Measurement-Free Quantum Classifier for Medical Image Classification

A hybrid quantum-classical architecture for detecting metastatic tissue in lymph node histopathology using PatchCamelyon dataset.

Team

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Guide

Dr. S. Gunasundari, Professor

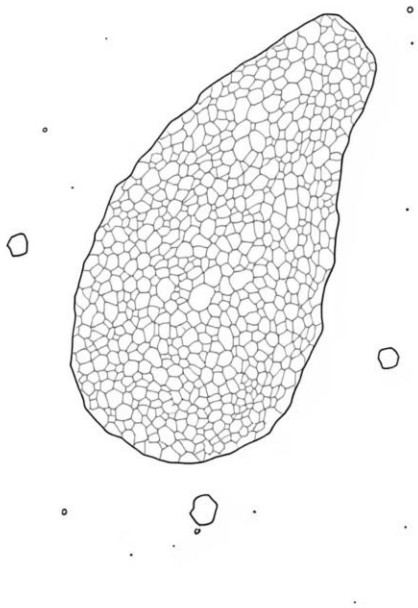
Duration

20 weeks | Active Research

QUANTUM COMPUTING

MEDICAL AI

The Challenge



Current Limitations

Deep learning achieves high accuracy but requires massive computational resources and millions of parameters, creating barriers for resource-constrained clinical settings.

Core Technology

SWAP-test based distance classifier computing fidelity between test images and learned class prototypes through quantum interference.

Our Innovation

A truly measurement-free quantum classifier preserving quantum coherence throughout classification, avoiding wavefunction collapse that limits conventional quantum ML approaches.

327K	96×96	2
Image Patches	Resolution	Classes
PatchCamelyon dataset size	Pixel dimensions per patch	Binary classification task

Literature Foundation

Recent publications establish the research landscape and identify critical gaps in measurement-free quantum approaches for medical imaging.

1. Radhi, E.A., et al. (2025)

   Systematic review identifying that measurement-free methods are a critical research gap, offering theoretical advantages over standard VQA but lacking empirical exploration.

2. Int. J. for Future Innovations (2025)

   Evaluates encoding standards like FRQI and NEQR, concluding that hybrid architectures are the only viable path to overcome current NISQ hardware constraints.

3. Am. J. Botany & Bioengineering (2025)

   Validates the superior parameter efficiency of quantum models across imaging modalities, supporting the move toward lightweight quantum classifiers.

4. Open Medscience (2025)

   Connects quantum algorithmic efficiency to practical clinical deployment, emphasizing the need for models that can run on resource-constrained edge devices.

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Literature Foundation

5. Medical Sciences (MDPI, 2024)

   Provides the theoretical basis for quantum noise resilience, supporting our hypothesis that measurement-free designs can naturally suppress image noise.

6. Springer Professional (2024)

   Details NISQ-era limitations (decoherence/error rates), validating our design choice to limit circuit depth to 50-100 gates.

7. Springer Nature (2023)

   Establishes the framework for hybrid quantum-classical optimization, which is the core architectural approach used in this project.

8. Neurocomputing (2023)

   Sets the empirical baseline, documenting current state-of-the-art accuracies for standard quantum classifiers in tumor detection tasks.

9. IET Quantum Communication (2022)

   Foundational text on quantum image processing that justifies the trade-offs involved in selecting amplitude encoding for feature representation.

10. Bentham Science (2025)

    Showcases the latest trends in robustness analysis, confirming that stability against noise is a primary metric for evaluating new quantum models.

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Summary

Paper Context	Their Focus	Their Limitation	Our Solution
Reviews (1, 8)	Surveying trends	Identifies gaps but doesn't fill them	We implement the "Measurement-Free" gap
Encoding (2, 9)	Raw pixel encoding	Too many gates/qubits	**Hybrid CNN + Amplitude Encoding**
Applications (3, 7)	Standard VQC/QSVM	Measurement collapses state	**SWAP-test (Coherence preserved)**
Deployment (4, 6)	Hardware constraints	Problem identification	**Shallow Circuit (<100 gates)**
Noise (5, 10)	Pre-processing/Theory	Pre-classification focus	**Robustness in Classification**

