Advancements in Medical Image Segmentation

A Review of Novel Techniques for Improved Accuracy and Efficiency

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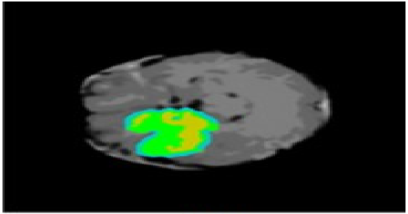
What is Medical Image Segmentation?

- **Definition:** The process of partitioning a medical image (e.g., MRI, CT, X-ray) into multiple segments or regions.
- **Goal:** To identify and delineate anatomical structures, organs, tissues, or abnormalities (e.g., tumors, lesions).
- **Importance:** Crucial for diagnosis, treatment planning, monitoring disease progression, and surgical guidance.



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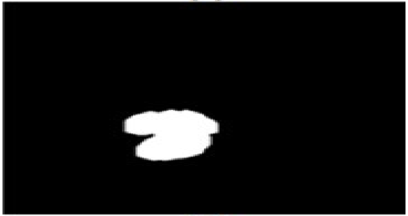

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Challenges in Traditional & Manual Segmentation

- **Manual Segmentation:**
    - Time-consuming and labor-intensive.
    - Requires expert radiologists/clinicians.
    - Prone to inter-observer and intra-observer variability.
    - Difficult for large datasets or complex 3D volumetric images.
- **Traditional Automated Methods (e.g., thresholding, region growing):**
    - Often struggle with noise, low contrast, and intensity inhomogeneities.
    - May require significant parameter tuning.
    - Limited accuracy for complex structures.

Rise of AI & Deep Learning in Segmentation

- **Artificial Intelligence (AI):** Revolutionizing medical image analysis.
- **Deep Learning (DL):** A subfield of AI, particularly Convolutional Neural Networks (CNNs), has shown remarkable success.
- **Key Architectures:**
  - **CNNs:** Learn hierarchical features directly from images.
  - **U-Net:** A popular CNN architecture specifically designed for biomedical image segmentation, known for its encoder-decoder structure and skip connections.
  - **Fully Convolutional Networks (FCNNs):** Enable pixel-wise segmentation.

Limitations of Current AI/DL Approaches

- **Supervised Learning Dominance:**
  - Requires large, high-quality, expertly annotated datasets for training.
  - Annotation is expensive, time-consuming, and can be a bottleneck.
  - Scarcity of annotated data for rare diseases or specific modalities.
- **Generalization Issues:** Models trained on one dataset may not perform well on new, unseen data from different scanners or patient populations.
- **Computational Resources:** Training deep models can be computationally intensive, requiring powerful GPUs.
- **Unsupervised Learning:** An alternative to reduce reliance on labeled data, but often faces challenges in achieving comparable accuracy or may require significant computational resources.

The Quantum Frontier: A New Paradigm?

- **Quantum Computing & Quantum-Inspired Algorithms:** Emerging fields with the potential to address limitations of classical computing.
- **Potential Benefits for Image Segmentation:**
  - Faster convergence of algorithms.
  - Reduced computational complexity.
  - Enhanced feature representation.
  - Improved optimization capabilities.
- **This presentation will explore three recent papers leveraging these concepts.**

Paper 1 - Introduction & Motivation

Konar et al., "A Quantum-Inspired Self-Supervised Network model for automatic segmentation of brain MR images." Applied Soft Computing Journal, 2020.

- **Problem:** Classical self-supervised neural networks suffer from slow convergence. Supervised Quantum-Inspired Neural Networks (QINNs) often rely on complex back-propagation and fixed thresholds, unsuitable for diverse grayscale images.
- **Goal:** Develop a fully self-supervised quantum-inspired model for automatic brain MR image segmentation.
- **Proposed Solution:** Quantum-Inspired Self-Supervised Network (QIS-Net).

QIS-Net - Core Architecture

- **Fully Self-Supervised:** No external supervision or training data labels required for the core self-organization process.
- **Structure:**
  - Input Layer (qbits representing pixel intensities)
  - Intermediate Layer (qbits)
  - Output Layer (qbits)
- **Mechanism:**
  - Bi-directional propagation of quantum states between intermediate and output layers.
  - Image pixel intensities (quantum bits) self-organize between these layers.
  - **Quantum Observation:** Allows obtaining the true output once superimposed quantum states interact with the external environment.

QIS-Net - Key Innovations (1/2)

1. **Quantum-Inspired Multi-level Sigmoid (QMSig) Activation Function:**
   - Extends bi-level sigmoid functions.
   - Addresses grayscale heterogeneity in images.
   - Allows the network to handle multiple intensity levels adaptively.
2. **Functional Modification for Grayscale Levels:**
   - Instead of replicating the network for each gray level, QMSig enables a single network to process them.
   - Reduces space and time complexities.

