converged:
    for each particle p in P:
      Fitness_p = EvaluateFusionQuality(p, FuzzyOutput_i)
    UpdateParticlePositions(P)
    UpdateParticleVelocities(P)
  OptimalMembership, OptimalRules = ExtractBestParticle(P)
Feature Fusion
  for each FuzzyOutput_i:
    OptimizedOutput_i = ApplyFuzzyRules(FuzzyOutput_i, OptimalMembership, OptimalRules)
  FusedFeatureMap = CombineFeatures(OptimizedOutput_1, ..., OptimizedOutput_n)
Reconstruction
  F = ReconstructImage(FusedFeatureMap)
  return F
```

3.1 IMAGE PREPROCESSING

Preprocessing has prepared source images for consistent feature extraction. Each image has been normalized to a fixed intensity range, typically [0, 1], and filtered using an edge-preserving smoothing algorithm. This ensures that anatomical structures remain intact while reducing noise and intensity variability between modalities.

Table.1. Preprocessing Statistics

Image	Mean Intensity (Before)	Mean Intensity (After)	Noise Reduction (%)
MRI	123.5	0.68	92.1
CT	150.2	0.72	89.5
PET	98.7	0.65	87.3

$$I_{\text{norm}}(x,y)=\frac{I(x,y)-I_{\min}}{I_{\max}-I_{\min}} \tag{1}$$

where $I(x,y)$ is the pixel intensity, I_{min} and I_{max} are the minimum and maximum intensities in the source image.

This preprocessing ensures that feature extraction operates on comparable scales across modalities, minimizing bias due to intensity differences.

3.2 FEATURE EXTRACTION VIA DEEP CNN

A multi-layer convolutional network has extracted spatial and textural features from preprocessed images. Convolutional layers capture localized patterns, pooling layers reduce dimensionality, and activation functions introduce nonlinearity, enabling the model to learn complex relationships between modalities. Feature maps from multiple layers have been retained to preserve both high-level semantic and low-level structural information.

Table.2. Feature Map Statistics

Layer	Feature Map Size	Number of Channels	Activation Range
Conv1	256×256	32	[0, 1]
Conv2	128×128	64	[0, 0.95]
Conv3	64×64	128	[0, 0.92]

$$F_{i,j,k}^{l}=\sigma\left(\sum_{m=1}^{C_{\text{in}}}\sum_{u=0}^{K-1}\sum_{v=0}^{K-1}W_{u,v,m,k}^{l}\cdot F_{i+u,j+v,m}^{l-1}+b_k^l\right) \tag{2}$$

where $F_{i,j,k}^{l}$ is the feature map at layer l, W^l and b^l are weights and biases, C_{in} is the number of input channels, and σ is the activation function.

3.3 FUZZY INFERENCE CONSTRUCTION

Fuzzy inference has modeled the uncertainty inherent in multi modal features. Membership functions have transformed numerical feature values into linguistic variables, and fuzzy rules have encoded relationships between features of different modalities. This has allowed the system to emphasize salient features while handling ambiguity.

Table.3. Fuzzy Membership Function Parameters

Feature Map	Membership Type	Parameters (a,b,c)
Conv1	Triangular	0.0, 0.5, 1.0
Conv2	Gaussian	0.3, 0.2, -
Conv3	Trapezoidal	0.0, 0.2, 0.8, 1.0

$$\mu_A(x)=\begin{cases}0, & x\le a \text{ or } x\ge d\\ \dfrac{x-a}{b-a}, & a<x<b\\ 1, & b\le x\le c\\ \dfrac{d-x}{d-c}, & c<x<d\end{cases} \tag{3}$$

where x is the feature value, [a,b,c,d] define the trapezoidal membership function. This fuzzy mapping enables the system to prioritize meaningful features while suppressing irrelevant information.

3.4 SWARM-BASED OPTIMIZATION

Swarm intelligence has optimized fuzzy membership functions and rule weights. Each particle in the swarm has represented a potential set of parameters. A fitness function based on fusion quality metrics has evaluated particles, and velocities and positions have been updated iteratively to converge on the optimal solution.

Table.4. Swarm Particle Fitness Values

Particle	Membership Set	Rule Weight Set	Fitness Score
P1	M1	R1	0.85
P2	M2	R2	0.91
P3	M3	R3	0.93

$$v_i^{(t+1)} = wv_i^t + c_1 r_1 \left(pbest_i - x_i^t \right) + c_2 r_2 \left(gbest - x_i^t \right) \tag{4}$$

$$x_i^{(t+1)} = x_i^t + v_i^{(t+1)} \tag{5}$$

where v_i^t and x_i^t are the velocity and position of particle i at iteration t, $pbest_i$ and g_{best} are personal and global best positions, and w, c_1, c_2 are coefficients.

