MEDQML

IEG313 : QUANTUM COMPUTING PROJECT

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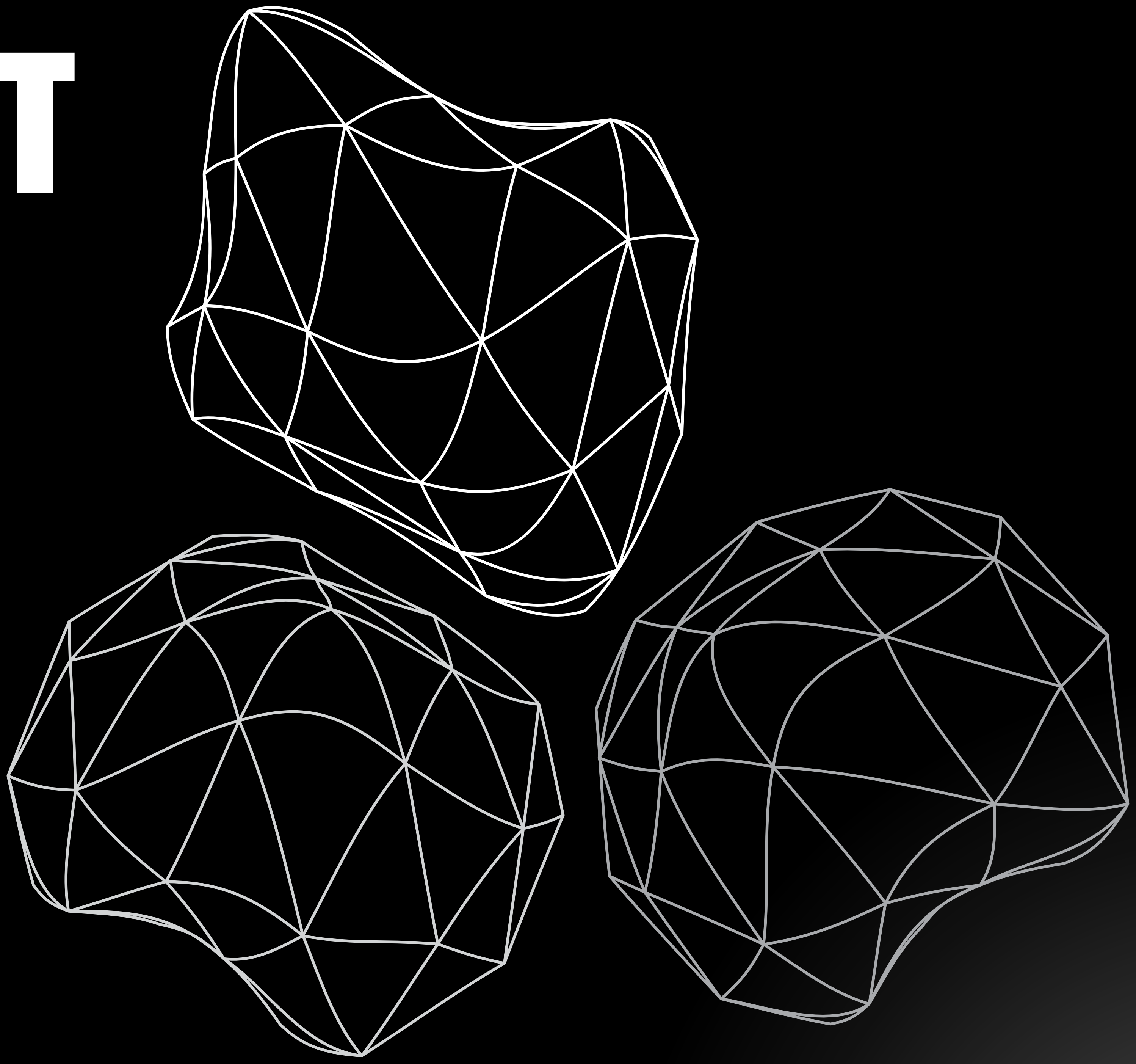
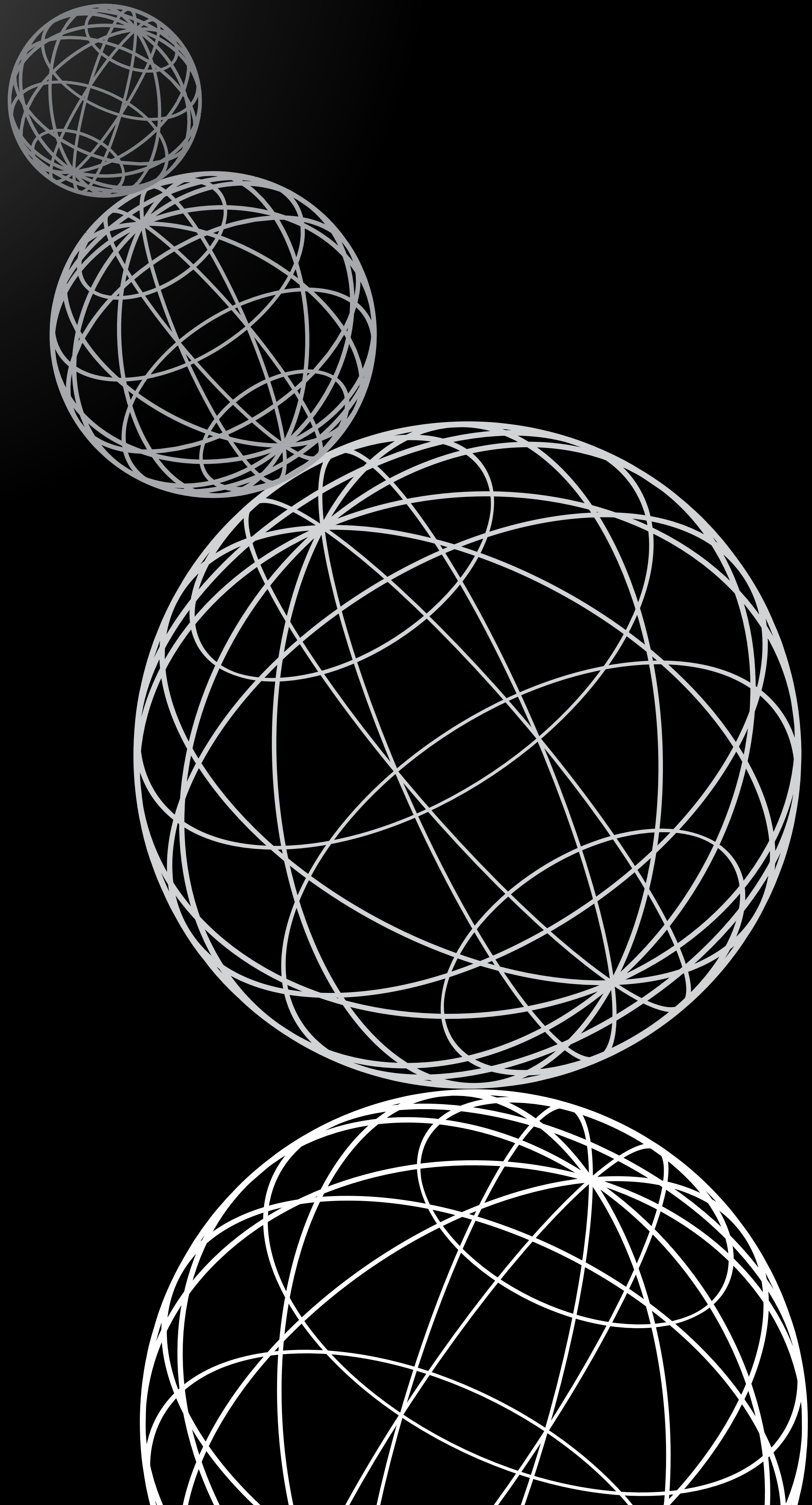
PROBLEM STATEMENT