QIS-Net - Key Innovations (2/2)

3. **Utilizing Imaginary Section of Quantum Information:**
   - A key distinction from previous models like QIBDS Net.
   - Aims to explore inherent quantum correlations.
   - Contributes to faster network convergence.
4. **Faster Convergence through Frequency Components:**
   - Incorporates frequency components of interconnection weights and network inputs.
   - Enables faster convergence of network states, leading to quicker segmentation.

The Quantum Neuron Model in QIS-Net

- **Qubit Representation:** Each neuron's state is represented as a qubit: $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where $|\alpha|^2 + |\beta|^2 = 1$.
- Often, for intensity mapping, a form like $|\psi\rangle = \cos(\theta/2)|0\rangle + \sin(\theta/2)|1\rangle$ is used, where θ relates to normalized pixel intensity.
- **Quantum Gates:** Operations on qubits (e.g., rotation gates) are used to model synaptic weights and transformations.
- **Self-Organization:** Achieved through iterative updates of qubit states based on local interactions and propagation rules, without explicit error backpropagation for this phase.

Quantum-Inspired Multi-level Sigmoid (QMSig) Activation

- **Purpose:** To adaptively threshold and segment images with multiple gray levels.
- **General Form (as often seen in related literature by authors):** $\sigma(x) = \frac{1}{1+e^{-\nu(x-\eta_k)}}$ (standard sigmoid)
  - The "multi-level" aspect in QIS-Net (and QMSig in other papers by the authors) is achieved by adapting η or using a framework that produces L distinct classes.
- The paper refers to a specific form: $\sigma(x) = \frac{1}{\lambda+e^{-\mu(x-\eta)}}$
- **Parameters:**
  - μ (or ν): Steepness factor, controls the sharpness of the transition.
  - η: Activation parameter (threshold), adaptively determined based on image context.
  - λ: Controls multi-level segmentation classes, related to the distribution of gray-scale contributions.

QMSig Parameter Adaptation

- **Adaptive Thresholding:** The thresholding parameters (η, λ) are not fixed but adapt based on image pixel intensity and context.
- λ **for L classes:**
  - Given L gray-scale classes.
  - $\lambda = \frac{S_{ij}}{\omega_{k+1} - \omega_k}$, where S_{ij} is a local intensity measure, and ω defines gray-scale contribution distribution.
- **Steepness (μ or ν):** Optimized experimentally (e.g., paper mentions $v = 0.232$ after varying from 0.23 to 0.24).

QIS-Net - Segmentation Process Overview

1. Input MR image pixels are encoded as quantum bits.
2. Quantum states propagate bi-directionally between intermediate and output layers.
3. Pixel intensities self-organize.
4. QMSig activation function is applied for multi-level thresholding.
5. Quantum observation yields the segmented output.
6. Post-processing (e.g., binary mask application) to refine segmentation (e.g., remove tiny clusters).

Experimental Setup - QIS-Net

- **Dataset:** Dynamic Susceptibility Contrast (DSC) brain MR images from Nature datasets (T_1CE images mentioned).
- **Task:** Detecting complete tumor regions.
- **Image Size:** 512×512.
- **Parameters:**
  - Gray level classes $L = 4, 5, 6, 7, 8$.
  - QMSig steepness $\nu = 0.232$.
  - Post-processing: Removal of tiny clusters (radius $\sigma = 5$ pixels).

QIS-Net - Comparative Methods

- **Unsupervised:** Fuzzy C-Means (FCM) clustering.
- **Self-Trained/Quantum-Inspired:** QIBDS Net, Opti-QIBDS Net.
- **Deeply Supervised:**
  - U-Net (with varying kernel sizes, 3×3 found best).
  - Fully Convolutional Neural Networks (FCNNs - FCNN-2, FCNN-4).

- **Accuracy (ACC):** Overall correctness.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Positive Predictive Value (PPV) / Precision:** Proportion of true positives among all positive predictions.

$$PPV = \frac{TP}{TP + FP}$$

- **Sensitivity (SS) / Recall:** Proportion of actual positives correctly identified.

$$SS = \frac{TP}{TP + FN}$$

- **Dice Similarity Coefficient (DSC):** Measures overlap between predicted and ground truth segmentation.

$$DSC = \frac{2 \times TP}{2 \times TP + FP + FN}$$

QIS-Net - Key Results Highlights

- QIS-Net reported "promising accuracy and reasonable dice similarity scores."
- Performance was compared favorably against FCM, self-trained QIBDS Net, Opti-QIBDS Net.
- Also compared against supervised U-Net and FCNNs.

