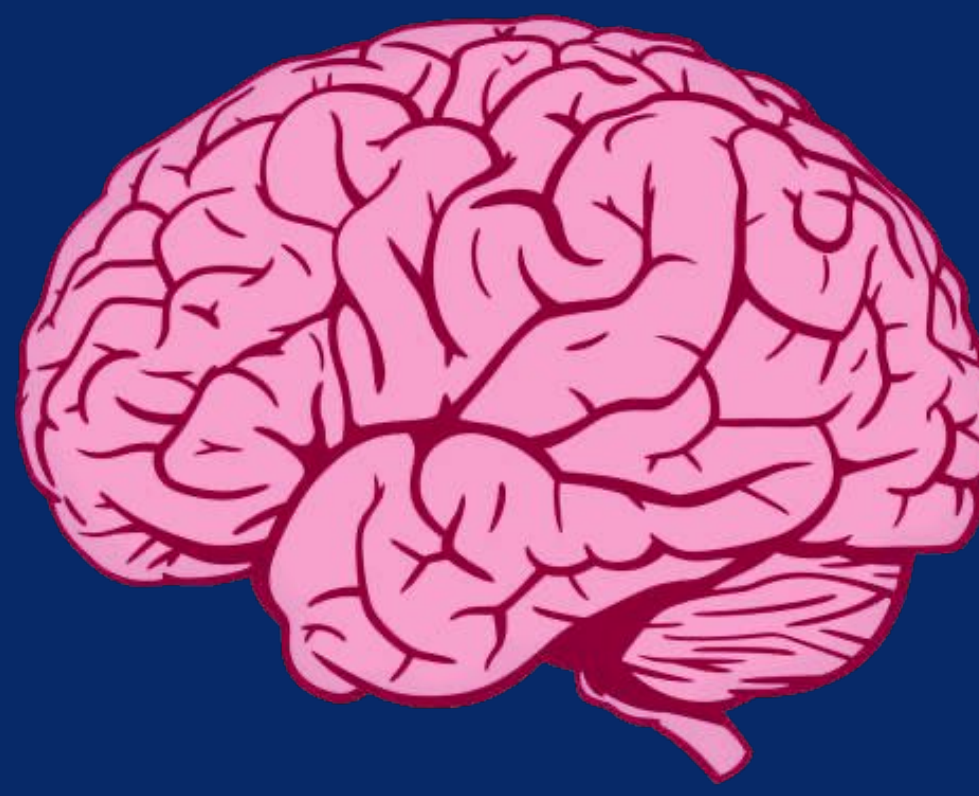
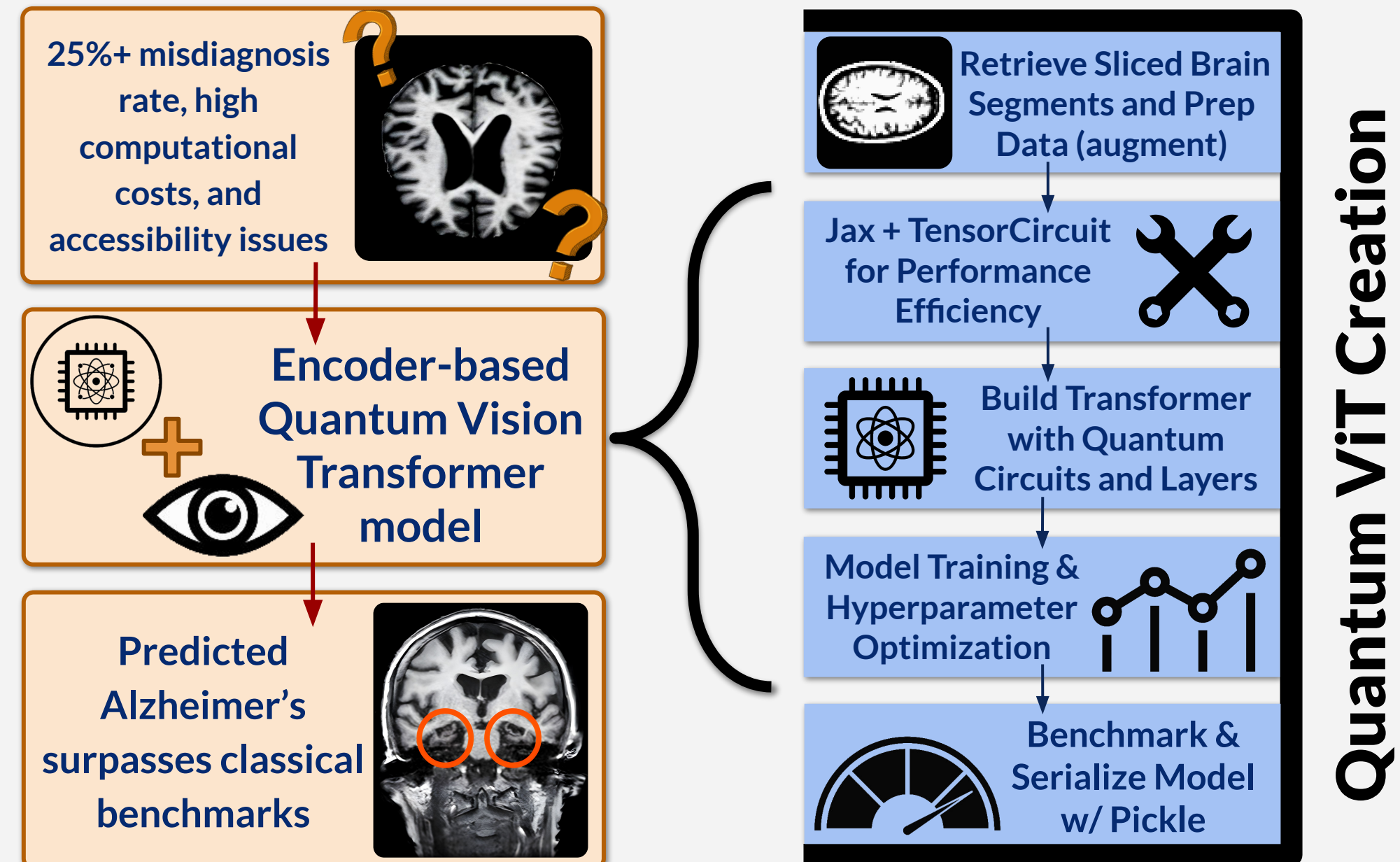


QViSTA: Quantum Vision Transformers for Enhanced Alzheimer's Detection Using Variational Quantum Circuits

