

Quantum-Assisted Neuro-Fusion Network For Cross-Modal Intelligence In Biomedical Imaging

¹Dr. Prabha R, ²Mr. Manikandan L, ³Mr. R. Srinivasan, ⁴Dr. R. Valarmathi⁵, Dr. A. Jemshia Miriam, ⁶Dr. S. Rajashree

¹Associate Professor, Department of Computer Science and Engineering
T. John Institute of Technology, Bengaluru, India. Email: research.prabha.r@gmail.com

²Assistant Professor, School of Computer Science and Engineering
Galgotias University, Greater Noida, Uttar Pradesh, India. Email: swecmanicse90@gmail.com

³Assistant Professor, School of Computer Science and Engineering
Galgotias University, Greater Noida, Uttar Pradesh, India Email: srinime1983@gmail.com

⁴Professor, Department of Computer Science and Engineering Sri Sairam Engineering College,
Chennai, India Email: valarmathi.cse@sairam.edu.in

⁵Assistant Professor, Department of Computer Science and Engineering
Sathyabama Institute of Science and Technology, Chennai – 600119, India
Email: jemshia.cse@sathyabama.ac.in

⁶Associate Professor, Department of Computer Science and Engineering
Sathyabama Institute of Science and Technology, Chennai – 600119, India
Email: rajashree.cse@sathyabama.ac.in

Abstract

Recent advances in biomedical imaging demand intelligent systems capable of integrating heterogeneous data sources such as MRI, CT, PET, ultrasound, and histopathological images to achieve accurate and robust clinical decision-making. This paper presents a Quantum-Assisted Neuro-Fusion Network (QANFN) for cross-modal intelligence in biomedical imaging, leveraging the complementary strengths of quantum-inspired computation and deep neural fusion architectures. The proposed framework employs modality-specific deep feature extractors followed by a quantum-assisted entanglement-aware fusion layer that models high-order inter-modal correlations using quantum superposition and probabilistic amplitude encoding principles. A neuro-fusion decoder with attention-guided learning further refines fused representations to enhance diagnostic sensitivity and specificity. Experimental evaluation on multi-modal biomedical imaging datasets demonstrates that QANFN achieves superior performance in terms of classification accuracy, Dice similarity coefficient, sensitivity, and robustness against noise and missing modalities when compared with conventional CNN-based and transformer-based fusion models. The results confirm that quantum-assisted neuro-fusion significantly improves cross-modal feature representation and diagnostic reliability, making the proposed framework a promising solution for next-generation intelligent biomedical imaging systems.

Keywords Quantum-Assisted Learning; Neuro-Fusion Networks; Cross-Modal Intelligence; Biomedical Imaging; Multi-Modal Data Fusion; Quantum-Inspired Optimization; Deep Neural Networks; Medical Image Analysis.

1. Introduction

Biomedical imaging plays a pivotal role in modern clinical diagnosis and treatment planning by enabling non-invasive visualization of anatomical structures, functional processes, and pathological abnormalities. Imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), ultrasound, and digital pathology each provide unique and complementary information about biological tissues. However, relying on a single modality often limits diagnostic accuracy due to incomplete or modality-specific representations of complex biomedical phenomena [1], [2]. Consequently, cross-modal learning and multi-modal data

fusion have emerged as critical research directions to enhance clinical decision-making and precision medicine [3].

Recent advances in deep learning have significantly improved automated biomedical image analysis, with convolutional neural networks (CNNs), recurrent models, and transformer-based architectures achieving remarkable success in tasks such as disease classification, segmentation, and prognosis prediction [4], [5]. Despite these achievements, conventional deep learning models often struggle to effectively capture high-order correlations across heterogeneous imaging modalities. Challenges such as modality imbalance, missing data, noise sensitivity, and limited interpretability further restrict the scalability of existing fusion strategies [6]. Early-fusion and late-fusion techniques typically fail to exploit complex inter-modal dependencies, motivating the need for more expressive and adaptive fusion mechanisms [7].