Our mission is to delve into the unique convergence of quantum computing and image analysis. Specifically, we aim to implement a model classifying face image data set to predict disorders (i.e.,Parkinson’s, Autism, etc), And to unravel the mysteries of QCNN architecture and its application in classifying images



MOTIVATION

- Early diagnosis of neurological disorders like Autism is crucial but challenging.
- MRI-based diagnosis requires high accuracy and efficient pattern recognition.
- Classical deep models need large data and high computation.
- Quantum Machine Learning (QML) can extract richer features using fewer data points.
- Integrating Quantum Feature Extraction (QFE) with deep learning can enhance diagnostic accuracy.

LITERATURE REVIEW

- Li et al. (2021): Hybrid QML models improve feature separability in biomedical tasks.
- Schuld et al. (2020): Quantum circuits enhance non-linear data mapping.
- Henderson et al. (2020): Introduced PennyLane for hybrid quantum–classical modeling.
- Limited prior work applying QML to Autism diagnosis using MRI images.

GAPS IDENTIFIED IN EXISTING RESEARCH

- Traditional CNNs and DNNs require massive, well-balanced datasets.
- Overfitting and poor generalization on limited medical data.
- Few works leverage quantum circuits for medical feature representation.
- Lack of hybrid pipelines integrating quantum encoding + deep learning classification.

PROPOSED WORK / METHODOLOGY

Pipeline Overview:
MRI → Preprocessing → Quantum Encoding → QFE Output → DNN Classifier → Prediction

- **Use Quantum Feature Extraction to represent MRI images in quantum space.**
- **Construct quantum circuits with trainable parameters using PennyLane.**
- **Feed extracted quantum features into a DNN classifier (TensorFlow).**
- **Optimize both quantum and classical parameters jointly in a hybrid learning loop.**

IMPLEMENTATION DETAILS

Environment: Google Colab with PennyLane + TensorFlow backend.

Libraries: PennyLane, NumPy, Scikit-learn, Matplotlib, TensorFlow.