Aryan Singhal and Hursh Shah



VISUAL ABSTRACT



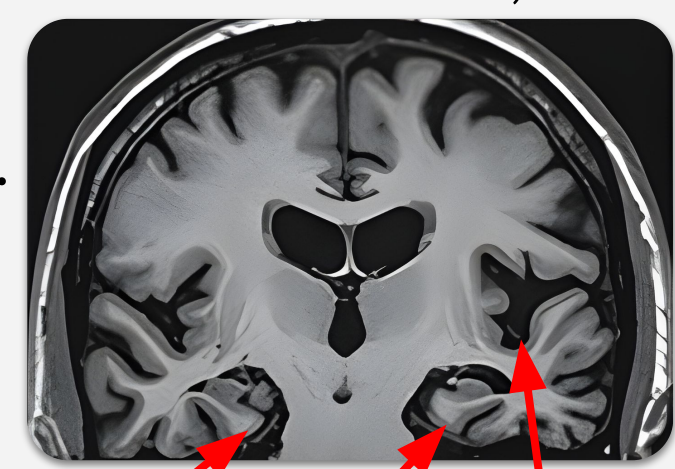
INTRODUCTION

ALZHEIMER'S DISEASE

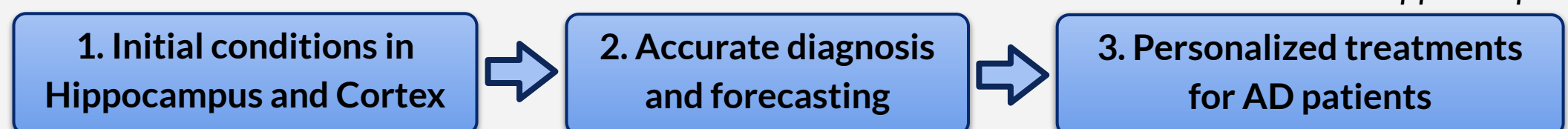
Alzheimer's disease (AD) is the leading progressive form of dementia, affecting 6.2 million Americans aged 65 and older. Progresses in 3 stages: Mild, Moderate, and Severe.

Radiologists primarily use Magnetic Resonance Imaging (MRI) for non-intrusive detection.

However, radiologist expertise, high costs, and accessibility issues lead to a 25% misdiagnosis rate (2022), causing memory loss & poor judgement.



Hippocampus Atrophy
Early signs include Brain Atrophy and deterioration in Hippocampus



QUANTUM VISION TRANSFORMERS

Quantum Vision Transformers (QViTs) effectively leverage Quantum Multi-Head Self-Attention (QMHA) modules and variational quantum circuits (VQCs), significantly enhancing Vision Transformers (ViTs). Equation: El A. Cherrat defines $Load(x_j) = W \cdot Load(x_i)$ quantum circuit to compute a single attention coefficient

- Full analysis for early diagnosis is expensive and time-consuming.
- Classical models, Convolutional Neural Networks (CNNs), are computationally intensive, inefficient, and prone to overfitting.
- QViTs provide speed improvements, handle high-dimensional data effectively, offer better optimization, and generalize better on large amounts of data.

RESEARCH OBJECTIVES

RESEARCH QUESTION – Can QViTs improve the accuracy and efficiency of Alzheimer's detection in MRI scans compared to existing deep-learning methods such as ViTs and CNNs (ResNet-18)?

HYPOTHESIS – Implementing a QViT architecture for Alzheimer's disease diagnosis will enhance diagnostic accuracy and computational efficiency compared to current classical methodologies, such as ViTs and CNNs (ResNet-18), due to its quantum-enhanced feature extraction capabilities.

Design Criteria for Quantum Vision Transformer

- Robustness:** Train model on 3 stages of Alzheimer's + Control and augmented data
- Functionality:** Quantum extracts distinct features from stages of Alzheimer's efficiently
- Specification:** Accepts MRI imaging (JPG); more accurate & efficient than classical

Primary Endpoints: Predict with high AUC & ROC accuracy and reduce training time for computational efficiency.

Secondary Endpoints: Show effectiveness of Self-Attention and FeedForward layers, as well as quantum circuits, for extracting complex features.

BRAINSTORMING A SOLUTION – how should we achieve the criteria?

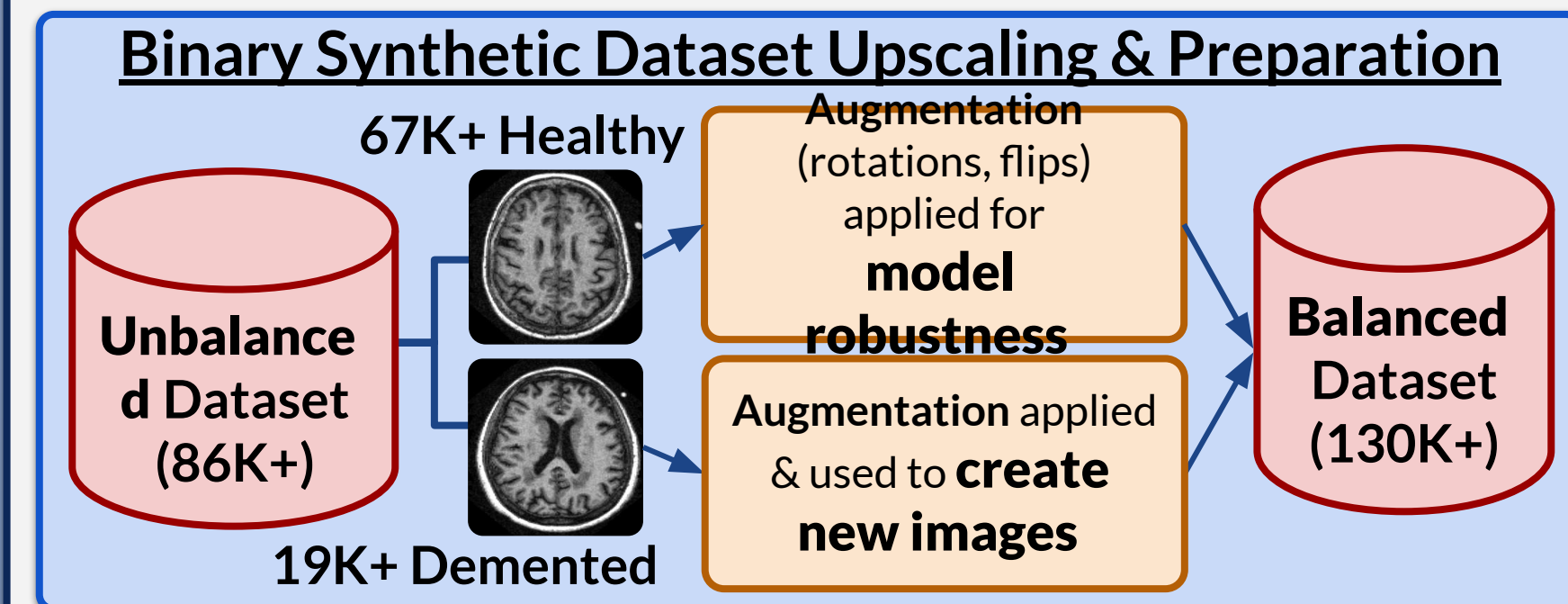
- Curation:** Utilize public datasets and data augmentation for building generalized datasets and robust models.
- Efficiency:** Utilize efficient frameworks (Jax, PyTorch, TensorCircuit, PennyLane) and reduced parameters for faster computation.
- Quantum Implementation:** Angle embedding for encoding images into quantum states with parameterized Rotation-X (RX) gates. Series of VQCs entangled through Controlled-NOT (CNOT) across qubits.