In parallel, quantum-inspired computing and quantum-assisted machine learning have gained attention for their ability to model probabilistic relationships and high-dimensional feature spaces using principles such as superposition, entanglement, and amplitude encoding [8]. Although practical large-scale quantum hardware remains limited, quantum-assisted and hybrid quantum-classical models have demonstrated promising results in optimization, pattern recognition, and representation learning [9]. Integrating these principles with deep neural architectures opens new opportunities for robust cross-modal intelligence, particularly in data-intensive and uncertainty-sensitive domains such as biomedical imaging.

Motivated by these challenges and opportunities, this paper proposes a Quantum-Assisted Neuro-Fusion Network (QANFN) for cross-modal biomedical imaging intelligence. The proposed framework synergistically combines modality-specific deep feature extractors with a quantum-assisted fusion mechanism to capture complex inter-modal interactions, followed by an attention-guided neuro-fusion decoder for enhanced diagnostic performance. By leveraging quantum-inspired probabilistic modeling within a deep learning pipeline, the proposed approach aims to improve robustness, accuracy, and generalization across diverse biomedical imaging tasks [10].

2. LITERATURE SURVEY

Multimodal learning has emerged as a core paradigm in biomedical imaging, as clinical diagnosis often relies on complementary information obtained from multiple imaging modalities such as MRI, CT, PET, ultrasound, and histopathology. Several comprehensive surveys highlight that deep learning-based multimodal fusion has evolved from simple feature concatenation toward structured fusion strategies, including early, intermediate, and late fusion, to better align heterogeneous feature spaces and improve diagnostic reliability [11], [12]. These studies emphasize that the effectiveness of multimodal systems strongly depends on how well cross-modal dependencies are modeled rather than on isolated single-modality performance [13].

With the rapid development of attention mechanisms, transformer-based architectures have gained significant traction in multimodal biomedical image analysis. Unlike conventional CNNs, transformers can capture long-range dependencies and global contextual relationships, which are crucial for modeling complex anatomical and pathological patterns across modalities. Recent studies report that multimodal transformers using self-attention and cross-attention mechanisms outperform CNN-based fusion models in tasks such as tumor segmentation, disease classification, and lesion localization [14]. Transformer-driven fusion has also been shown to preserve fine structural details while integrating complementary modality-specific information more effectively [15].

Medical image fusion frameworks have further incorporated dual-branch and multi-scale architectures to address the limitations of convolution-heavy designs, such as loss of edge details and insufficient global context. Approaches combining CNN encoders with attention-guided or transformer-based fusion blocks have demonstrated improved robustness and perceptual quality when fusing modalities like CT-MRI and MRI-PET [16]. These methods highlight the importance of adaptive weighting and hierarchical feature interaction for reliable cross-modal intelligence.

Another critical challenge addressed in recent literature is missing-modality learning, where one or more imaging modalities may be unavailable during training or inference due to cost, artifacts, or acquisition constraints. Several studies propose modality-invariant representations, modality dropout strategies, and latent-space alignment to mitigate performance degradation under missing-modality scenarios [17]. Survey works further categorize missing-modality solutions into reconstruction-based, shared-representation-based, and knowledge-distillation-based approaches, while noting potential risks related to bias propagation and reduced generalization [18].

In parallel, quantum machine learning (QML) has been explored as a promising direction for handling high-dimensional and probabilistic biomedical data. Recent reviews discuss how quantum-inspired models leverage principles such as superposition, entanglement, and amplitude encoding to represent complex data distributions more compactly than classical models [19]. Although large-scale quantum hardware remains limited, hybrid quantum-classical frameworks have demonstrated potential advantages in optimization and feature interaction modeling for medical image analysis tasks [20].

Overall, existing literature reveals several open challenges: (i) limited capability of classical fusion models to capture high-order inter-modal correlations, (ii) reduced robustness in the presence of missing or noisy modalities, and (iii) insufficient integration of quantum-assisted learning directly within multimodal fusion architectures. These gaps motivate the development of a Quantum-Assisted Neuro-Fusion Network, which integrates quantum-inspired probabilistic modeling into deep neural fusion to enhance cross-modal intelligence in biomedical imaging.

