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Classical vs Quantum Machine Learning: Benchmarking Hybrid Architectures for Classification, Regression, and Generative Modelling

Anum Iqbal, Zahra Tul Ain, Ateeqa Siddiqui, Kanak Pandit*, Muhammad Saeed

***Presenting Authors**

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Benchmarked Models for Classical vs Quantum ML

1. Convolutional Neural Networks (CNN) vs Quantum Convolutional Neural Networks (QCNN)
2. Variational Quantum Circuits (VQC) vs Support Vector Machines (SVM)
3. Quantum Neural Networks (QNN) vs Convolutional Neural Networks (CNN)

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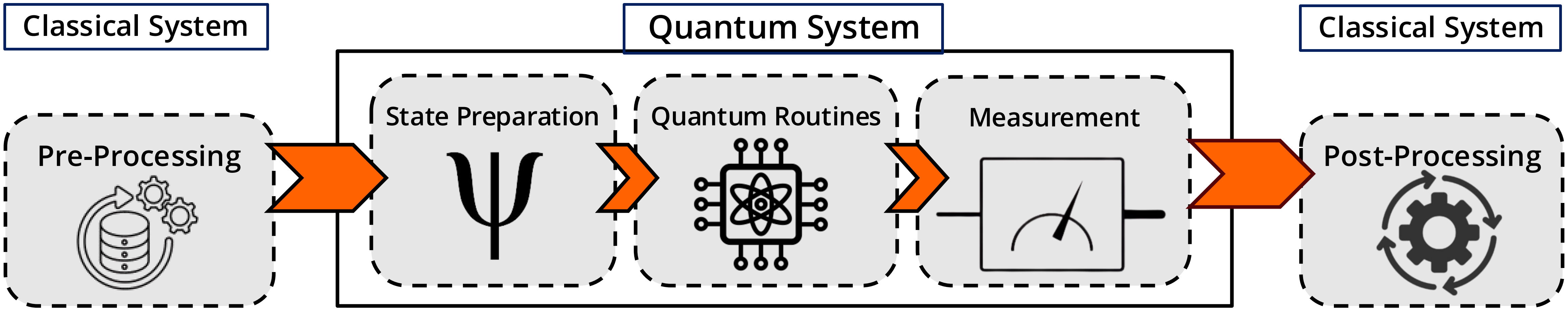
Motivation

The Need for Benchmarking

- **Quantum Machine Learning (QML)** has shown promise, but results are often fragmented and task-specific.
- **Hybrid quantum–classical approaches** may balance expressivity and practicality by using Quantum Computing principles to access high-dimensional Hilbert spaces for feature extraction.
- Previous research mainly emphasizes theoretical potential, but few evaluate end-to-end performance under realistic constraints including noise, dataset size, training time.