ENGINEERING METHODOLOGY

Data Curation & Preparation

Retrieve brain MRI scans and segment:

- Binary Classification:** 130K+ images from OASIS.
 - Sliced along z-axis into pieces ranging from 100 - 160.
 - Upsampled from 86K+ → 130K+ to balance classes.
- Multi Classification:** 40K+ images compiled (ADNI & NACC).
 - 4 classes of severity: very mild demented, mild demented, moderately demented, and non demented.
- 80% for training, 20% for val/test.

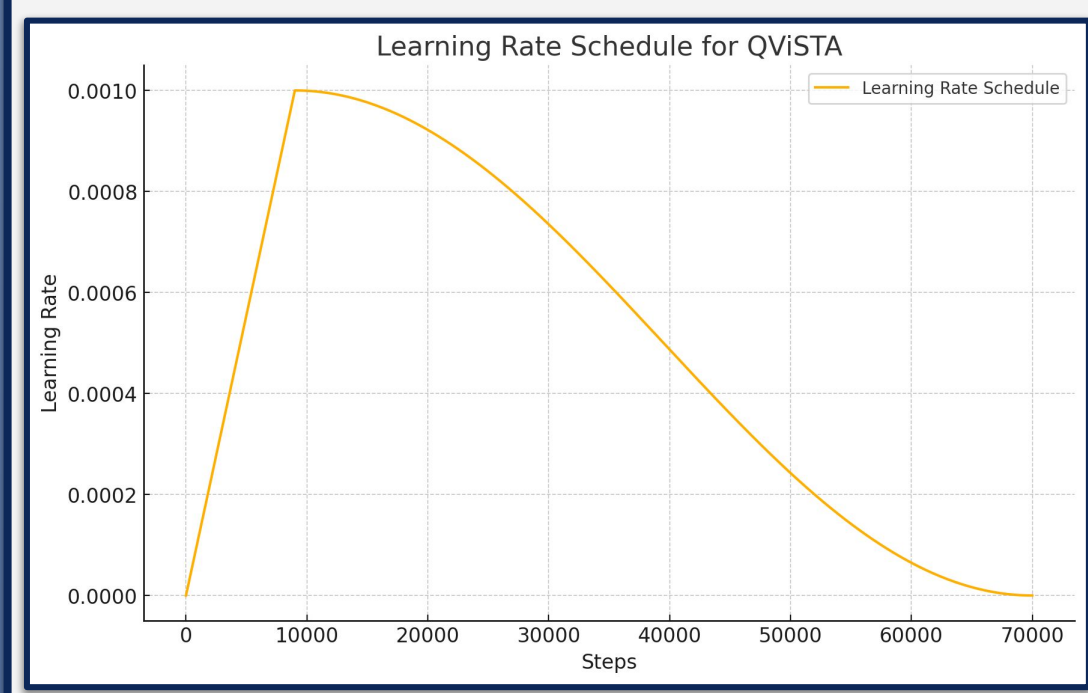


QML Framework Performance Comparison

Comparing quantum libraries and frameworks (Jax, PyTorch, PennyLane, TensorCircuit) to identify the most efficient, evaluating MLP-5/20 and ViT for time and AUC accuracy.

Model Fine Tuning

- Linear warmup and cosine decay to find optimal learning rate.
- AdamW & gradient clipping to optimize reduce overfitting.
- Iterated through trainable hyperparameters for further tuning.
- Jax gradient function tuned for optimal angle of quantum layer.



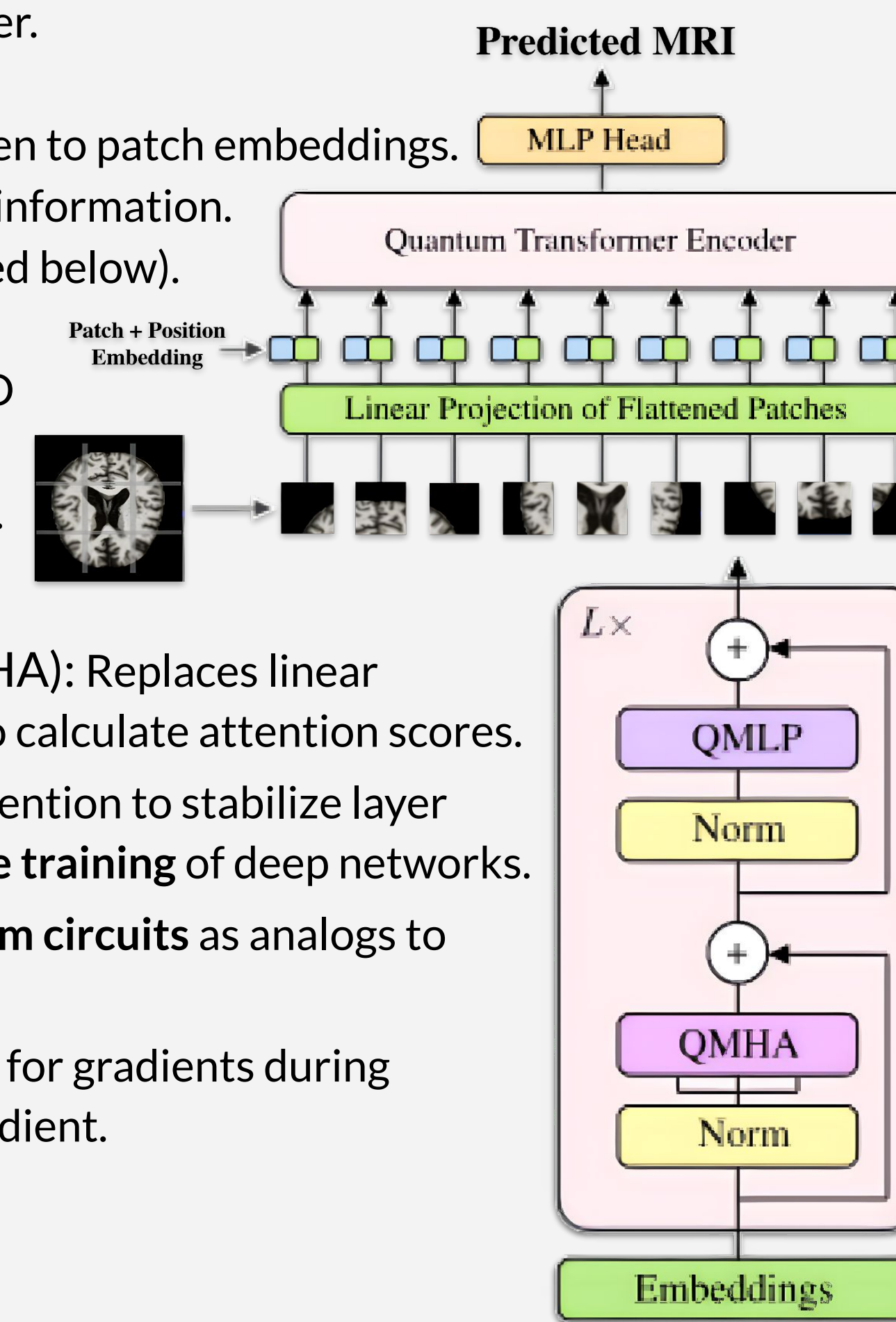
GELU Activation Function

$$\text{GELU}(x) = xP(X \leq x) = x\Phi(x)$$

Takes magnitude of input into account and is smoother than other functions (ELU & RELU), helping distinguish nuanced patterns of MRI images.