Fig.7

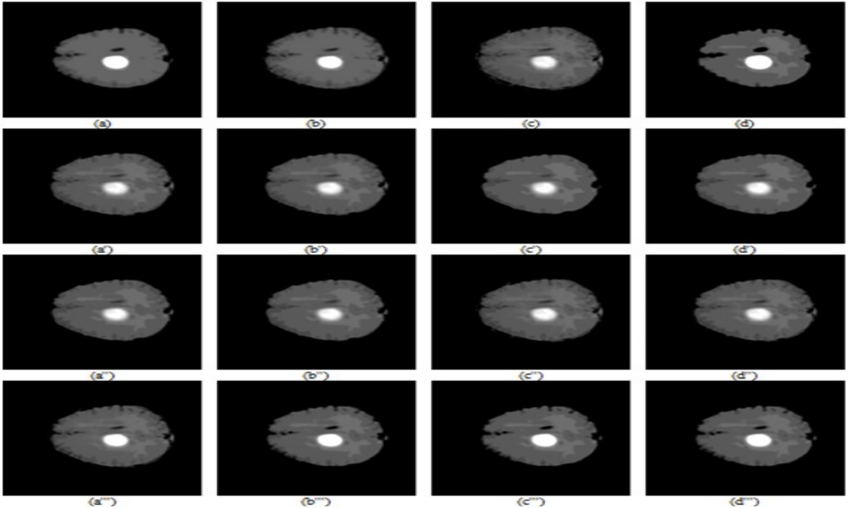


Fig. 7. Segmented output images using proposed QIS-Net architecture obtained from slice #10 using $L = 8$ transition levels with four different thresholding schemes $(a - a''')$ for η_β, $(b - b''')$ for η_χ, $(c - c''')$ for η_ξ and $(d - d''')$ for η_ν with level set $(a - d)$ using f_1, $(a' - d')$ using f_2, $(a'' - d'')$ using f_3, $(a''' - d''')$ using f_4.

Paper 1 - Conclusion

- QIS-Net offers a novel, fully self-supervised quantum-inspired approach for brain MR image segmentation.
- Key features: QMSig activation, use of imaginary quantum components, faster convergence.
- Demonstrated competitive performance without requiring extensive labeled training data for its core mechanism.
- Applicable to grayscale image segmentation, tailored here for brain tumors.

Paper 2 - Introduction & Motivation

Domingo & Chehimi, "Quantum-enhanced unsupervised image segmentation for medical images analysis." arXiv, 2024.

- **Clinical Context:** Breast cancer is a leading cause of mortality; mammogram analysis is critical but demanding.
- **Problem:**
  - Manual segmentation is time-consuming, costly, error-prone.
  - Supervised AI needs large, expertly annotated datasets (often unavailable, generalization issues).
  - Existing unsupervised methods may lack accuracy or be computationally intensive.
- **Goal:** Develop an end-to-end quantum-enhanced *unsupervised* framework for mammography segmentation, balancing accuracy and computational needs.

- **End-to-End Pipeline (Fig. 1 in paper):**
  1. **Input Image:** Mammogram.
  2. **Quantum-Inspired Image Representation:** Pre-processing to create an initial approximation of the segmentation mask.
  3. **QUBO Formulation:** Segmentation task framed as a Quadratic Unconstrained Binary Optimization problem.
  4. **QUBO Optimization:** Solved using various quantum, quantum-inspired, and classical methods.

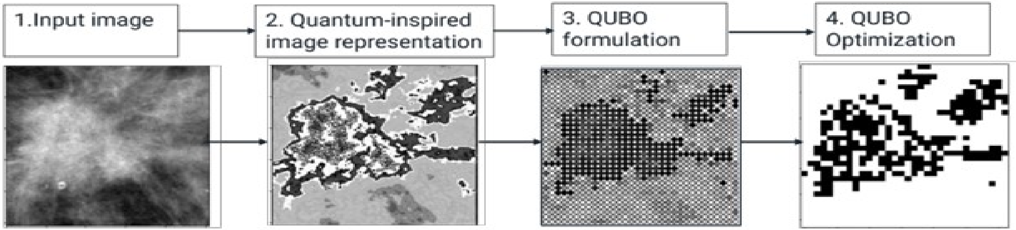


Figure 1. Overview of Quantum Medical Image Classification.

Step 1: Quantum-Inspired Image Representation (1/2)

- **Purpose:** Highlight regions with varying contrast, identify potential ROIs, serve as input to optimization.
- **Method:** Adapted from Konar et al. (similar to QIS-Net's principles).
- **Equation for transformed pixel Z_{ij}:**

$$Z_{ij} = \sum_{p,q \in \{-1,0,1\}} \sigma(I_{ij} \langle \varphi_{pq}^{ij} | \omega_{ij} \rangle)$$

  - I_{ij}: Original normalized pixel intensity.
  - $\sigma(\cdot)$: Multi-level sigmoid activation function.