Dataset: Consolidated Autism MRI Dataset

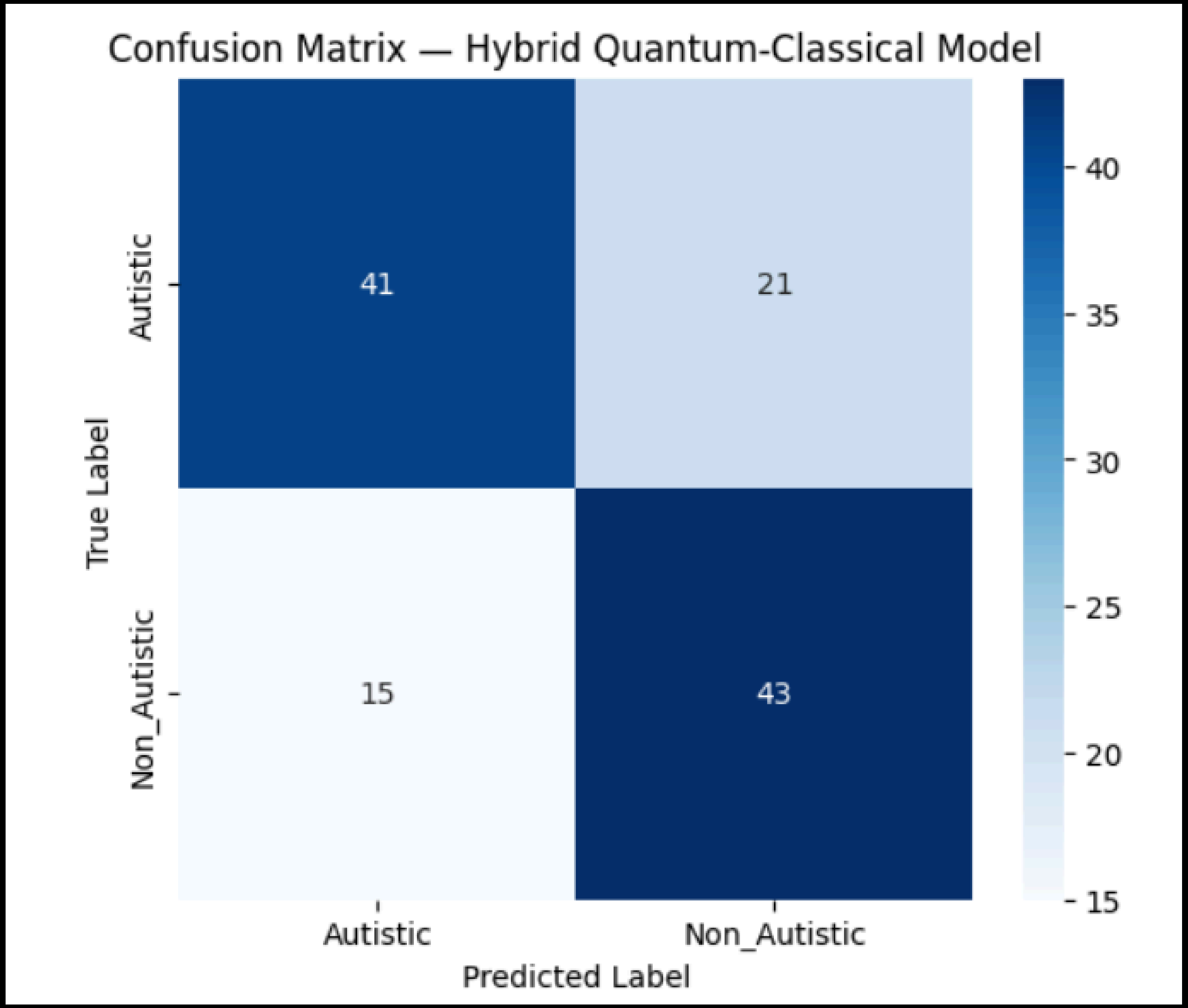
- ~300 images per class (Autistic / Non-Autistic).
- Images preprocessed: resized, normalized, flattened for encoding.

Quantum Circuit:

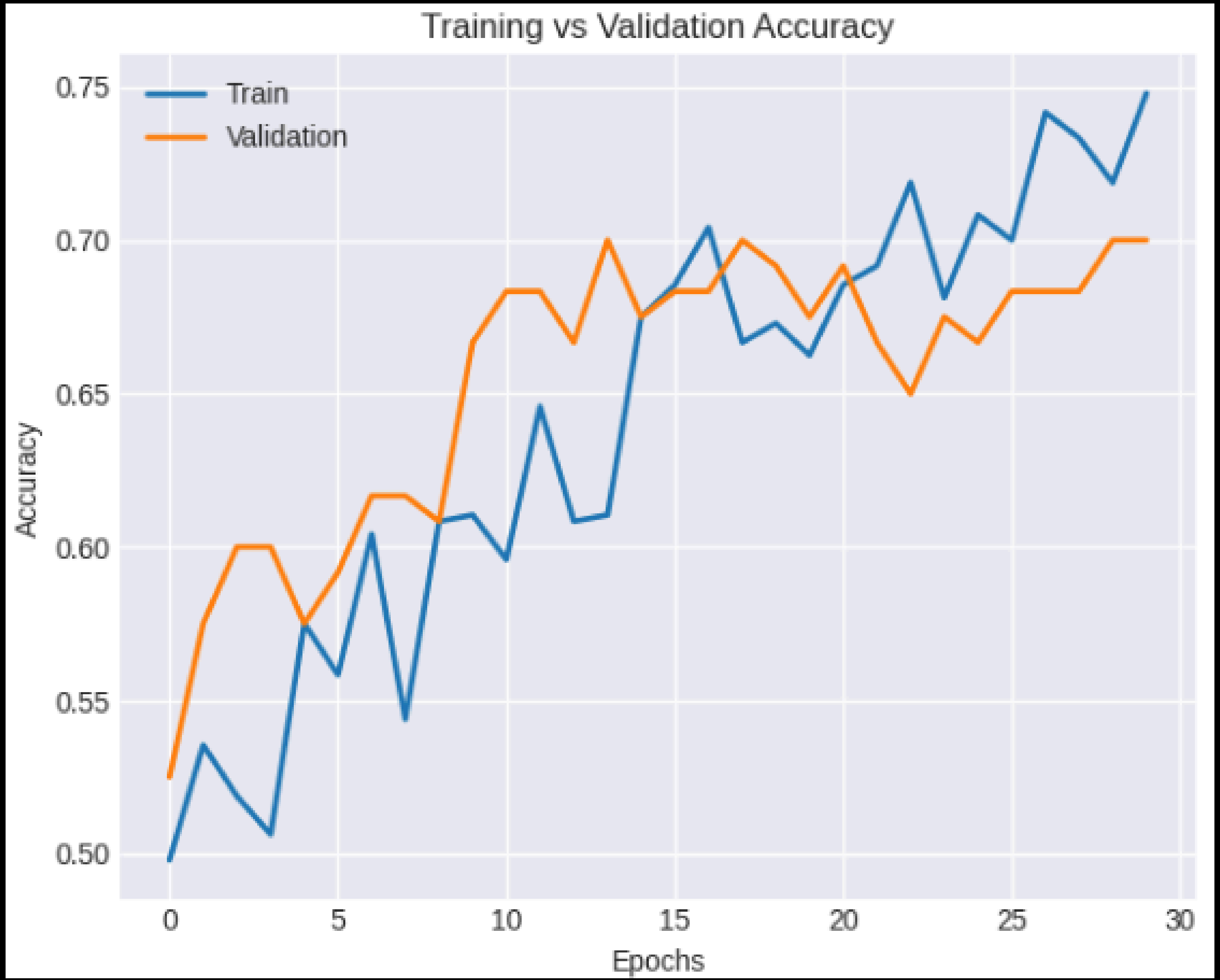
- Parameterized rotation gates (RX, RY, RZ)
- 4-qubit feature extractor
- Expectation value measurements for feature output.