Quantum Vision Transformer Architecture

- Input:** MRI image fed into the transformer.
- Image Patching & Embedding:**
 - Input split to fixed-size patches; flatten to patch embeddings.
 - Pos. embeddings maintain sequence information.
- Quantum Transformer Encoder:** (detailed below).
- Multi-Layer Perceptron (MLP) Head:**
 - Sequence of encoded patches → 1-D vector rep. for classification.
 - Learn patterns through non-linearity.



QViT Encoder

- Quantum Multi-Head Attention (QMHA):** Replaces linear projections with quantum circuits (QC) to calculate attention scores.
- Normalization (Norm):** Applied post-attention to stabilize layer outputs. Facilitates faster and more stable training of deep networks.
- Quantum MLP (QMLP):** Utilizes quantum circuits as analogs to dense layers in feed-forward networks.
- Skip Connections (Plus Sign):** Pathways for gradients during backpropagation, mitigating vanishing gradient.

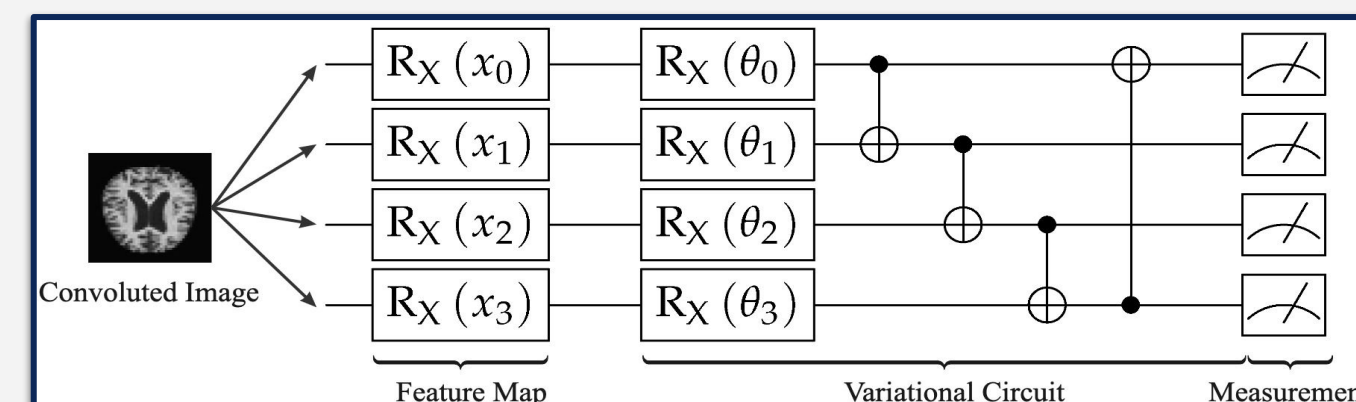
Quantum Layer

1) Angle Embedding:

- Maps classical input data to quantum states.
- Applying rotations around X-Axis to each qubit based on value of input features.

2) Variational Quantum Circuit (VQC):

- Constructs parameterized quantum layers. Configuration consists of 4 circuits.
- Rotations Rotation-X gates to each qubit, with angles as learnable weights.
- Ring of CNOT gates for entanglement across qubits. 2 qubits: single CNOT between them. >2 qubits: chain of CNOTs, ring like entanglement structure.
- Weights are tunable params. allowing the circuit minimize cost effectively while training.



RESULTS & VALIDATION

Fig 1. QViT Confusion Matrix (Binary)

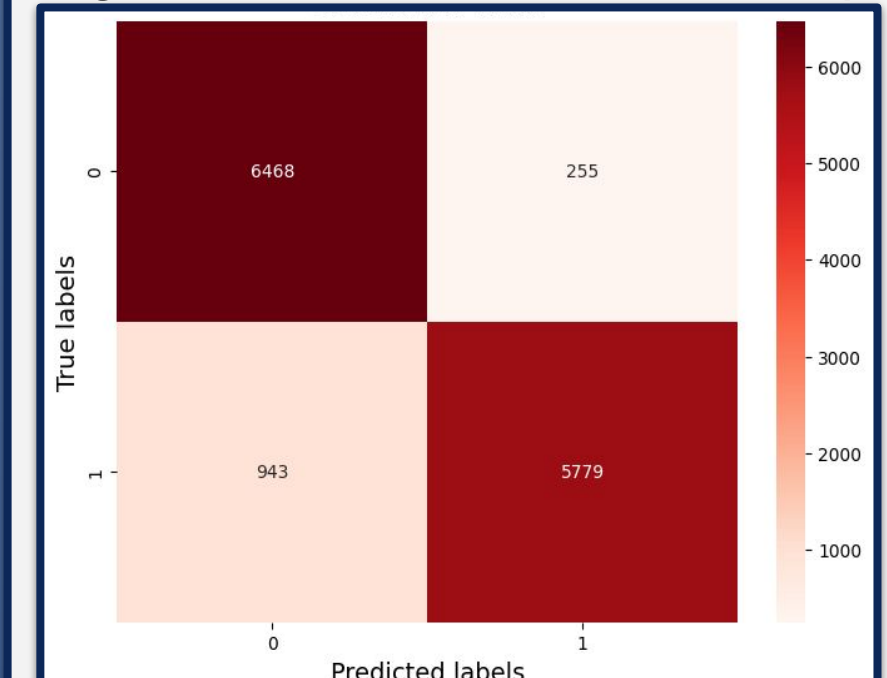


Fig 2. QViT ROC Curve (Binary)