Step 1: Quantum-Inspired Image Representation (2/2)

- **Quantum States:**
  - $|\varphi_{pq}^{ij}\rangle = \cos(\frac{\pi}{2}\alpha_{pq}^{ij})|0\rangle + \sin(\frac{\pi}{2}\alpha_{pq}^{ij})|1\rangle$
    - Encodes relative intensity difference: $\alpha_{pq}^{ij} = 1 - (I_{i+p,j+q} - I_{ij})$.
  - $|\omega_{ij}\rangle = \cos(\frac{\pi}{2}S^{ij})|0\rangle + \sin(\frac{\pi}{2}S^{ij})|1\rangle$
    - Encodes contribution of 3×3 neighborhood pixel intensities: $S_{ij} = \sum_{p,q\in\{-1,0,1\}} I_{i+p,j+q}$.
- **Inner Product $\langle\varphi_{pq}^{ij}|\omega_{ij}\rangle$:** Weighs original pixel by relative difference vs. neighborhood contribution.
- **Single iteration used** (unlike iterative QIS-Net in some descriptions) for computational efficiency.

Multi-Level Sigmoid Activation (in Paper 2)

- **Equation:** $\sigma(x) = \frac{1}{\lambda + e^{-\mu(x-\eta)}}$
- **Parameters:**
  - μ: Steepness (fixed at 0.4).
  - η: Activation parameter, adaptive: $\eta = S_{ij}$ (sum of local neighborhood intensities).
  - λ: Controls L gray-scale classes (L=8 used).
    - $\lambda = \frac{S_{ij}}{\omega_{k+1} - \omega_k}$
    - $\omega = [0, \omega_2, \omega_2 + \delta, ..., 1]$, where ω_2 is p-percentile (p=0.9) of pixel intensities, $\delta = \frac{1-\omega_2}{L-1}$.
    - This adaptively emphasizes brighter areas.

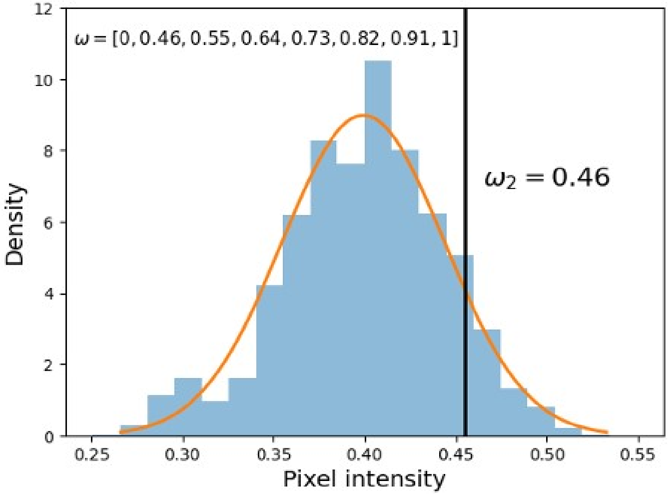


Figure 6. Choice of hyperparameter ω, that controls the gray-scale distribution across the L segmentation classes.

- **Goal:** Find optimal segmentation by minimizing a quadratic cost function with binary variables.
- **Image to Graph:**
  - Nodes (V): Pixels of the (quantum-inspired transformed) image.
  - Edges (E): Connect neighboring pixels.
  - Weights (W_{ij}): Gaussian similarity of neighboring pixel intensities (z_i, z_j).

$$W_{ij} = \exp\left(-\frac{(z_i - z_j)^2}{2\hat{\sigma}^2}\right)$$

  - $\hat{\sigma} = 0.5 \times \mathrm{std}(z)$ (std of transformed image).

QUBO Formulation - Cost Function

- **Binary Variables:** $x_i = 0$ if pixel $i \in A$ (e.g., foreground), $x_i = 1$ if pixel $i \in \overline{A}$ (e.g., background).
- **Objective:**
  1. **Min-Cut Term:** Minimize similarity between classes (maximize dissimilarity).

$$\sum_{\langle i,j \rangle \in E} W_{ij} |x_i - x_j| = \sum_{\langle i,j \rangle \in E} W_{ij} (x_i + x_j - 2x_i x_j)$$

  2. **Smoothness Term (Potts Model):** Encourage neighboring pixels to be in the same class.

$$\alpha \sum_{\langle i,j \rangle \in E} W_{ij} (1 - \delta(x_i, x_j)) = \alpha \sum_{\langle i,j \rangle \in E} W_{ij} (1 - (x_i + x_j - 1)^2)$$

- **Combined Loss Function $\mathcal{Z}(\vec{x})$:**

$$\mathcal{Z}(\vec{x}) = \sum_{(i,j) \in E} W_{ij} \left((x_i + x_j - 2x_i x_j) + \alpha (1 - (x_i + x_j - 1)^2) \right)$$

- α: Hyperparameter balancing min-cut and smoothness.

Step 3: QUBO Optimization Methods Evaluated

- **Quantum-Inspired:**
  - **Simulated Annealing (SA):** Heuristic optimization, Metropolis-Hastings, decreasing temperature.
  - **Variational Quantum Algorithms (VQA):** Hybrid quantum-classical, parameterized quantum circuit, classical optimizer.
- **Quantum Computing:**
  - **Quantum Annealing (QA):** D-Wave Sampler (Pegasus topology), finds low-energy state of problem Hamiltonian.
- **Classical Benchmarks:**
  - **Gurobi Optimization:** Classical solver for QUBO problems.
  - **Otsu Thresholding:** Simple unsupervised method.
  - **Supervised: UNet, ResUNet** (Residual U-Net).