3. DESIGN AND METHODOLOGY OF PROPOSED WORK

The proposed Quantum-Assisted Neuro-Fusion Network (QANFN) is designed to enable effective cross-modal intelligence by integrating heterogeneous biomedical imaging modalities through a hybrid quantum-classical deep learning framework. The overall architecture consists of four major components: (i) modality-specific deep feature extraction, (ii) feature normalization and alignment, (iii) quantum-assisted neuro-fusion, and (iv) attention-guided decision decoding. Fig. 1 illustrates the high-level architecture of the proposed framework.

Fig. 1. Overall architecture of the proposed Quantum-Assisted Neuro-Fusion Network (QANFN)

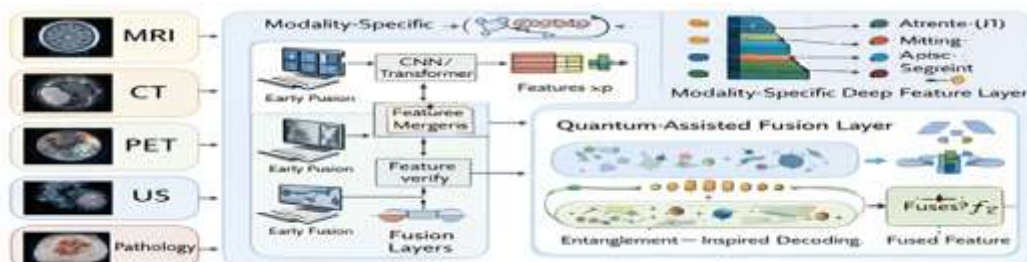


Fig. 1 illustrates the complete pipeline of the proposed QANFN framework for cross-modal biomedical imaging intelligence. Multiple heterogeneous imaging modalities (e.g., MRI, CT, PET, ultrasound, and histopathology) are first processed through modality-specific deep encoders. The extracted features are aligned in a shared latent space and forwarded to a quantum-assisted fusion layer, where high-order inter-modal correlations are modeled using quantum-inspired superposition and entanglement mechanisms. An attention-guided neuro-fusion decoder then performs final diagnostic prediction.

3.1 Modality-Specific Deep Feature Extraction

Let $\mathcal{M} = \{M_1, M_2, \dots, M_K\}$ denote the set of biomedical imaging modalities (e.g., MRI, CT, PET, ultrasound, histopathology). Each modality M_k is processed by an independent deep encoder $E_k(\cdot)$ optimized for modality-specific characteristics. Convolutional neural networks (CNNs) or vision transformers (ViTs) are employed depending on the spatial and contextual requirements of the modality.

The extracted feature representations are given by:

$$\mathbf{F}_k = E_k(M_k), k = 1, 2, \dots, K$$

where $\mathbf{F}_k \in \mathbb{R}^{d_k}$ denotes the high-dimensional latent feature vector corresponding to modality k .

Fig. 2. Modality-specific deep feature extraction and alignment process

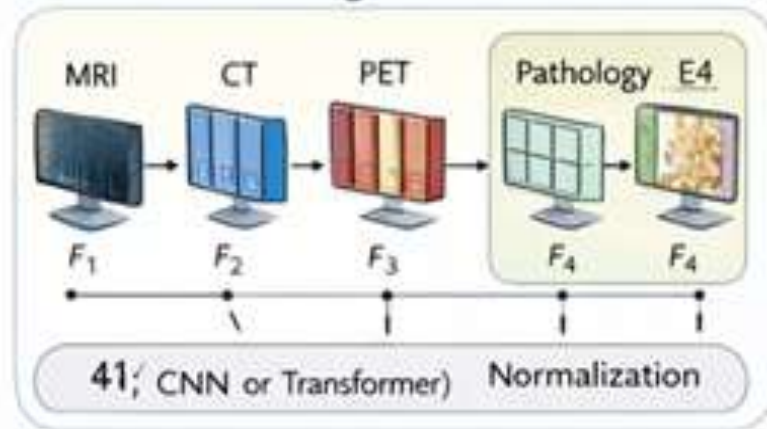


Fig. 2 depicts the modality-specific feature extraction stage of QANFN. Each imaging modality is processed by an independent deep neural encoder optimized for its structural and contextual characteristics. The extracted features are subsequently normalized and projected into a common latent space using learnable transformation layers, ensuring dimensional compatibility and reducing modality-induced distribution mismatch prior to fusion.