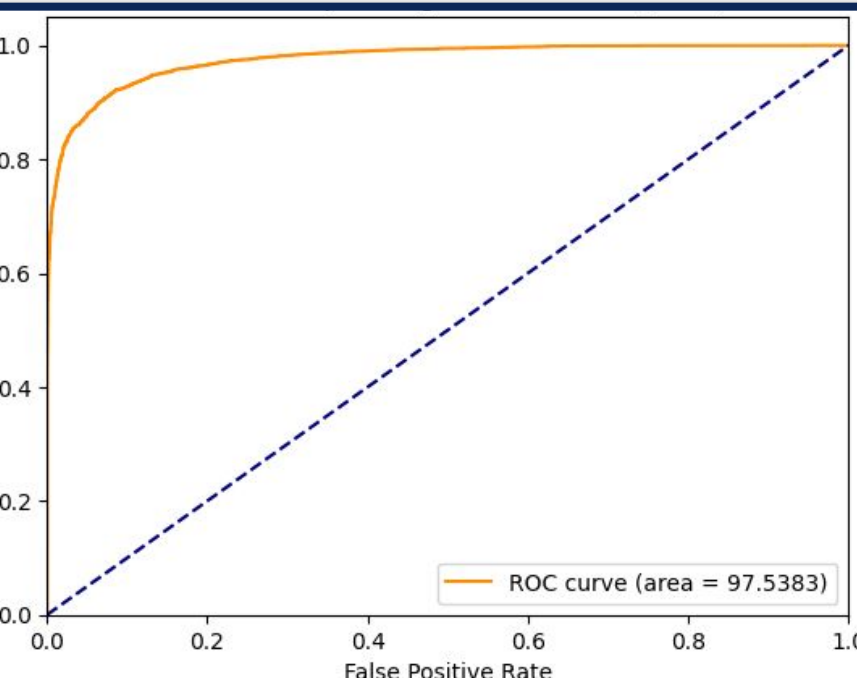


Fig 3. QViT Confusion Matrix (Multi)

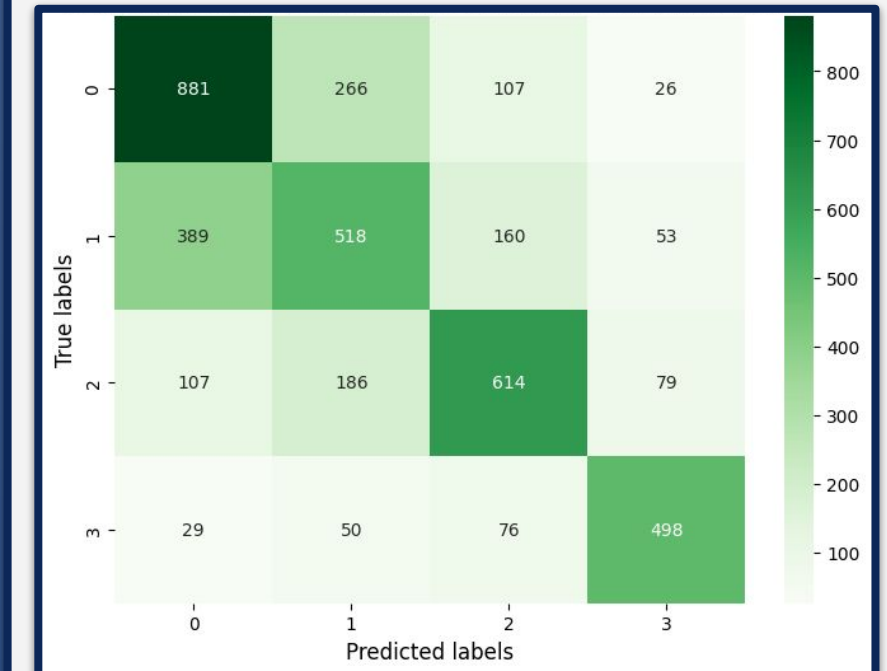
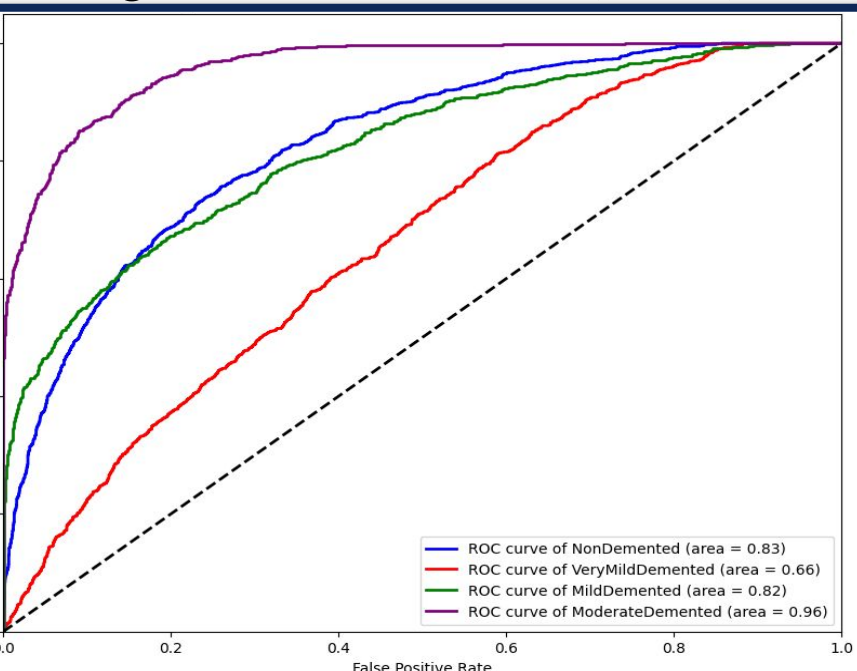
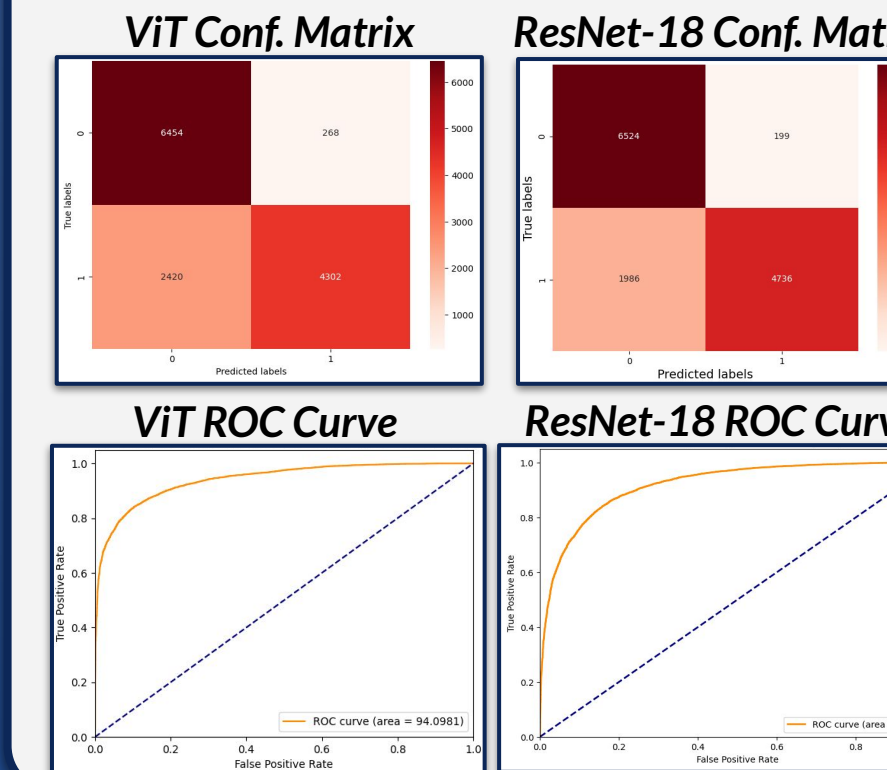