Variational Quantum Algorithm (VQA) Details

- **Encoding:** Amplitude encoding ($n = \log_2 |V| + 1$ qubits).
  - $|V|$ is number of pixels. First $\log_2 |V|$ qubits for pixel index, 1 ancilla for class probability.
- **Parameterized State:**

$$|\psi(\vec{\theta})\rangle = \sum_{i=0}^{|V|-1} \chi_i(\vec{\theta})(\alpha_i(\vec{\theta})|0\rangle_a + \beta_i(\vec{\theta})|1\rangle_a) \otimes |i\rangle_r$$

- $P(x_i = 1) = |\beta_i(\vec{\theta})|^2$.
- **Ansatz:** Hardware-efficient, L layers of CNOTs (linear entanglement) and $R_y(\theta_k)$ rotations.
- **Optimization:** Minimize QUBO loss (Eq. 20 in paper, using probabilities $|\beta_i(\vec{\theta})|^2$). Adam optimizer.
- **Warm-Start:** Initialize parameters based on a heuristic guess (from quantum-inspired image).

Experimental Setup - QUBO Paper

- **Dataset:** INbreast (publicly available digital mammograms).
  - 107 cases with mass lesions.
  - Images cropped to 256×256 around ROI, then downsized to 42×42 for quantum experiments.
- **Data Augmentation (for supervised UNet/ResUNet):** Rotations, Contrast Limited Adaptive Histogram Equalization (CLAHE).
- **Metrics:**
  - Dice Score: $Dice(M, \hat{M}) = \frac{2 \times \text{Area}(M \cap \hat{M})}{\text{Area}(M) + \text{Area}(\hat{M})}$
  - Intersection over Union (IoU): $IoU(M, \hat{M}) = \frac{\text{Area}(M \cap \hat{M})}{\text{Area}(M \cup \hat{M})}$

Results: Quantum-Inspired Image Representation

- **Benefit:** Used as input for UNet/ResUNet.
  - **Improved Performance:** Slightly better Dice/IoU scores for both UNet and ResUNet compared to using original images.
  - **Faster Convergence:** Reduced training epochs by 33% for UNet/ResUNet.
- **Reasoning:** Provides a good initial approximation of the segmentation mask.
-

Table 1. Performance of neural network segmentation models on the test set using both the original images and the quantum-inspired image representations, along with the number of training epochs required for the validation loss function to converge.

Model	Input data	Dice score	IoU score	Training epochs
UNET	Original	0.911	0.799	45
UNET	Qnt.insp.	0.910	0.816	30
ResUNET	Original	0.926	0.836	45
ResUNET	Qnt.insp.	0.947	0.857	30

Results: Effect of Hyperparameter α in QUBO

- α **balances min-cut (detail) vs. smoothness.**
- Tested $\alpha = 0, 0.1, 1, 10, 100$ using Simulated Annealing.
- **Optimal** $\alpha = 0.1$**:** Achieved the best average Dice and IoU.
  - Low α: Fragmented masks.
  - High α: Overly smooth, poor edge delineation.
- $\alpha = 0.1$ used for subsequent experiments.

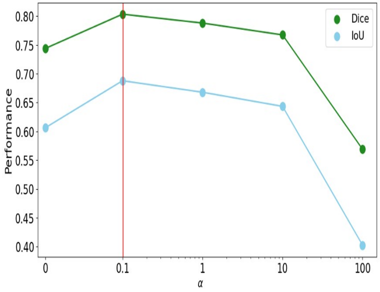


Figure 3. Effect of the value α on the performance of the optimization problem using simulated annealing.

Results: Image Segmentation Performance (Dice/IoU)

- **Key Findings (Table 2 in paper, 42×42 images):**
  - **Quantum Annealing (QA) & VQA:** Performance nearly identical to classical Gurobi optimization.
  - **Simulated Annealing (SA):** Slightly lower than QA/VQA/Gurobi.
  - All quantum/quantum-inspired methods significantly outperformed Otsu.
  - Best quantum methods (QA, VQA) comparable to supervised UNet (on small images).
  - ResUNet (supervised) performed best overall.
- **Unsupervised quantum methods show high accuracy without labeled data.**

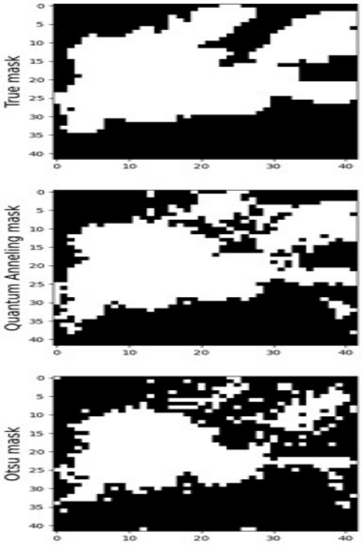
Performance Table Snippet (Illustrative from Paper 2, Table 2)