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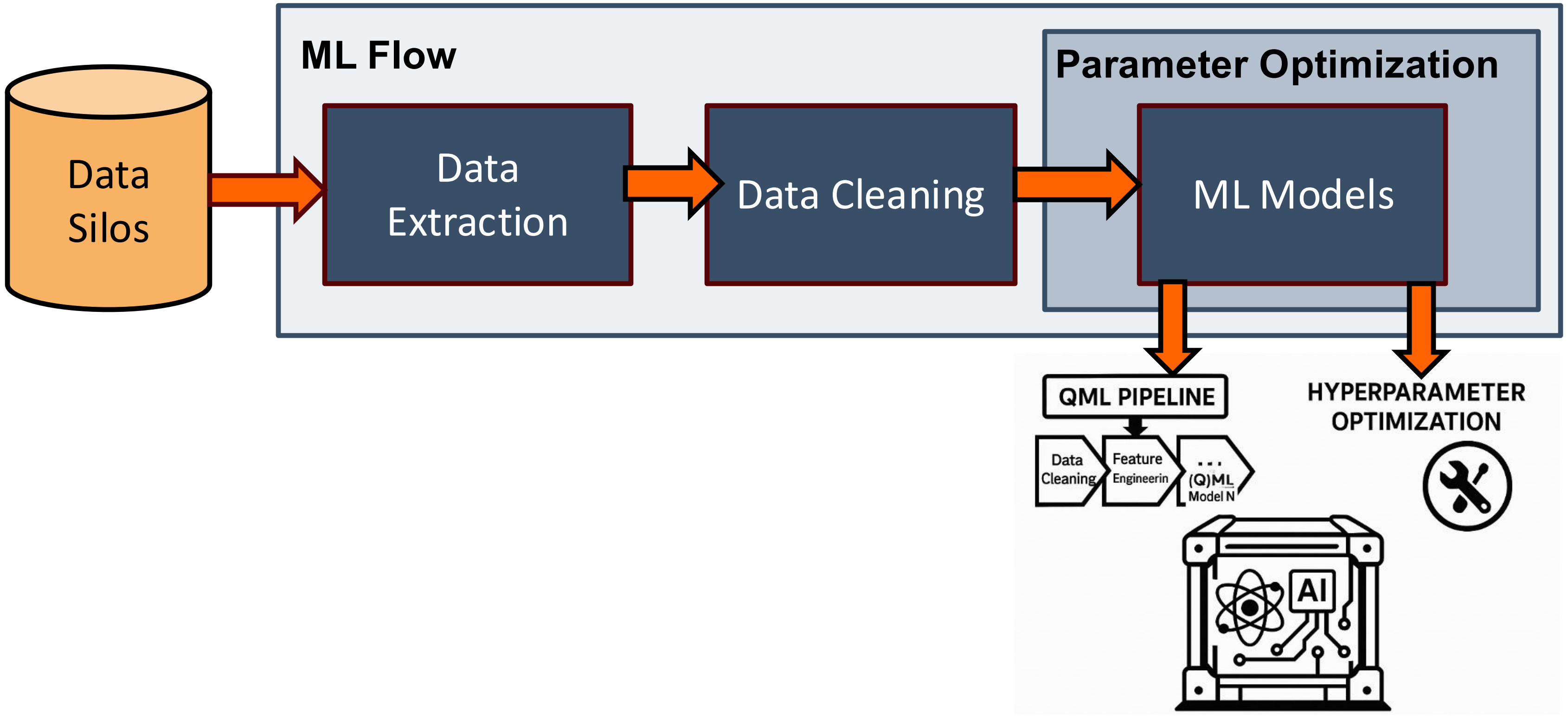
Introduction

- This work systematically benchmarks classical vs hybrid quantum–classical models across classification and regression tasks, evaluating their performance on accuracy, convergence, and computational cost.

- **Parametrized quantum circuits** combined with classical optimizers form **hybrid QML architectures**, which can leverage quantum expressivity and classical robustness.



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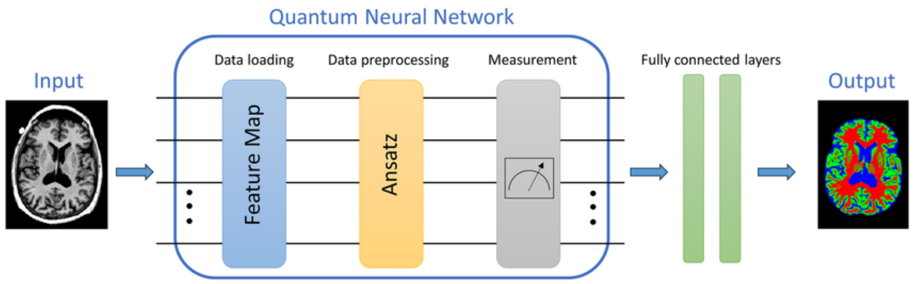
Vision in QML