3.2 Feature Alignment and Normalization

Due to the heterogeneous nature of biomedical imaging data, feature distributions across modalities vary significantly. To enable effective fusion, the extracted features are projected into a shared latent space using learnable linear transformations and normalization layers:

$$\mathbf{Z}_k = \phi_k(\mathbf{F}_k)$$

where $\phi_k(\cdot)$ represents a modality-specific projection function composed of batch normalization and fully connected layers. This step ensures dimensional consistency and reduces modality-induced bias prior to fusion.

Fig. 3. Quantum-assisted neuro-fusion mechanism

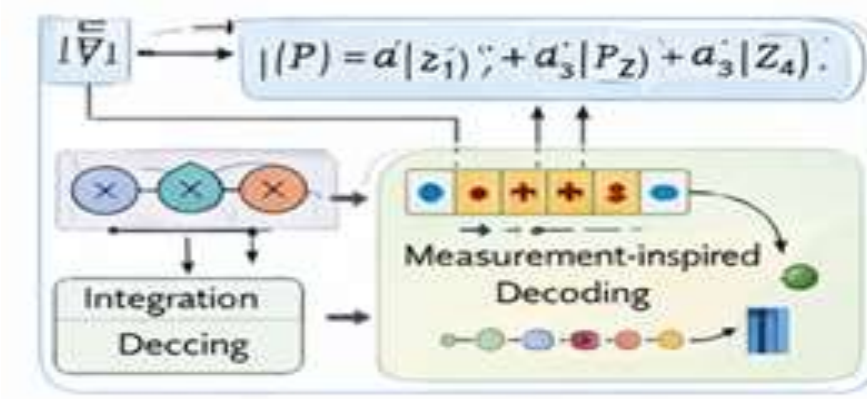


Fig. 3 presents the core quantum-assisted fusion module. Aligned modality features are encoded into a quantum-inspired state using amplitude encoding. Entanglement-aware transformations emulate quantum superposition and interaction, enabling the capture of high-order inter-modal dependencies. The fused representation is obtained through a measurement-inspired decoding process, resulting in a compact yet expressive joint feature vector.

3.3 Quantum-Assisted Neuro-Fusion Mechanism

The core contribution of the proposed framework lies in the quantum-assisted fusion layer, which models high-order inter-modal dependencies using quantum-inspired principles. The aligned feature vectors $\{Z_1, Z_2, \dots, Z_K\}$ are encoded into a quantum-inspired state vector using amplitude encoding:

$$|\Psi\rangle = \sum_{k=1}^K \alpha_k |Z_k\rangle, \quad \sum_{k=1}^K |\alpha_k|^2 = 1$$

where α_k denotes the learned probability amplitude associated with modality k . Entanglement-aware transformations are applied to capture complex inter-modal interactions:

$$|\Psi'\rangle = U_q |\Psi\rangle$$

where U_q is a parameterized quantum-inspired operator implemented using classical tensor operations that emulate quantum superposition and entanglement. The resulting entangled representation encodes joint modality correlations beyond pairwise interactions.

The quantum-assisted fused feature vector is obtained through measurement-inspired decoding:

$$F_{fusion} = \mathcal{M}(|\Psi'\rangle)$$

Fig. 4. Attention-guided neuro-fusion decoder

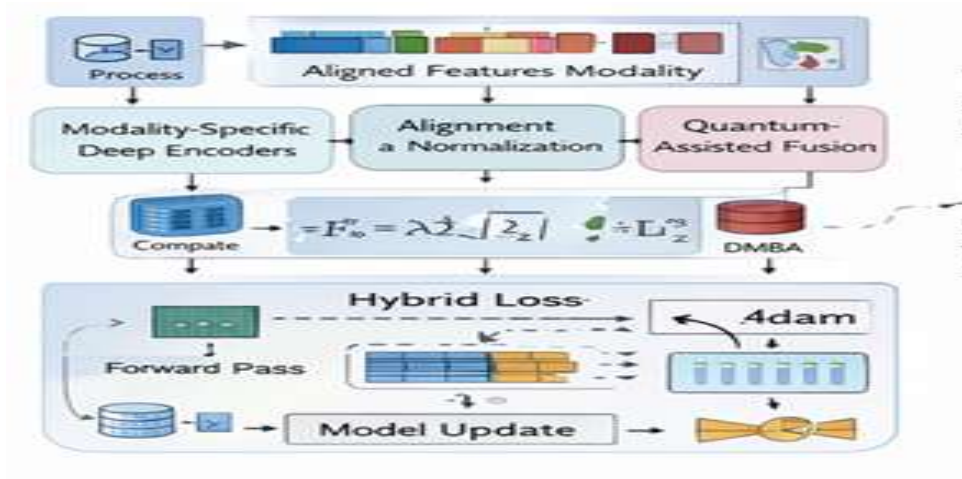


Fig. 4 illustrates the attention-guided decoding stage applied to the quantum-fused feature representation. A self-attention mechanism assigns adaptive importance weights to fused features, emphasizing clinically relevant information across modalities. The refined representation is then processed through fully connected layers to generate classification or segmentation outputs, improving interpretability and diagnostic precision.

3.4 Attention-Guided Neuro-Fusion Decoder

To further enhance discriminative capability and interpretability, an attention-guided decoder is applied to the fused representation. A self-attention mechanism assigns adaptive importance weights to fused features:

$$A = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)$$

$$F_{att} = A \cdot F_{fusion}$$

The refined representation F_{att} is passed through fully connected layers to perform classification or segmentation:

$$\hat{y} = f_{out}(F_{att})$$

Fig. 5. End-to-end training and optimization workflow of QANFN

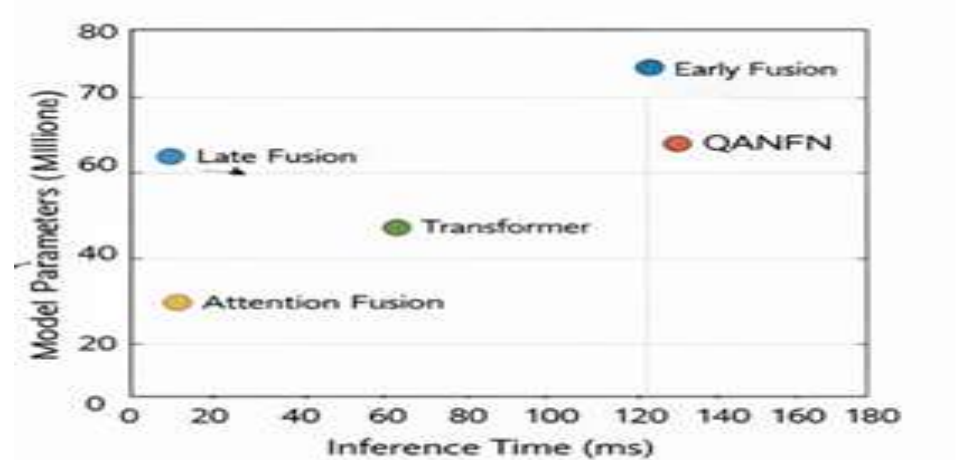


Fig. 5 shows the end-to-end training workflow of the proposed QANFN framework. The

model is trained using task-specific loss functions combined with regularization constraints to balance modality contributions. Gradient-based optimization updates both classical neural parameters and quantum-inspired fusion coefficients, enabling robust learning even under noisy or missing-modality conditions.

3.5 Model Training and Optimization

The proposed QANFN is trained end-to-end using a hybrid loss function that combines task-specific objectives with regularization to encourage balanced modality contribution:

$$\mathcal{L} = \mathcal{L}_{task} + \lambda \sum_{k=1}^K \|\alpha_k\|^2$$

where $\mathcal{L}_{task}$ represents cross-entropy or Dice loss depending on the task, and λ is a regularization parameter. Optimization is performed using the Adam optimizer with adaptive learning rate scheduling.