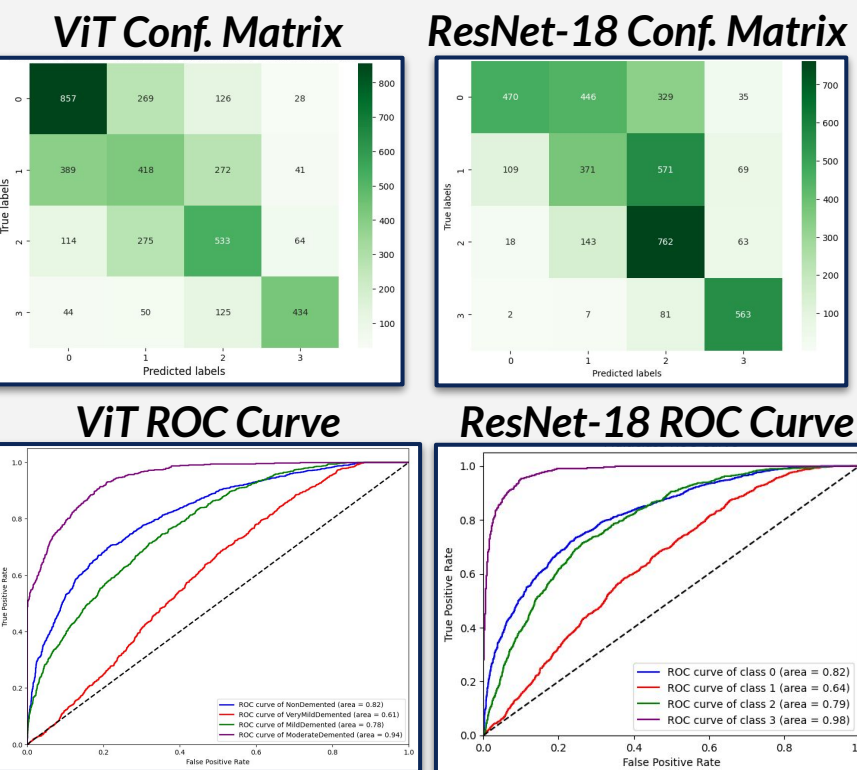
Fig 4. QViT ROC Curve (Multi)