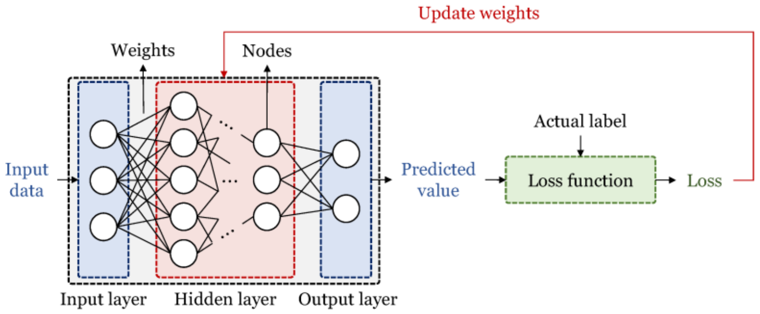
- Quantum Machine Learning (QML) combines quantum computing principles with machine learning techniques.
- The aim is to explore whether quantum circuits can provide richer data representations or more efficient training than classical methods.

QML Approaches Tested

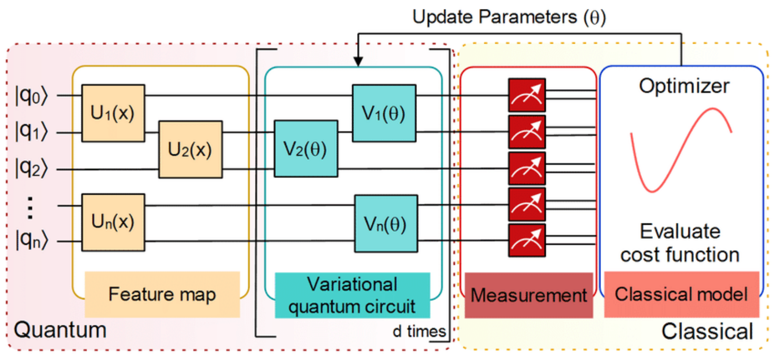
Quantum Convolutional Neural Networks (QCNNs)



Quantum Neural Networks (QNNs)



Variational Quantum Circuits (VQCs)

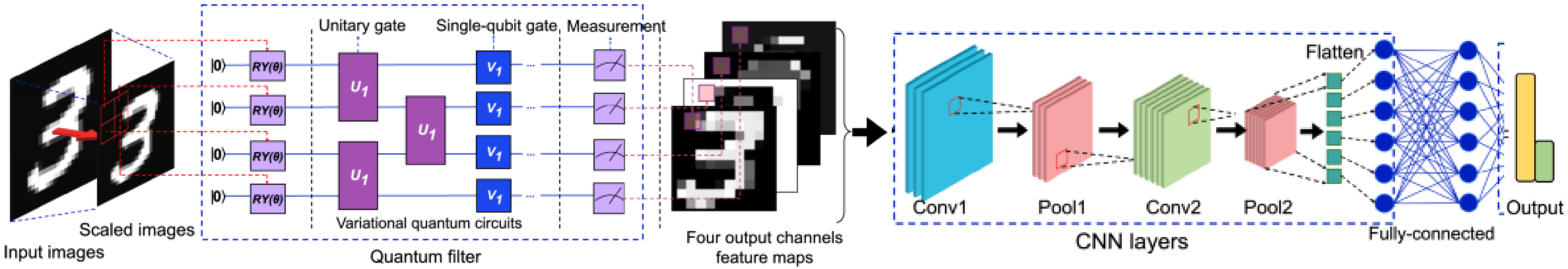


Quantum-Enhanced CNN: Introduction

Why Benchmark QCNNs vs CNNs?

- QCNNs mimic CNN’s structure but exploit superposition & entanglement to represent features more compactly.
- Potential advantages include improved generalization, fewer parameters, and robustness to noise in limited data regimes.
- **Goals:**

1. To compare training efficiency and scalability under realistic noise and dataset constraints.
2. Explore hybrid QCNN architectures: quantum layers for feature extraction and classical optimizers.