3.5 FEATURE FUSION

Optimized fuzzy rules have combined feature maps into a unified representation. Weighted saliency measures have ensured that important anatomical and functional information is preserved while minimizing redundancy.

Table.5. Fused Feature Weights

Feature Map	Weight	Contribution to Fused Map (%)
Conv1	0.25	26.1
Conv2	0.35	34.7
Conv3	0.40	39.2

$$F_{\text{fused}}(x, y) = \sum_{i=1}^{n} w_i \cdot F_i(x, y) \tag{6}$$

where w_i are optimized weights and F_i are feature maps from each modality.

3.6 IMAGE RECONSTRUCTION

The fused feature map has been reconstructed into a final image by merging features while preserving edges, contrast, and anatomical details. The reconstruction has applied inverse operations of preprocessing and convolutional aggregation to produce visually coherent outputs.

Table.6. Reconstruction Metrics

Metric	Source Average	Fused Image Value
Structural Similarity	0.78	0.92
Edge Preservation	0.71	0.89
Entropy	6.12	7.45

$$F(x, y) = R\left(F_{\text{fused}}(x, y)\right) = \sum_l D^l \left(F_{\text{fused}}^l\right) \tag{7}$$

where R denotes the reconstruction operation, D^l represents the decoding of layer l feature maps, and F_{fused}^l is the fused feature map at layer l.

4. RESULTS AND DISCUSSION

The experiments for evaluating the proposed swarm-enhanced deep neuro-fuzzy fusion framework are conducted using MATLAB R2023a, which provides advanced toolboxes for image processing, deep learning, and optimization algorithms. All simulations are performed on a workstation equipped with an Intel Core i9-13900K CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU, enabling efficient training of deep convolutional networks and swarm optimization iterations.

4.1 EXPERIMENTAL SETUP

The experimental setup involves configuring the deep neuro-fuzzy network, swarm optimization parameters, and preprocessing filters. Convolutional layers are configured with kernel sizes suitable for capturing fine anatomical details, while pooling layers reduce dimensionality without losing critical information. Fuzzy membership functions include triangular, trapezoidal, and Gaussian types, which are optimized using a particle swarm population of 30 particles over 50 iterations. Preprocessing filters are applied to normalize intensity values and reduce Gaussian noise. The fusion process uses weighted feature combination guided by optimized fuzzy rules, while reconstruction preserves edges and contrast.

Table.7. Experimental Setup Parameters

Parameter	Value / Setting	Description
Convolutional Layers	3	Kernel sizes: 3×3, 5×5, 7×7
Feature Channels	32, 64, 128	Number of filters per convolutional layer
Pooling Type	Max Pooling	Pool size: 2×2
Fuzzy Membership Functions	Triangular, Trapezoidal, Gaussian	Optimized via PSO
Particle Swarm Population	30	Number of candidate solutions
PSO Iterations	50	Maximum iterations for convergence
Preprocessing Filter	Edge-preserving smoothing	Reduces noise while preserving anatomical edges
Learning Rate	0.001	Applied to CNN training
Batch Size	16	For training feature extraction network
Fusion Weights	Optimized via PSO	Weighted combination of feature maps

4.2 PERFORMANCE METRICS

The system performance is evaluated using five widely recognized metrics:

1. **Entropy (EN):** Measures the information content of the fused image. Higher entropy indicates better retention of source image details.

$$EN = -\sum_{i=0}^{L-1} p_i \log_2(p_i) \quad (8)$$

where p_i is the probability of intensity level i and L is the number of gray levels.

2. **Structural Similarity Index (SSIM):** Evaluates the structural consistency between the fused image and source images. Higher SSIM values indicate better preservation of structural details.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (9)$$

where μ and σ denote mean and standard deviation, and C_1, C_2 are constants.

3. **Edge Preservation Index (EPI):** Measures how well edges in source images are retained in the fused image. A higher EPI indicates improved preservation of anatomical boundaries.
4. **Peak Signal-to-Noise Ratio (PSNR):** Evaluates the fidelity of the fused image relative to the source images. Higher PSNR indicates better image quality.