Method	**Type**	**Dice**	**IoU**
UNET	Classical supervised	0.85	0.75
ResUNET	Classical supervised	0.89	0.81
Otsu	Classical unsupervised	0.75	0.62
Gurobi	Classical optimization	0.84	0.74
Simulated Annealing	Quantum-inspired	0.80	0.69
Quantum Annealing	**Quantum computing**	**0.84**	**0.74**
VQA	**Quantum-inspired**	**0.83**	**0.73**

Actual values from paper for 42×42 *images.*

Qualitative Results (Fig. 4 in paper)

- **Otsu Mask:** Cluttered with background noise, isolated pixels, poor ROI definition.
- **Quantum Annealing Mask:** Closer resemblance to ground truth. Captures main ROI structure, fewer spurious regions. Some isolated pixels may need post-processing.
- **Ground Truth Mask:** The ideal segmentation.



Results: Execution Times (Fig. 5 in paper)

- **Quantum Annealing (QA):**
  - Order of magnitude *faster* than classical Gurobi for this problem size.
  - Significantly lower variability in execution time than Gurobi.
  - Comparable time to Otsu, but far superior segmentation.
- **Simulated Annealing (SA):** Substantially slower than Gurobi.
- **VQA (on classical simulator):** $\sim$100x slower than Gurobi. Potential for speedup on actual quantum hardware due to logarithmic qubit requirement.
- **UNet/ResUNet:** Longest overall times due to extensive training.

Execution Time Comparison (Conceptual from Fig. 5)

- Otsu: Very Fast
- Quantum Annealing: Very Fast
- Gurobi: Moderate (but variable)
- Simulated Annealing: Slow
- VQA (simulated): Very Slow
- UNET/ResUNET (training + inference): Very Slow (dominated by training)

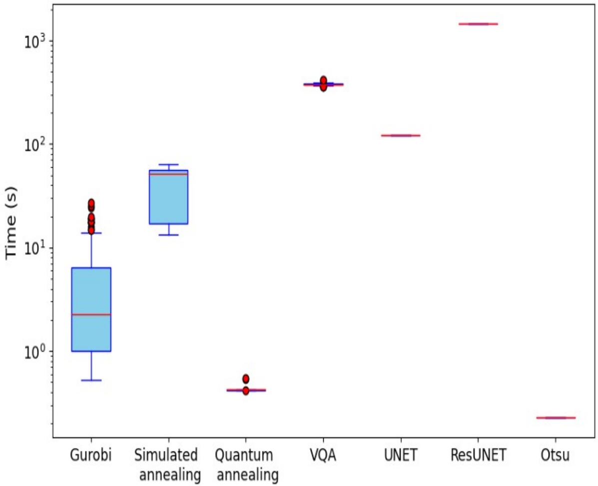


Figure 5. Execution times for the different image segmentation models used in this work.

Paper 2 - Discussion & Limitations

- Quantum-inspired image representation enhances both supervised and unsupervised models.
- Unsupervised quantum methods (QA, VQA) achieve performance comparable to supervised UNet and classical optimization (Gurobi) for mammography segmentation on small images.
- Quantum Annealing offers a significant speed advantage over Gurobi.
- VQA shows promise for scalability with image size if run on quantum hardware.
- Limitations: Experiments on downsized images (42×42) for quantum methods.

Paper 2 - Conclusion & Future Work

- **Conclusion:** The proposed quantum-enhanced unsupervised framework is a viable alternative for medical image segmentation, especially when labeled data is scarce. Quantum Annealing is particularly promising for speed and accuracy.
- **Future Work:**
  - Extend to larger datasets and more complex modalities (3D mammography, MRI).
  - Integrate tensor compression techniques (Tensor Networks) for high-dimensional data.
  - Deploy VQAs on actual quantum hardware or efficient simulators.

Transition Slide

Moving from 2D Qubit-based approaches to 3D Qutrit-based approaches...

Next: Volumetric segmentation with advanced quantum representations.