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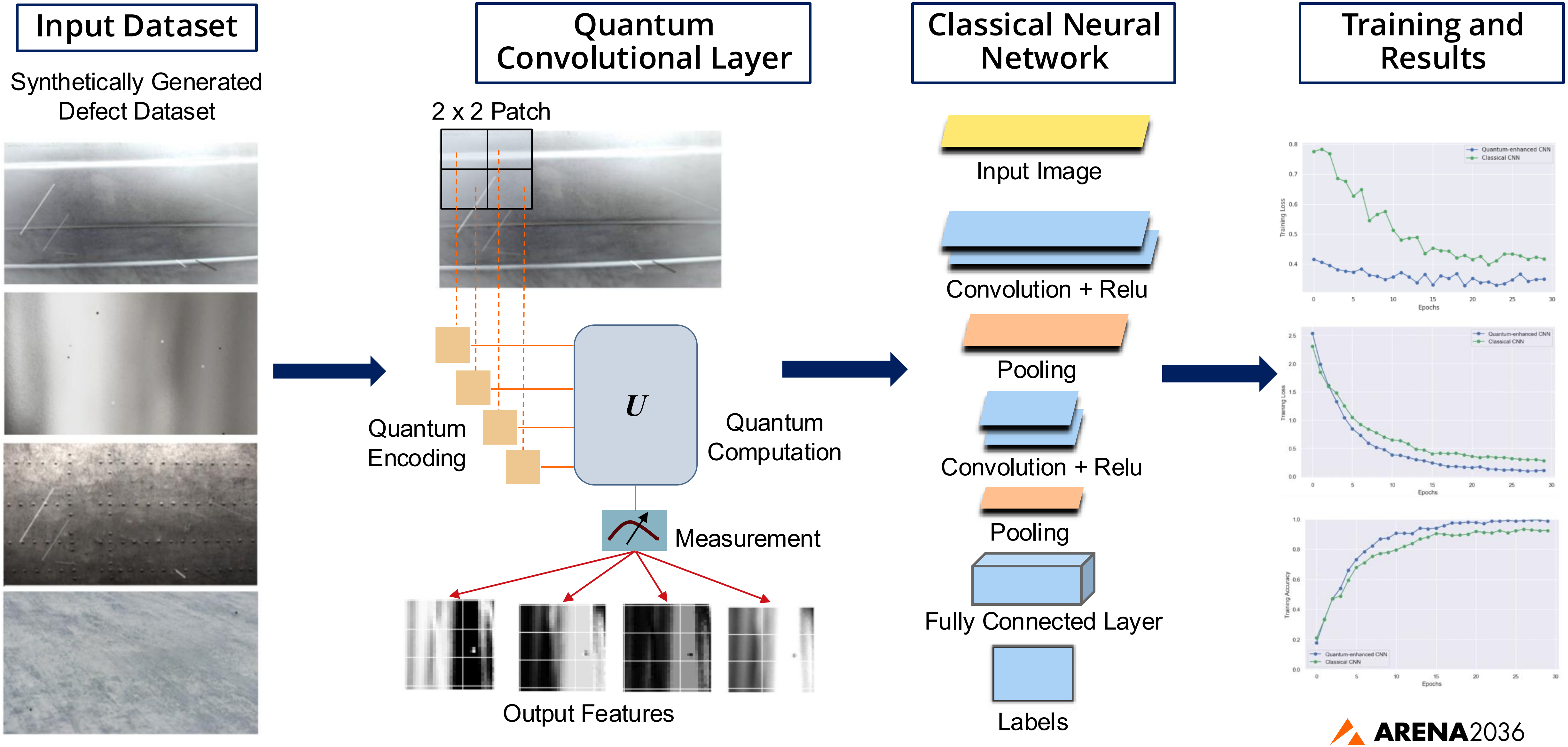
Methodology