Key Research Insights

Measurement-Free Advantage

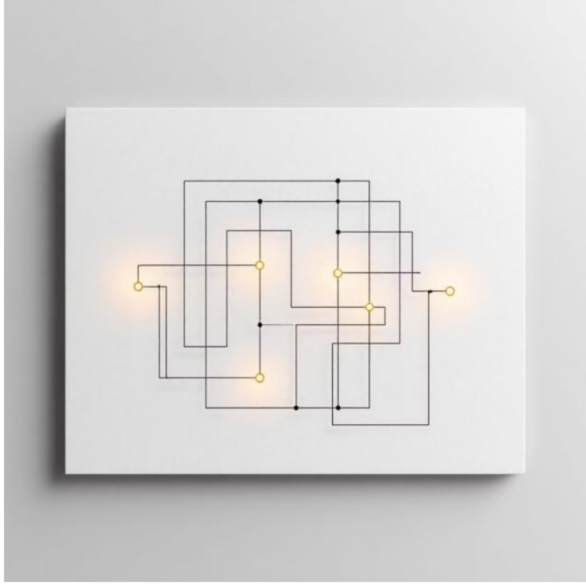
SWAP-test protocols preserve quantum advantage by avoiding wavefunction collapse that destroys entanglement.

Parameter Efficiency

40-60% parameter reduction vs. classical CNNs while maintaining comparable accuracy.

NISQ Feasibility

50-200 gate circuits practical for near-term implementation on current quantum hardware.



Noise Resilience: Quantum noise in NISQ devices provides natural denoising benefits for medical imaging. Measurement-free approaches preserve this advantage throughout the pipeline.

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Technical Infrastructure

Quantum Platform

- Qiskit 0.43+ framework
- Qiskit Aer GPU-accelerated simulator
- IBM Quantum 27-qubit Hummingbird
- NISQ-realistic noise models

Deep Learning Stack

- PyTorch 2.0+ for CNN extraction
- TorchVision pre-trained models
- Adam optimizer with parameter-shift rule
- Binary cross-entropy loss

Hardware Requirements

- NVIDIA RTX 4070 GPU (8GB+ VRAM)
- Intel i9 or AMD Ryzen 9 CPU
- 32GB RAM minimum (64GB recommended)
- 500GB SSD storage

Cost-Effective: Total estimated cost Rs.0-5000 using free cloud services and institutional GPUs. All frameworks are open-source.

System Architecture

Classical Feature Extraction

Lightweight CNN (3-4 conv layers) extracts 16-32D feature vectors from 96×96 RGB histopathology patches.

Amplitude Encoding

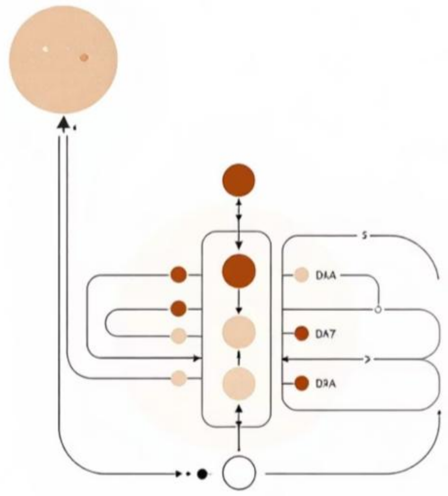
Features normalized to [0,1] and encoded into quantum states using 4-5 qubits, preserving relationships through superposition.

SWAP-Test Classification

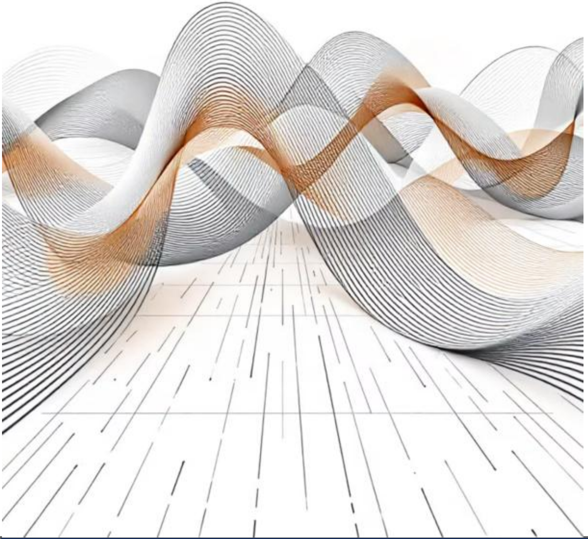
Quantum fidelity computed between test state and learned benign/malignant prototypes through quantum interference.