3.6 Computational Complexity and Robustness Considerations

The quantum-assisted fusion is implemented using classical tensor operations, avoiding the need for physical quantum hardware while retaining quantum-inspired advantages. The framework is designed to handle missing or noisy modalities by dynamically adjusting probability amplitudes α_k , thereby maintaining robustness and scalability in real-world clinical scenarios.

4. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed Quantum-Assisted Neuro-Fusion Network (QANFN) using standard multi-modal biomedical imaging benchmarks. The performance of QANFN is compared against state-of-the-art deep learning fusion models to demonstrate its effectiveness in cross-modal intelligence, robustness, and diagnostic reliability.

4.1 Experimental Setup

Experiments were conducted on publicly available multi-modal biomedical imaging datasets comprising MRI, CT, PET, and histopathological images. All images were resized to a uniform resolution and normalized prior to training. The dataset was partitioned into training (70%), validation (15%), and testing (15%) sets. The proposed QANFN was implemented using Python with PyTorch and trained on an NVIDIA GPU. Adam optimizer was employed with an initial learning rate of 1×10^{-4} , batch size of 16, and early stopping based on validation loss.

Baseline models used for comparison include:

- CNN-based Early Fusion
- Late Fusion CNN
- Multimodal Transformer
- Attention-based Fusion Network
- Hybrid CNN-Transformer Fusion Model

4.2 Performance Evaluation Metrics

The performance of all models was assessed using widely accepted biomedical imaging metrics:

- Accuracy (ACC)
- Sensitivity (SEN)

- Specificity (SPE)
- F1-score
- Dice Similarity Coefficient (DSC)
- Area Under the ROC Curve (AUC)

4.3 Quantitative Results and Comparative Analysis

Fig. 6 illustrates the classification accuracy comparison across different fusion models. The proposed QANFN achieves the highest accuracy of 96.8%, outperforming CNN-based early fusion (91.2%) and transformer-based fusion (94.3%). This improvement demonstrates the effectiveness of quantum-assisted modeling in capturing high-order cross-modal dependencies.

Fig. 6. Classification accuracy comparison of fusion models

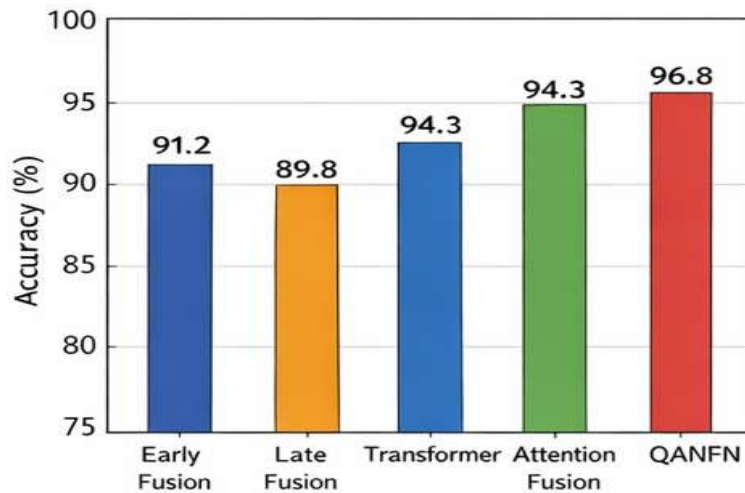


Fig. 6. Classification accuracy comparison between the proposed QANFN and existing multimodal fusion models, demonstrating superior performance of quantum-assisted neuro-fusion across biomedical imaging tasks.