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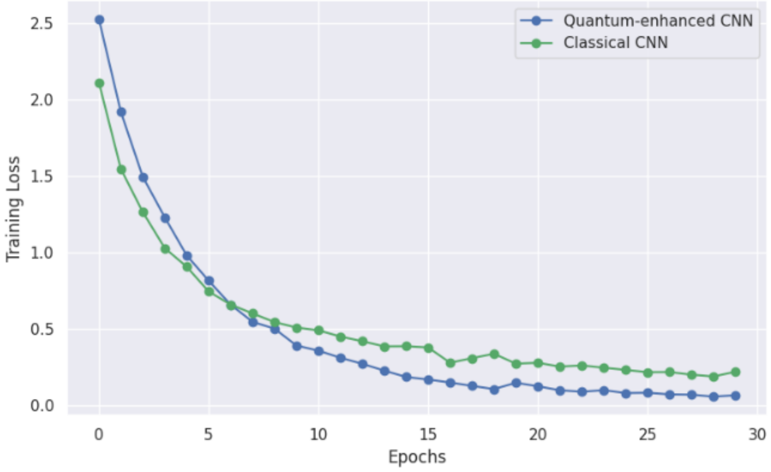
Results

MNIST Digit Dataset

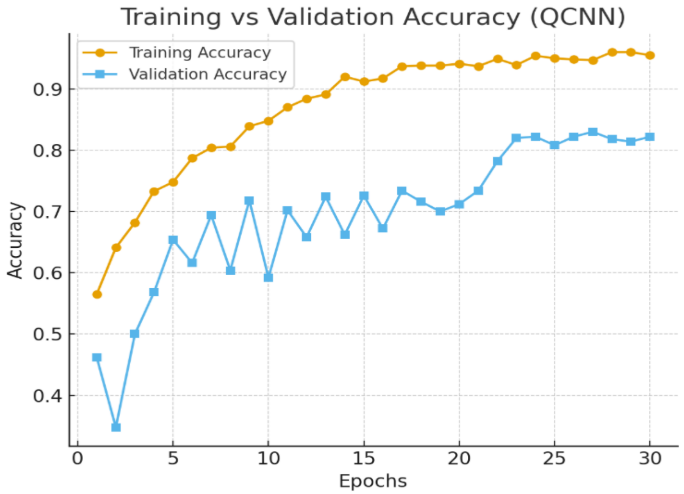
10 classes (0-9)
Around 7000 images per class



	Overall Accuracy	Precision	Recall	F1-score
QCNN	0.98	0.98	0.98	0.98
CNN	0.800	0.850	0.800	0.760

Brain Tumor Classification

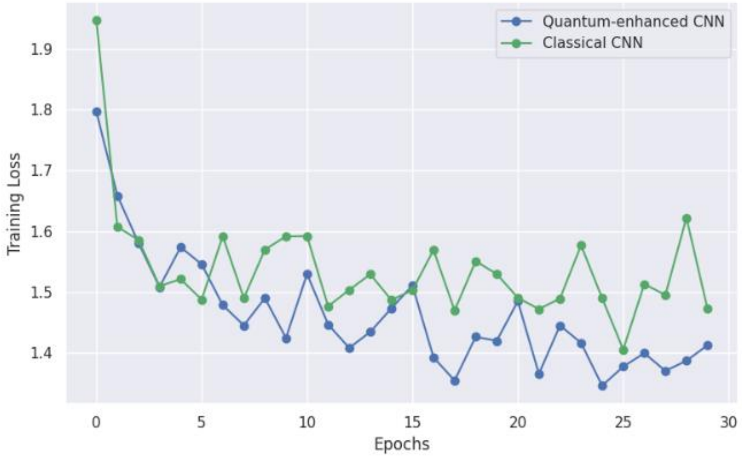
- 4 classes (glioma, meningioma, pituitary, no tumor)
- Around 1300 images per class



	Overall Accuracy	Precision	Recall	F1-score
QCNN	0.830	0.834	0.830	0.832
CNN	0.782	0.849	0.782	0.744

Synthetically Generated Defect Dataset

- 3 classes: Scratch, Pit, Non-defect
- 600 images per classes



	Overall Accuracy	Precision	Compute Time
QCNN	0.730	0.673	16 min
CNN	0.810	0.821	55 min