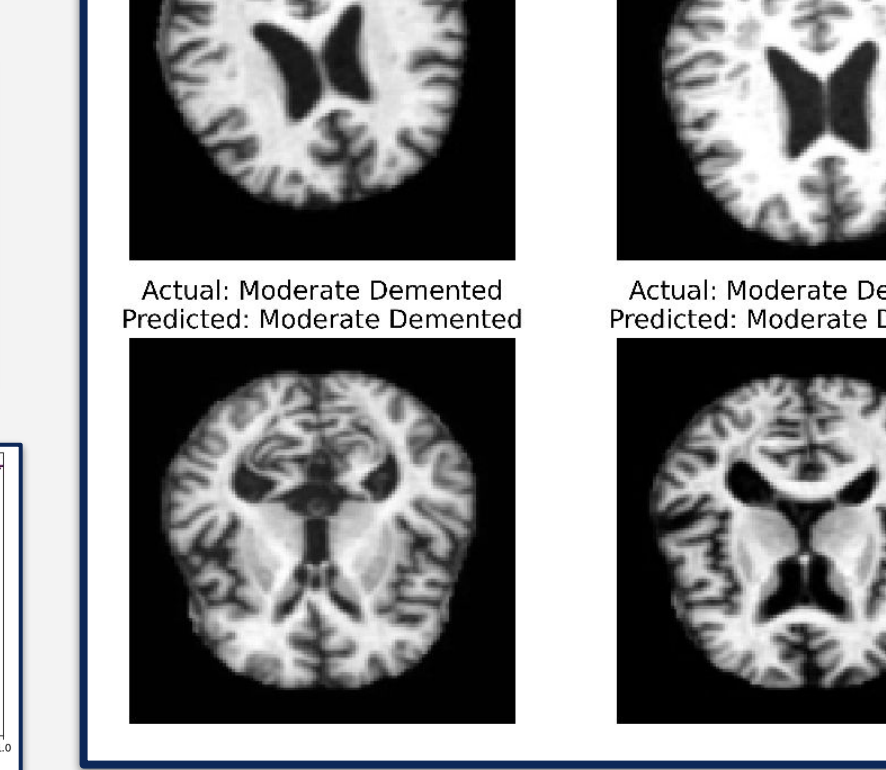
Binary



Benchmarked Models



Multi



ROC Area Determination

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Hits over actual positives

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

False alarms over negatives

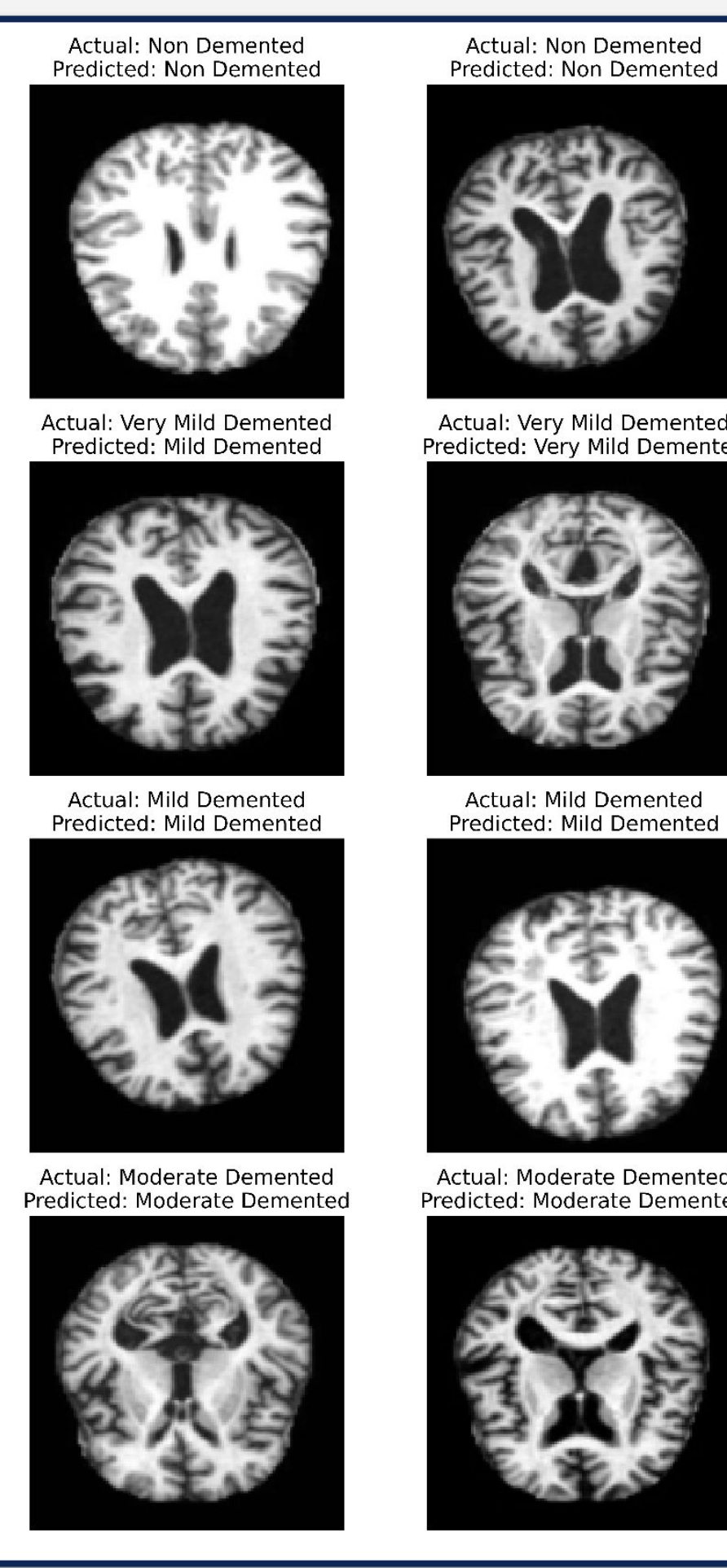


Fig 5. QViT preds. on Multi dataset

Fig 7. Training time per epoch for models on Binary dataset

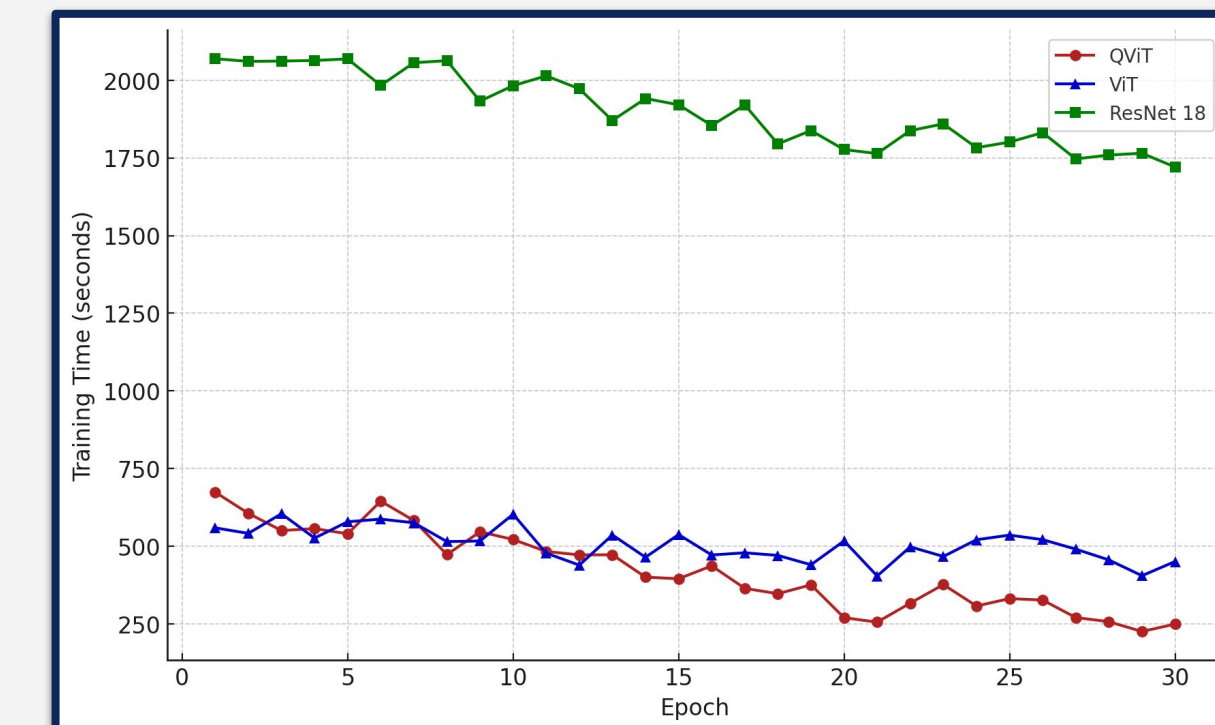
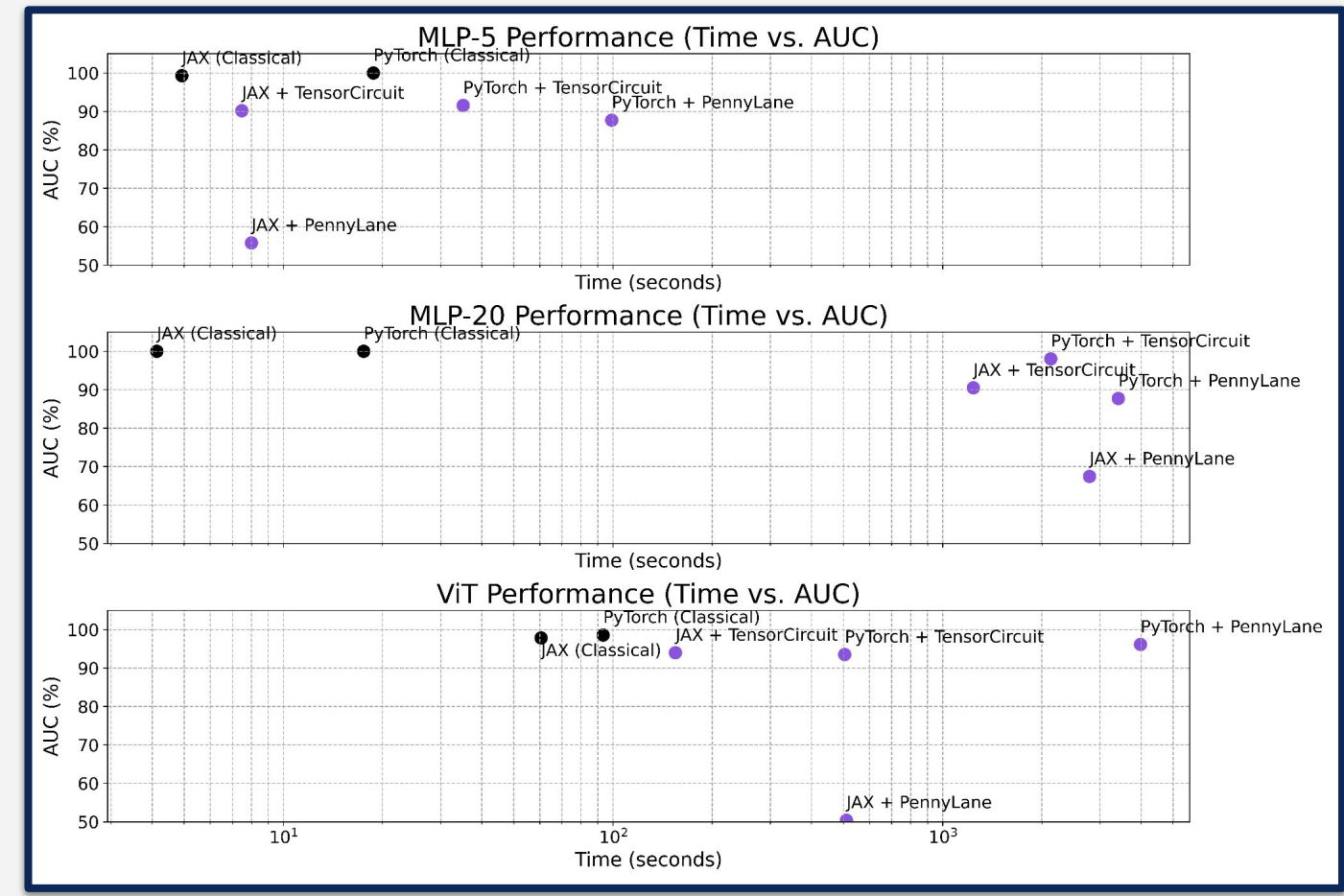