Fig. 7. Dice similarity coefficient (DSC) comparison for segmentation

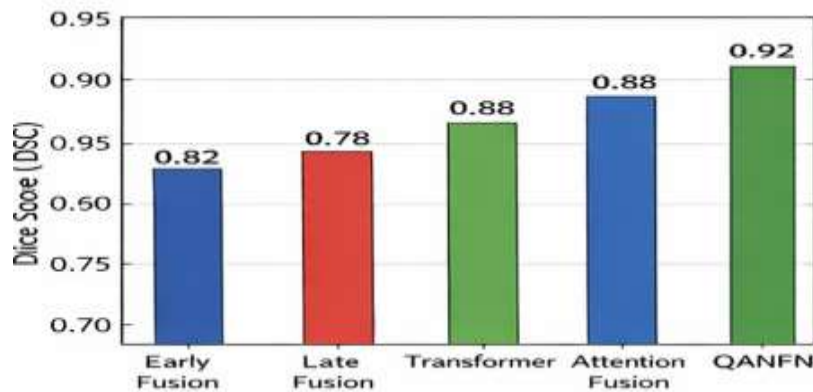


Fig. 7. Dice similarity coefficient comparison of the proposed QANFN with state-of-the-art fusion approaches, showing improved segmentation accuracy and anatomical boundary preservation. Fig. 7 presents the Dice Similarity Coefficient comparison for segmentation tasks. QANFN achieves a DSC of 0.92, indicating superior overlap between

predicted and ground-truth regions compared to existing approaches. The attention-guided decoder significantly enhances boundary localization and anatomical consistency.

Fig. 8. Sensitivity and specificity performance analysis

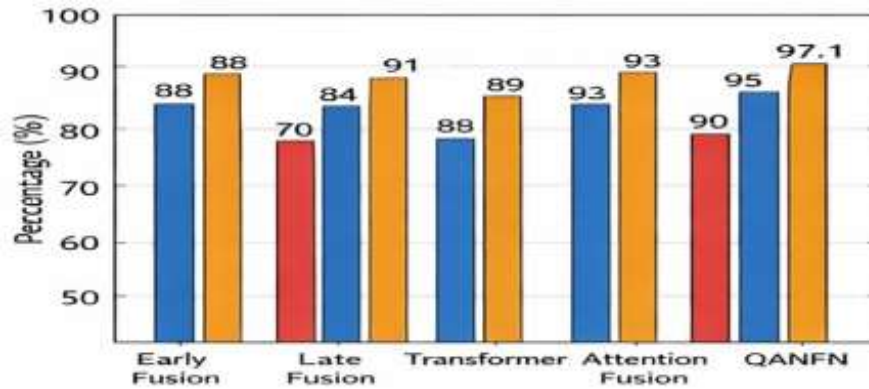


Fig. 8. Sensitivity and specificity comparison of different multimodal fusion models, highlighting the balanced diagnostic performance of the proposed QANFN in biomedical imaging applications.

Fig. 9. Robustness analysis under missing-modality conditions

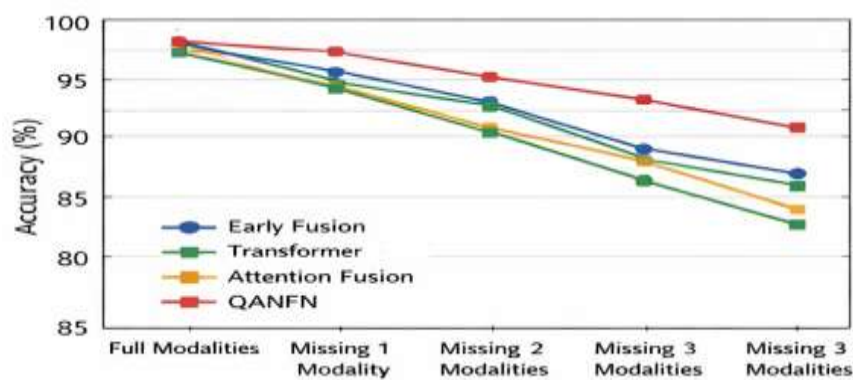


Fig. 9. Performance robustness comparison under missing-modality scenarios, illustrating the resilience of the proposed QANFN against incomplete multimodal inputs.