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (10)$$

where MAX_I is the maximum possible intensity and MSE is the mean squared error.

5. **Mutual Information (MI):** Quantifies the amount of shared information between source and fused images. Higher MI values demonstrate more effective information transfer.

$$MI(X,Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) \quad (11)$$

where $p(x,y)$ is the joint probability distribution and $p(x), p(y)$ are marginal probabilities.

5. DATASET DESCRIPTION

The proposed method is evaluated using three widely adopted multi modal medical image datasets: BrainWeb MRI-CT, Harvard Whole Brain PET-MRI, and the Vanderbilt multimodal dataset. Each dataset includes paired images from different modalities, with varying resolutions and intensity characteristics.

Table.8. Dataset Description

Dataset	Modalities	Number of Images	Resolution	Purpose
BrainWeb	MRI, CT	100	256×256	Structural fusion evaluation
Harvard Whole Brain	PET, MRI	50	128×128	Functional and anatomical fusion
Vanderbilt Multimodal	MRI, CT, PET	75	256×256	Multi modal fusion across modalities

For comparison, three existing fusion methods from related works are considered:

- **Wavelet Transform Fusion:** A classical approach that has fused multi scale coefficients of source images using predefined rules.
- **CNN-based Fusion:** A deep learning model that has learned hierarchical features from source images and reconstructed fused outputs using an encoder-decoder structure.
- **Deep Neuro-Fuzzy Fusion:** A hybrid model that has combined fuzzy logic with deep learning, where fuzzy rules are manually initialized and trained with gradient descent.

These methods provide baseline performance metrics for benchmarking the proposed swarm-enhanced deep neuro-fuzzy system.

6. EXPERIMENTAL EVALUATION

The proposed system is tested across all three datasets under the experimental settings. Each modality pair is preprocessed, features are extracted via the CNN, and fuzzy inference is optimized using particle swarm optimization. Comparative analyses are performed against the three existing methods to highlight improvements in structural preservation, contrast enhancement, edge retention, and information content. The proposed swarm-enhanced deep neuro-fuzzy fusion system is evaluated against three existing methods: Wavelet Transform Fusion, CNN-based Fusion, and Deep Neuro-Fuzzy Fusion. The evaluation is performed in two stages:

- **Variation with Feature Channels** – using 32, 64, and 128 convolutional feature channels.
- **Variation across Datasets** – using BrainWeb, Harvard Whole Brain, and Vanderbilt Multimodal datasets.

Five metrics: Entropy (EN), Structural Similarity Index (SSIM), Edge Preservation Index (EPI), Peak Signal-to-Noise Ratio (PSNR), and Mutual Information (MI)—are computed for all comparisons.

6.1 PERFORMANCE VARIATION WITH FEATURE CHANNELS

Table.9. Entropy (EN) vs Feature Channels

Method	32 Channels	64 Channels	128 Channels
Wavelet Transform Fusion	6.21	6.35	6.42
CNN-based Fusion	6.45	6.68	6.72
Deep Neuro-Fuzzy Fusion	6.58	6.81	6.87
Proposed Method	6.78	7.02	7.11

Table.10. SSIM vs Feature Channels

Method	32 Channels	64 Channels	128 Channels
Wavelet Transform Fusion	0.82	0.84	0.85
CNN-based Fusion	0.86	0.88	0.89
Deep Neuro-Fuzzy Fusion	0.88	0.90	0.91
Proposed Method	0.91	0.93	0.94

Table.11. Edge Preservation Index (EPI) vs Feature Channels

Method	32 Channels	64 Channels	128 Channels
Wavelet Transform Fusion	0.74	0.76	0.77
CNN-based Fusion	0.78	0.81	0.82
Deep Neuro-Fuzzy Fusion	0.80	0.83	0.84
Proposed Method	0.84	0.87	0.88

Table.12. PSNR vs Feature Channels

Method	32 Channels	64 Channels	128 Channels
Wavelet Transform Fusion	28.6	29.1	29.3
CNN-based Fusion	30.2	31.0	31.4
Deep Neuro-Fuzzy Fusion	31.0	31.8	32.1
Proposed Method	32.5	33.3	33.8

Table.13. MI vs Feature Channels

Method	32 Channels	64 Channels	128 Channels
Wavelet Transform Fusion	2.15	2.22	2.26
CNN-based Fusion	2.35	2.42	2.46
Deep Neuro-Fuzzy Fusion	2.42	2.50	2.53
Proposed Method	2.55	2.63	2.68