Fig 8. Backend & QML framework comparisons



STATISTICAL ANALYSIS

We conducted an in-depth statistical analysis to quantify and verify the performance of our QViT. Testing conducted on 17K+ sample MRI images.

F1-Score
$$\text{F1-Score} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP} + \text{FN})}$$

Figures 1-4 demonstrate that QViT has strong performance on the F1-Score and ROC curve metrics.

Binary: For F1-Score, QViT scored 90.61%, exceeding benchmarks by nearly 10%. For ROC curve, QViT had an area of 97.53%, surpassing benchmarks by 3% and 7%. This implies a minimal tradeoff between false positives and negatives.

Multiclass: For macro F1-Score, QViT scored 63.33%, exceeding benchmarks by 6.7% and 7.62%. For ROC curve, the earliest stage of Alzheimer's (Very Mild) scored .66 highlighting the need for more data to improve accuracy. Moderate Alzheimer's scored .96, matching our understanding that moderate is the norm, and early detection is new territory.

Figure 7: QViT initially slower than ViT but outpaced within 8 epochs, surpassing ViT's by 25% and CNN's by 460%.

Figure 8: Statistical looping analysis determining Jax backend + TensorCircuit QML framework as the optimal tools for training QViTs.

Approach	Training Time
QViT	3.5 hours
ViT	4.5 hours
CNN	16 hours
Specialist	Weeks/Months

CONCLUSIONS & DISCUSSION

Our research demonstrates that QViTs come with significant benefits: (1) nuanced detection of early Alzheimer's features, (2) quick training and evaluation (shortening diagnosis by months), (3) on-site diagnosis without a specialist, and (4) universal architecture furthering QViT research. Reflecting its state-of-the-art (SOTA) capabilities, we have named our model **QViSTA**.

Engineering Criteria:

- Surpassed benchmarks in robustness, enhanced feature identification via quantum parallelism, and broadened specifications for MRI and PET scans, setting new standards for future research.
- QViTs are easy to use in hospitals with 97.6% accuracy, superior to human specialists (75%), and offering time that is 460% faster than benchmarks.

Research Impacts:

- SOTA** model for Alzheimer's detection in both early detection and accurate diagnosis by outperforming current SOTA published in Harvard from 2023 (97.6% vs. 90.1%) and our benchmarks.
- Universal parameters identified present paradigm shift for nascent QViT field.
- Multi-classification architecture allows for finer classification such as low, medium and high risks, advancing early detection.

Hospital Impacts:

- Healthcare specialists agreed QViTs help mitigate shortage of medical workers.
- Accelerates turnaround time for diagnosis, needing only one MRI scan and 3.5 hours vs. multiple months.
- SOTA** in early detection means identifying Alzheimer's variations confidently is easier for QViT than a specialist, potentially preventing 40% of Alzheimer's.

FUTURE WORKS

Our results have been very promising thus far. However, we have many ideas of future investigations to conduct to extend our current stage of research:

- Multimodality!** Create a multimodal QVT to improve accuracy by considering other aspects such as patient history.
- Implement PET scans and MRI into our data - improves early detection due to PET scans being able to determine chemical changes in the brain.
- Finally, **implement in hospitals!** Real-world testing is the final step to determining the true success of our novel technologies.

Not possible yet due to data availability:

- Apply Quantum-Inspired Acromyrmex Evolutionary Algorithm (QIAEA) for time-series analysis of Alzheimer's (determining the development of Alzheimer's in the patient after detection).

KEY REFERENCES

- Cara, Marçal. "Quantum Transformers in Google Summer of Code 2023 at ML4SCI | Marçal Comajano Cara." Salcc.github.io, 2023. salcc.github.io/blog/gsoc23/. Accessed 13 Mar. 2024.
- Cherrat, El Amine, et al. "Quantum Vision Transformers." Quantum, vol. 8, Feb. 2024, p. 1265. <https://doi.org/10.22331/q-2024-02-22-1265>. Accessed 13 Mar. 2024.
- DATASET: OASIS. "OASIS Alzheimer's Detection." Www.kaggle.com, 2023. www.kaggle.com/datasets/ninadithal/imagesoasis.
- gazzettebeckycoleman. "Using AI to Target Alzheimer's." Harvard Gazette, 3 Mar. 2023. news.harvard.edu/gazette/story/2023/03/using-ai-to-target-alzheimers. Accessed 13 Mar. 2024.
- Insight, Brain Health. "Why Is an Earlier Diagnosis of Alzheimer's Disease Key to Flattening the Growth Curve of Rapidly Escalating Patient Populations?" ViewMind, 12 May 2023. www.viewmind.com/why-is-an-earlier-diagnosis-of-alzheimers-disease-key-to-flattening-the-growth-curve-of-rapidly-escalating-patient-populations. Accessed 13 Mar. 2024.
- NHS. "Alzheimer's Disease - Diagnosis." Nhs.uk, 14 May 2018. www.nhs.uk/conditions/alzheimers-disease/diagnosis/.