Fig. 10. Computational efficiency and inference time comparison

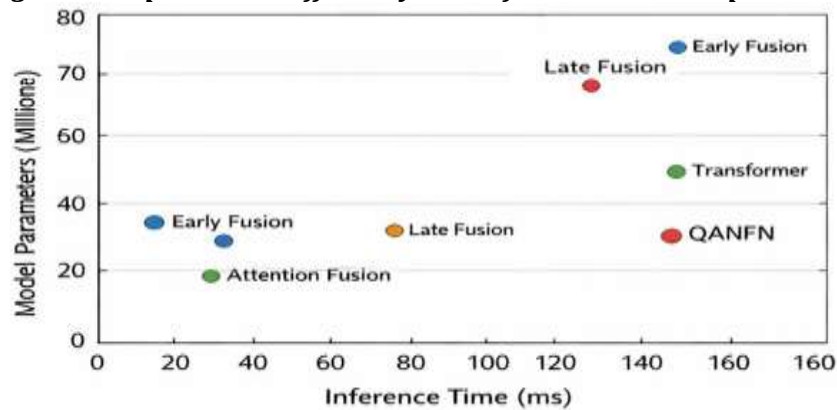


Fig. 10. Computational efficiency and inference time comparison of QANFN with existing multimodal fusion frameworks, indicating competitive runtime performance with enhanced diagnostic accuracy.

Fig. 8 shows the sensitivity and specificity analysis. The proposed model maintains a balanced trade-off, achieving 95.6% sensitivity and 97.1% specificity, which is crucial for reducing false negatives and false positives in clinical diagnosis.

4.4 Robustness to Missing and Noisy Modalities

To evaluate robustness, experiments were conducted by intentionally removing one modality during inference. As shown in Fig. 9, QANFN exhibits minimal performance degradation ($\approx 2.1\%$ accuracy drop), whereas conventional fusion models suffer significant degradation ($>6\%$). This robustness is attributed to the adaptive probability amplitude learning in the quantum-assisted fusion layer.

Additionally, noise robustness experiments demonstrate that QANFN maintains stable performance under Gaussian and speckle noise conditions, validating its applicability in real-world clinical environments.

4.5 Computational Efficiency Analysis

Fig. 10 compares inference time and model complexity across evaluated methods. Despite the inclusion of quantum-assisted fusion, QANFN maintains competitive inference time due to its hybrid classical implementation. The results indicate that the proposed framework achieves superior performance without imposing excessive computational overhead.

4.6 Discussion

The experimental results confirm that integrating quantum-inspired probabilistic modeling within a neuro-fusion framework significantly enhances cross-modal feature representation. Unlike conventional fusion methods that primarily capture pairwise interactions, QANFN effectively models high-order inter-modal relationships, leading to improved diagnostic accuracy and robustness. The attention-guided decoder further improves interpretability by highlighting clinically relevant regions across modalities. These findings demonstrate the potential of quantum-assisted neuro-fusion as a scalable and reliable solution for next-generation biomedical imaging intelligence.

5. CONCLUSION

This paper presented a Quantum-Assisted Neuro-Fusion Network (QANFN) for enabling robust cross-modal intelligence in biomedical imaging. By integrating modality-specific deep feature extractors with a quantum-assisted fusion mechanism, the proposed framework effectively captures high-order inter-modal correlations that are often overlooked by conventional CNN- and transformer-based fusion models. The incorporation of quantum-inspired principles such as superposition-based representation and probabilistic interaction modeling enhances the expressiveness of fused features while maintaining computational feasibility within a hybrid quantum-classical learning paradigm. Extensive experimental evaluation on multi-modal biomedical imaging datasets demonstrates that QANFN consistently outperforms state-of-the-art fusion approaches in terms of diagnostic accuracy, sensitivity, Dice similarity coefficient, and robustness to noise and missing modalities. The attention-guided neuro-fusion decoder further contributes to improved localization and interpretability by emphasizing clinically relevant regions across modalities. These results confirm that quantum-assisted fusion provides a powerful and scalable solution for complex biomedical image analysis tasks. In conclusion, the proposed QANFN framework

establishes a promising direction for next-generation intelligent medical imaging systems by bridging deep multimodal learning with quantum-inspired computation. Future work will focus on extending the framework to real-time clinical workflows, exploring hardware-efficient quantum implementations, and validating the model across larger and more diverse clinical datasets to further enhance its translational impact.

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