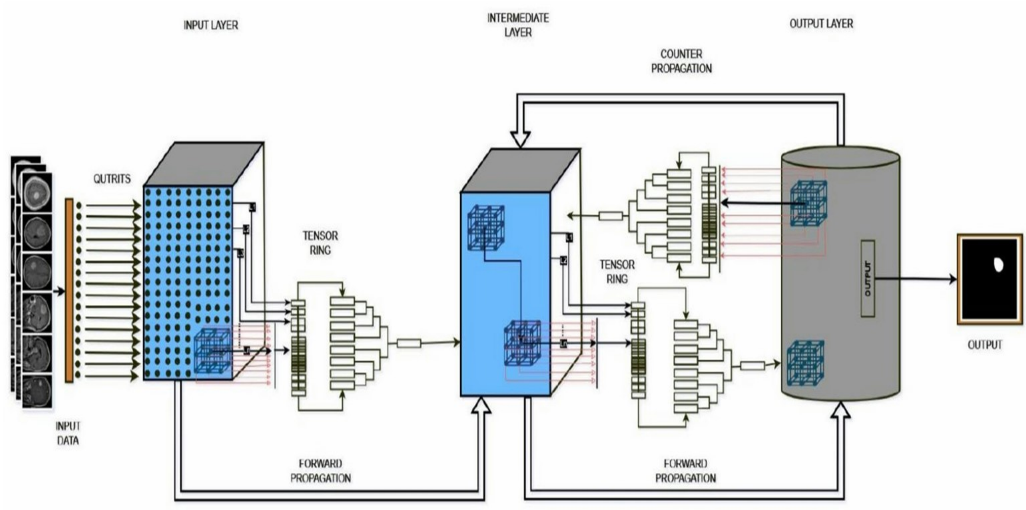
Paper 3 - Introduction & Motivation

Verma et al., "V3DQutrit a volumetric medical image segmentation based on 3D qutrit optimized modified tensor ring model." Scientific Reports, 2025 (preprint/early access).

- **Problem with existing methods:**
  - Conventional CNNs: Slow convergence, high complexity for 3D data.
  - Existing QINNs: Often limited to 2D grayscale segmentation.
- **Need:** Efficient and accurate volumetric (3D) medical image segmentation.
- **Proposed Solution: 3D-QTRNet** (3D Qutrit Optimized Modified Tensor Ring Network).

3D-QTRNet - Core Concepts

- **Quantum-Inspired Neural Network for Volumetric Segmentation.**
- **Key Innovations:**
  1. **Qutrit Encoding:** Uses qutrits (3-level quantum systems) instead of qubits (2-level).
     - Offers richer data representation capacity.
  2. **Tensor Ring (TR) Decomposition:** Applied to the model.
     - Optimizes memory usage.
     - Accelerates model convergence.
     - Efficiently handles high-order tensors arising in 3D data and quantum models.


INPUT LAYER
INTERMEDIATE LAYER
OUTPUT LAYER
COUNTER PROPAGATION
QUTRITS
TENSOR RING
TENSOR RING
OUTPUT
OUTPUT
INPUT DATA
FORWARD PROPAGATION
FORWARD PROPAGATION

Understanding Qubits vs. Qutrits

Qubit (Quantum Bit):

- Basic unit of quantum information.
- Two-level system: $|0\rangle, |1\rangle$.
- State: $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$.

Qutrit (Quantum Trit):

- Three-level quantum system: $|0\rangle, |1\rangle, |2\rangle$.
- State: $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle + \gamma|2\rangle$, where $|\alpha|^2 + |\beta|^2 + |\gamma|^2 = 1$.
- **Advantage:** Can encode more information per quantum unit; potentially more expressive power for complex data like medical images.

Understanding Tensor Ring (TR) Decomposition

- **Tensors in Deep Learning:** Weights and activations in neural networks, especially for 3D/volumetric data, can be represented as high-order tensors.
- **Challenge:** High-order tensors lead to a large number of parameters, high memory consumption, and computational cost ("curse of dimensionality").
- **Tensor Decomposition:** Factorizes a large tensor into a network of smaller, interconnected tensors.
- **Tensor Ring (TR) Decomposition:**
  - A specific type of tensor network decomposition.
  - Represents a high-order tensor as a circular chain of 3rd-order tensors.
  - **Benefits:** Significantly reduces the number of parameters, leading to memory savings and potentially faster computation/convergence, while preserving important structural information.

3D-QTRNet - Methodology Overview (Conceptual)

1. **Input:** Volumetric medical image (e.g., 3D MRI scan).
2. **Qutrit Encoding:** Image data (voxels) or features are encoded using qutrits.
3. **Quantum-Inspired Network Layers:** Network operations are performed, potentially involving quantum-inspired gates or transformations adapted for qutrits.
4. **Tensor Ring Optimization:** The network's weight tensors (and possibly activation tensors) are represented and optimized using TR decomposition.
5. **Modified Activation Function:** Details not fully specified in snippet, but mentions steepness parameter S (e.g., $S = 26$ for $3 \times 3 \times 3$ neighborhood) and learning rate.
6. **Output:** Segmented volumetric image.

Experimental Setup - 3D-QTRNet

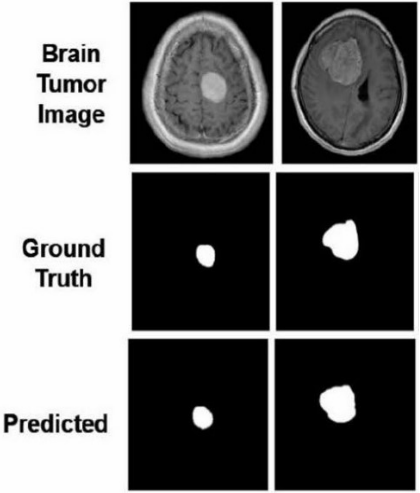
- **Datasets:**
  - **BRATS19 (BraTS2021 mentioned in Fig.2 caption):** Brain Tumor Segmentation Challenge dataset (volumetric MRI).
  - **Spleen Dataset:** (Volumetric CT likely, common for spleen segmentation).
- **Task:** Volumetric segmentation of tumors (BraTS) and spleen.
- **Parameters:**
  - Steepness varied (0.24 to 0.25), learning rate 0.001.
  - Neighborhood for activation: $3 \times 3 \times 3$ pixels ($S = 26$ neighbors).
- **Comparison:** State-of-the-art CNN and (other) quantum models.