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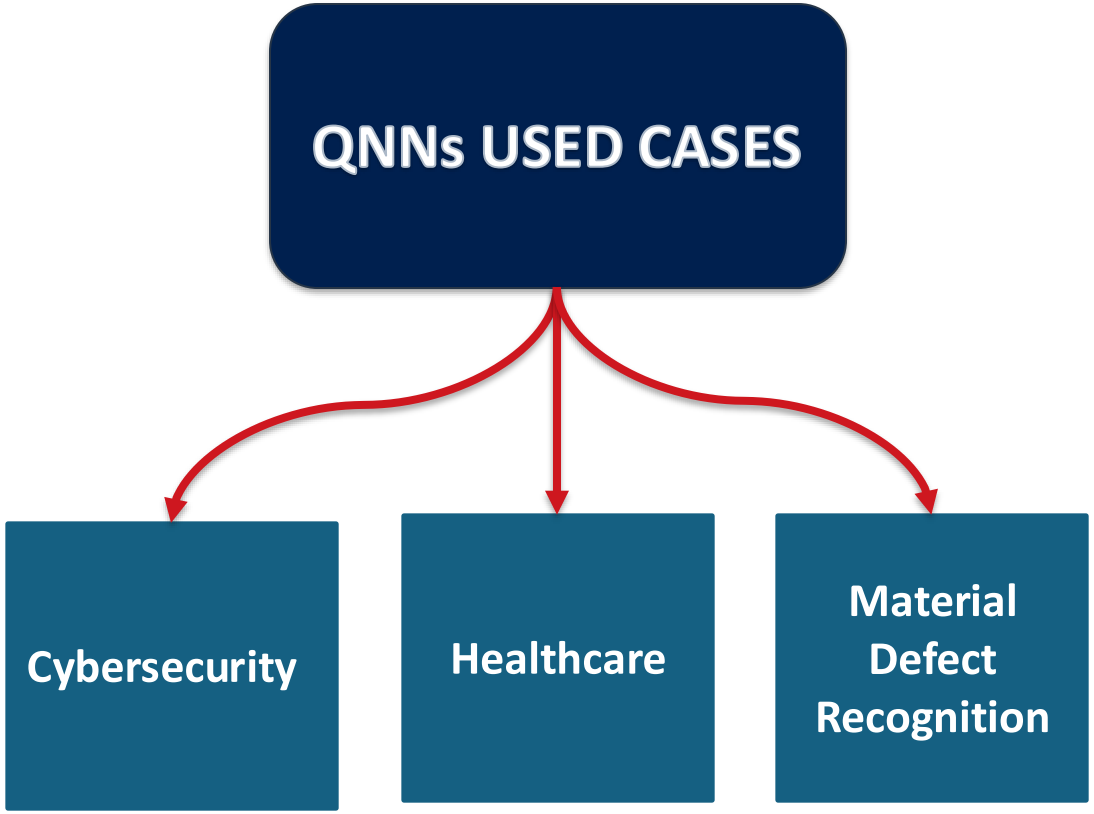
QUANTUM NEURAL NETWORK

- What are QNNs?

A **Quantum Neural Network (QNN)** is a machine learning model that uses the principles of quantum mechanics, such as superposition and entanglement, to process data in ways that classical neural networks cannot.