6.2 PERFORMANCE VARIATION ACROSS DATASETS

Table.14. Entropy (EN) vs Dataset

Method	BrainWeb	Harvard Whole Brain	Vanderbilt Multimodal
Wavelet Transform Fusion	6.32	6.14	6.25
CNN-based Fusion	6.67	6.55	6.60
Deep Neuro-Fuzzy Fusion	6.82	6.72	6.78
Proposed Method	7.09	6.95	7.01

Table.15. SSIM vs Dataset

Method	BrainWeb	Harvard Whole Brain	Vanderbilt Multimodal
Wavelet Transform Fusion	0.84	0.81	0.83
CNN-based Fusion	0.89	0.87	0.88
Deep Neuro-Fuzzy Fusion	0.91	0.89	0.90
Proposed Method	0.94	0.92	0.93

Table.16. Edge Preservation Index (EPI) vs Dataset

Method	BrainWeb	Harvard Whole Brain	Vanderbilt Multimodal
Wavelet Transform Fusion	0.76	0.73	0.75
CNN-based Fusion	0.82	0.79	0.81
Deep Neuro-Fuzzy Fusion	0.84	0.81	0.83
Proposed Method	0.88	0.85	0.87

Table.17. PSNR vs Dataset

Method	BrainWeb	Harvard Whole Brain	Vanderbilt Multimodal
Wavelet Transform Fusion	29.3	28.7	29.0
CNN-based Fusion	31.2	30.5	30.9
Deep Neuro-Fuzzy Fusion	32.0	31.4	31.8
Proposed Method	33.7	32.8	33.2

Table.18. MI vs Dataset

Method	BrainWeb	Harvard Whole Brain	Vanderbilt Multimodal
Wavelet Transform Fusion	2.21	2.13	2.17
CNN-based Fusion	2.45	2.36	2.39
Deep Neuro-Fuzzy Fusion	2.53	2.47	2.50
Proposed Method	2.68	2.61	2.65

The experimental results demonstrate that the proposed swarm-enhanced deep neuro-fuzzy fusion system consistently outperforms existing methods across both feature channel variations and datasets. As shown in Table.9-Table.13, increasing the number of convolutional feature channels from 32 to 128 significantly improves performance metrics for all methods. For instance, entropy rises from 6.78 to 7.11 for the proposed method, compared with only 6.42 for Wavelet Transform Fusion at 128 channels (Table.9). Similarly, SSIM improves from 0.91 to 0.94 for the proposed method, indicating better structural preservation than CNN-based Fusion (0.89) and Deep Neuro-Fuzzy Fusion (0.91) at the same configuration (Table.10). Edge Preservation Index and PSNR also show notable improvements, with EPI reaching 0.88 and PSNR 33.8 dB at 128 channels, highlighting superior retention of anatomical boundaries and intensity fidelity (Table.11-Table.13). Across datasets (Table.14-Table.18), the proposed method achieves the highest metric values. On the BrainWeb dataset, entropy reaches 7.09, SSIM 0.94, EPI 0.88, PSNR 33.7 dB, and MI 2.68, surpassing Wavelet Transform Fusion, CNN-based Fusion, and Deep Neuro-Fuzzy Fusion. Similar trends appear for Harvard Whole Brain and Vanderbilt datasets, with consistent improvements of approximately 5–8% in all metrics. The swarm-based optimization effectively tunes fuzzy parameters, enhancing feature saliency and fusion consistency. Overall, the results numerically confirm that the proposed method preserves structural, textural, and contrast information more effectively than existing techniques.

7. CONCLUSION

This work presents a swarm-enhanced deep neuro-fuzzy system for multi modal medical image fusion, which integrates deep convolutional feature extraction, fuzzy inference, and swarm intelligence-based optimization. The proposed framework demonstrates robust performance across multiple feature channel configurations and diverse datasets. By adaptively optimizing fuzzy membership functions and rule weights, the system effectively balances saliency preservation, structural consistency, and noise reduction. Experimental evaluations show that the proposed method achieves superior entropy (up to 7.11), SSIM (up to 0.94), edge preservation (up to 0.88), PSNR (up to 33.8 dB), and mutual information (up to 2.68), consistently outperforming Wavelet Transform Fusion, CNN-based Fusion, and conventional Deep Neuro-Fuzzy Fusion. These improvements indicate enhanced retention of anatomical details, sharper edges, and higher information content in the fused images. The results also demonstrate that increasing convolutional feature channels further enhances fusion quality without significant computational overhead.

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