3D-QTRNet - Evaluation Metrics

- **Precision:** $\frac{TP}{TP+FP}$
- **Accuracy:** $\frac{TP+TN}{TP+TN+FP+FN}$
- **Recall (Sensitivity):** $\frac{TP}{TP+FN}$
- **Specificity:** $\frac{TN}{TN+FP}$
- **Dice Similarity Coefficient (F1 Score):** $\frac{2\times\text{Precision}\times\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}}$
  - (Note: This is one way to express DSC; the earlier $2TP/(2TP + FP + FN)$ is also common and equivalent if TP, FP, FN are pixel counts).

3D-QTRNet - Results on BraTS Dataset (Fig. 2)

- **Visual Results:** The paper shows examples of input brain tumor images, ground truth segmentations, and 3D-QTRNet's predicted segmentations.
- **Quantitative:** The paper claims superior performance in Dice similarity and segmentation precision compared to other models.



Paper 3 - Conclusion

- 3D-QTRNet introduces a novel and effective quantum-inspired approach for volumetric medical image segmentation.
- The combination of qutrit encoding and tensor ring decomposition leads to improved accuracy, optimized memory usage, and faster convergence.
- This work represents a significant step towards leveraging more advanced quantum concepts for complex 3D medical image analysis tasks.

Common Themes Across the Papers

- **Addressing Classical Limitations:** All three papers aim to overcome challenges in traditional or standard deep learning segmentation methods (e.g., reliance on labeled data, computational cost, convergence speed).
- **Quantum-Inspired Paradigm:** Leveraging principles from quantum mechanics (qubits, qutrits, quantum states, entanglement-like correlations, quantum-inspired optimization) implemented on classical hardware.
- **Focus on Efficiency:** Seeking improvements in convergence speed, memory usage, or overall computational load.
- **Adaptive Mechanisms:** Employing adaptive thresholds or parameters based on image content (e.g., QMSig, adaptive η).

Comparison of the Three Approaches

Feature	**QIS-Net (Paper 1)**	**QUBO/QA Framework (Paper 2)**	**3D-QTRNet (Paper 3)**
Supervision	Self-Supervised	Unsupervised	Supervised (implied by loss/val curves)
Quantum Unit	Qubit	Qubit (for VQA/QA)	Qutrit
Dimensionality	2D (Brain MR)	2D (Mammography)	3D (Volumetric - Brain, Spleen)
Core Novelty	QMSig, Self-org., Imaginary components	Quantum-inspired rep. + QUBO + QA/VQA opt.	Qutrit encoding + Tensor Ring decomp.
Optimization	Self-organization, adaptive thresholds	QUBO Solvers (Classical, QA, VQA, SA)	Gradient-based (implied for NN)
Key Benefit Claim	Fast convergence, no labels (core)	Accuracy without labels, QA speed	3D accuracy, memory/conv. efficiency

Key Advantages Highlighted by these Approaches

- **Reduced Need for Labeled Data:** QIS-Net (self-supervised) and the QUBO framework (unsupervised) significantly reduce or eliminate the dependency on large annotated datasets.
- **Improved Convergence/Speed:**
  - QIS-Net: Faster convergence via quantum correlations.
  - Quantum Annealing (Paper 2): Order of magnitude faster than classical Gurobi for QUBO.
  - 3D-QTRNet: Accelerated convergence via Tensor Ring.
- **Computational Efficiency:**
  - QIS-Net: Functional modification reduces complexity.
  - 3D-QTRNet: Tensor Ring optimizes memory.
- **Enhanced Data Representation:**
  - QMSig (Paper 1 & 2): Better handling of grayscale heterogeneity.
  - Qutrits (Paper 3): Richer representation for volumetric data.

Challenges and Considerations

- **Current Quantum Hardware Limitations:**
  - True quantum computers (for QA, VQA) are still limited in qubit count, connectivity, and error rates.
  - Many "quantum-enhanced" methods are currently simulated or inspired, running on classical machines.
- **Scalability:** While promising, scaling these methods to very large, high-resolution clinical images needs further research.
- **Interpretability:** Like many deep learning models, some quantum-inspired networks can be complex to interpret.
- **Benchmarking:** Rigorous and standardized benchmarking against state-of-the-art classical methods on diverse datasets is essential.

Thank You & Questions

Thank You!

Questions?