Single Measurement

Only ancilla qubit measured at end. Probability encodes fidelity, enabling binary classification decision.



Core Innovation: SWAP-Test Protocol



Why Measurement-Free?

Coherence Preservation

Quantum states never collapsed until final readout, maintaining entanglement throughout.

Noise Resilience

Fewer measurement points reduce error accumulation on NISQ hardware.

Quantum Advantage

Preserves superposition and interference effects that enhance classification.

Fidelity-Based Decision

The SWAP-test computes quantum overlap between test image and class prototypes:

$$Fidelity(\rho_1, \rho_2) = Tr(\sqrt{\sqrt{\rho_1}\rho_2\sqrt{\rho_1}})^2$$

Classification Logic:

```
If Fidelity_benign > Fidelity_malignant:
    Predict: BENIGN (0)
Else:
    Predict: MALIGNANT (1)
```

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Project Timeline

Weeks 1-3

Data Preparation

Download PatchCamelyon, implement classical CNN baseline achieving ≥95% accuracy.

Weeks 4-7

Quantum Circuits

Design SWAP-test circuit, validate amplitude encoding, prototype on toy dataset.

Weeks 8-12

Hybrid Training

Train CNN + quantum classifier jointly, optimize prototypes, achieve ≥92% accuracy.

Weeks 13-16

Validation

Compare measurement-free vs. measurement-based, conduct ablation studies, robustness analysis.

Weeks 17-20

Publication

Document methodology, create visualizations, prepare manuscript, submit to arXiv.

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Experimental Design

Dataset & Metrics

PatchCamelyon Split:

- 60% training (196,000 images)
- 20% validation (65,000 images)
- 20% test (65,000 images)

Evaluation Metrics:

- Accuracy, Sensitivity, Specificity
- Precision, F1-Score, AUC-ROC
- Confusion matrices per class

95%

Classical Baseline

Target accuracy for CNN

92%

Quantum Target

Hybrid model goal

5%

Noise Advantage

Robustness improvement

Ablation Studies

Circuit Depth

Test 30, 50, 75, 100, 150 gates

Feature Size

Test 8D, 16D, 24D, 32D encodings

Noise Sensitivity

Add Gaussian noise, measure degradation

Cross-Validation

5-fold stratified splits

Risk Mitigation

If Accuracy Targets Not Met

- Increase CNN capacity (add convolutional layers)
- Try alternative encodings (angle encoding)
- Increase circuit depth to 150-200 gates if noise allows
- Reduce feature dimensionality for compact representations

If Quantum Hardware Access Delayed

- Continue with Qiskit Aer simulator (sufficient for validation)
- Implement realistic noise models matching IBM Hummingbird specs
- Plan hardware validation for future work

If NISQ Noise Degrades Performance

- Use error mitigation (zero-noise extrapolation, dynamical decoupling)
- Reduce circuit depth (prioritize robustness over expressivity)
- Shift emphasis to noise-robustness improvements

If Training Convergence Slow

- Implement learning rate scheduling (warm-up, exponential decay)
- Use mini-batch gradient accumulation
- Try alternative optimizers (RMSprop, SGD with momentum)

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APPENDIX: KEY TERMINOLOGY

Term	Definition
Amplitude Encoding	Encoding classical data as amplitudes of quantum state
Measurement-Free	Quantum protocol that avoids collapsing quantum states until final readout
SWAP-Test	Quantum circuit computing fidelity between two quantum states
PatchCamelyon	Dataset of 96×96 histopathology patches from lymph node tissue
Fidelity	Quantum measure of similarity between two quantum states
VQA	Variational Quantum Algorithm with parameterized circuits
NISQ	Noisy Intermediate-Scale Quantum (current hardware era)
Parameter-Shift Rule	Method for computing quantum circuit gradients classically
Amplitude Encoding	Encoding classical vector as quantum state amplitudes