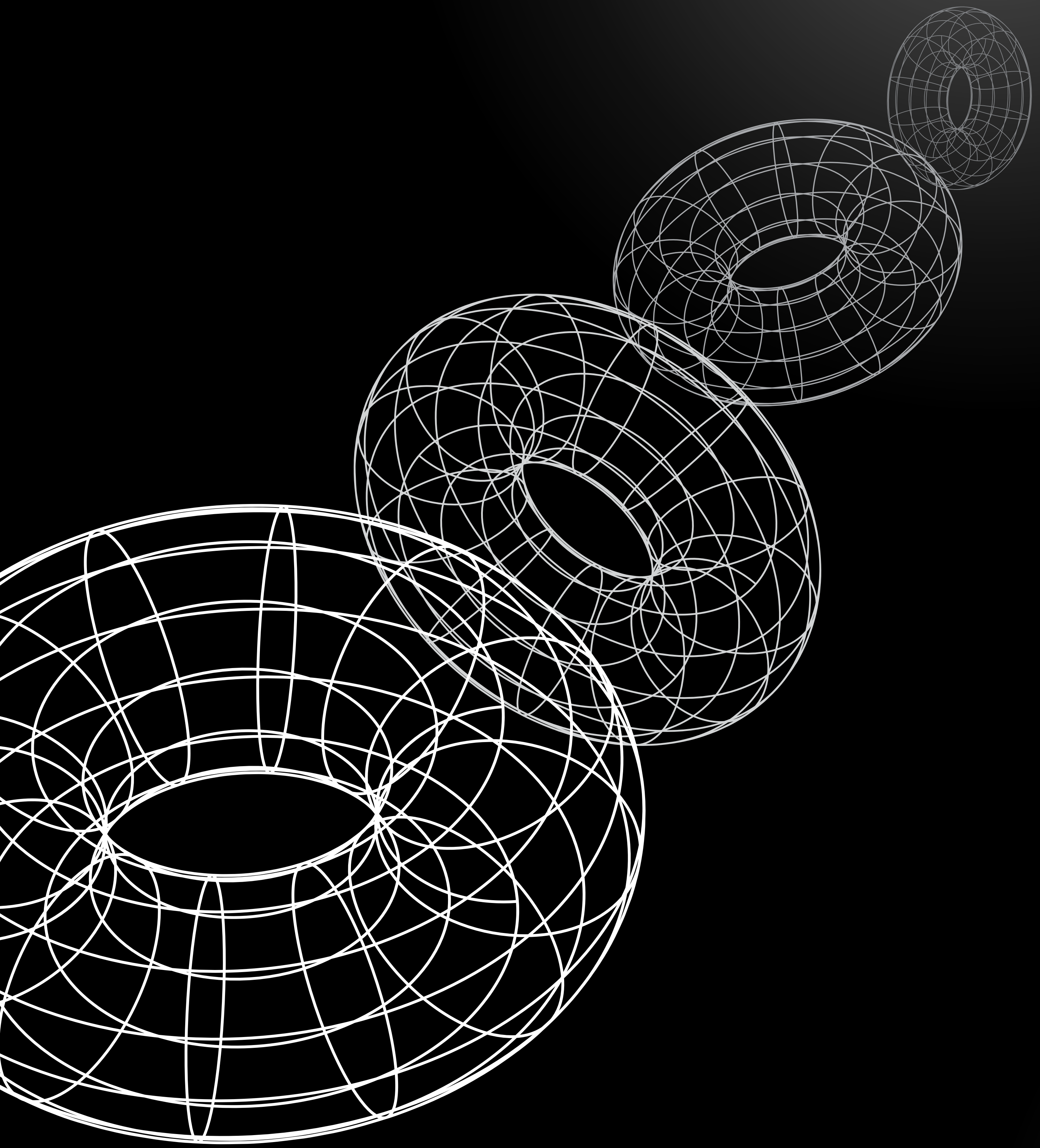
RESULTS

- Quantum Feature Extractor produced distinct feature clusters for both classes.
- Hybrid QFE–DNN achieved higher accuracy than the classical-only baseline.
- Training convergence was faster due to enhanced quantum feature separability.
- Visualization showed improved class boundary distinction in the latent space.




Training vs Validation Loss
Train
Validation
Loss
Epochs
1.35
1.30
1.25
1.20
1.15
1.10
1.05
0
5
10
15
20
25
30


Training vs Validation Accuracy
Train
Validation
Accuracy
Epochs
0.75
0.70
0.65
0.60
0.55
0.50
0
5
10
15
20
25
30



DISCUSSION

- Quantum-enhanced representations improve medical image classification.
- Hybrid models effectively combine quantum parallelism and deep learning generalization.
- QFE allows better pattern detection even in small datasets.
- Demonstrates feasibility of applying QML to real-world healthcare diagnostics.

REFERENCES (IEEE FORMAT)

1. *M. Schuld, I. Sinayskiy, and F. Petruccione, Machine Learning with Quantum Computers, Springer, 2021.*
2. *Y. Li et al., "Hybrid Quantum-Classical Neural Networks for Biomedical Image Analysis," IEEE Trans. Neural Netw., 2021.*
3. *H. Henderson, M. Schuld, and N. Killoran, "PennyLane: Hybrid quantum-classical ML framework," PennyLane Docs, 2020.*
4. *A. Marlingaplar, B. A. Sriram, "Automated Medical Image Diagnostics using Quantum ML," GitHub Repository, 2024.*
5. *A. W. Harrow and A. Montanaro, "Quantum computational supremacy," Nature, vol. 549, pp. 203–209, 2017.*

THANK YOU