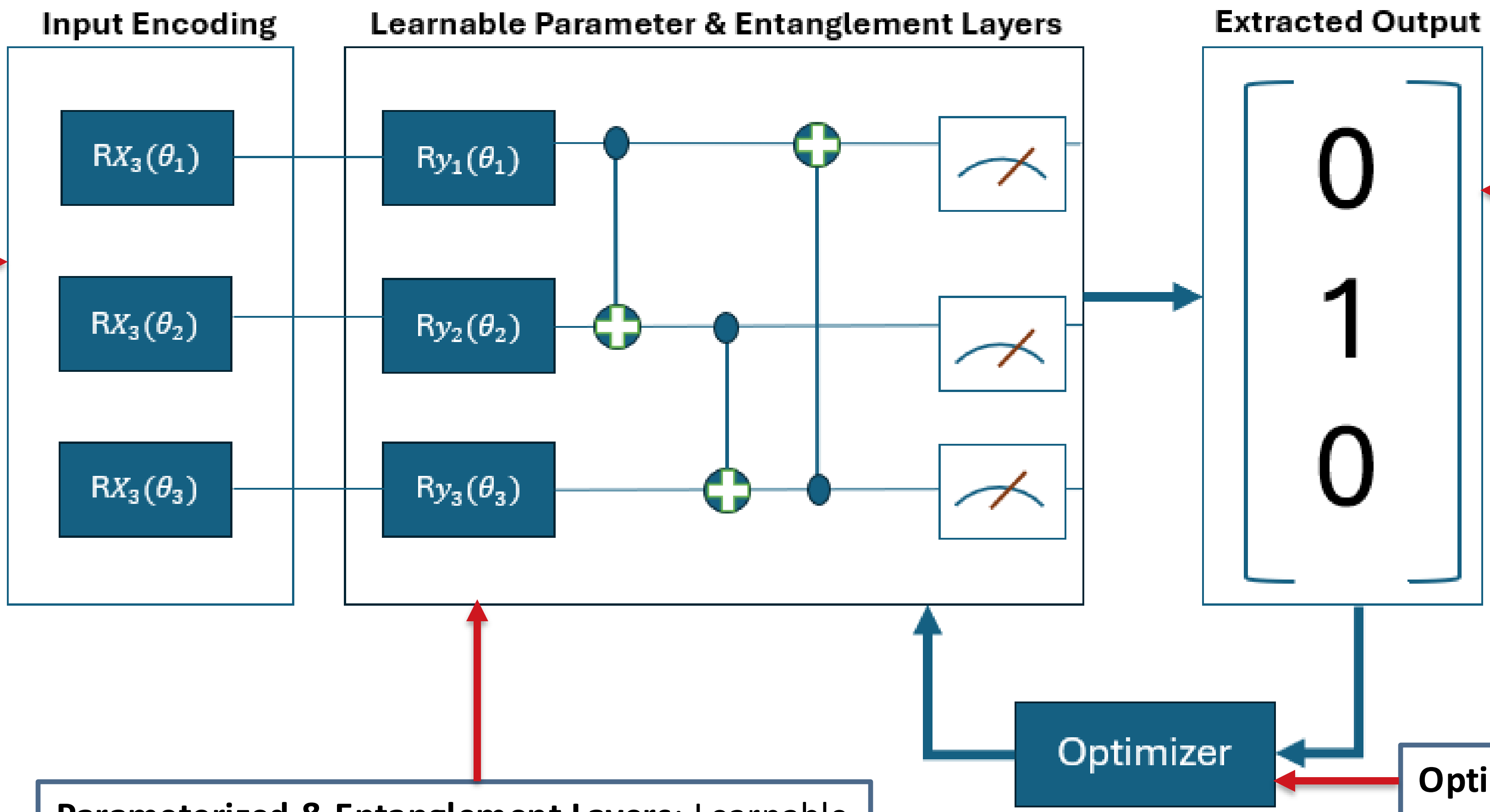
- How it works?

QNNs are useful for solving complex problems in areas like **optimization, pattern recognition, quantum chemistry, and medical data analysis**, where classical models face scalability limits.



ARCHITECTURE OF QNN

Input Encoding: Classical data is transformed into quantum states using rotation gates (e.g., RX).



Measurement: The quantum state is measured, producing classical outputs (0s and 1s).

Parameterized & Entanglement Layers: Learnable quantum gates (e.g., RY) with entanglement capture relationships between qubits, acting like trainable weights.

Optimizer: A classical optimizer adjusts the parameters of the quantum gates to improve performance.

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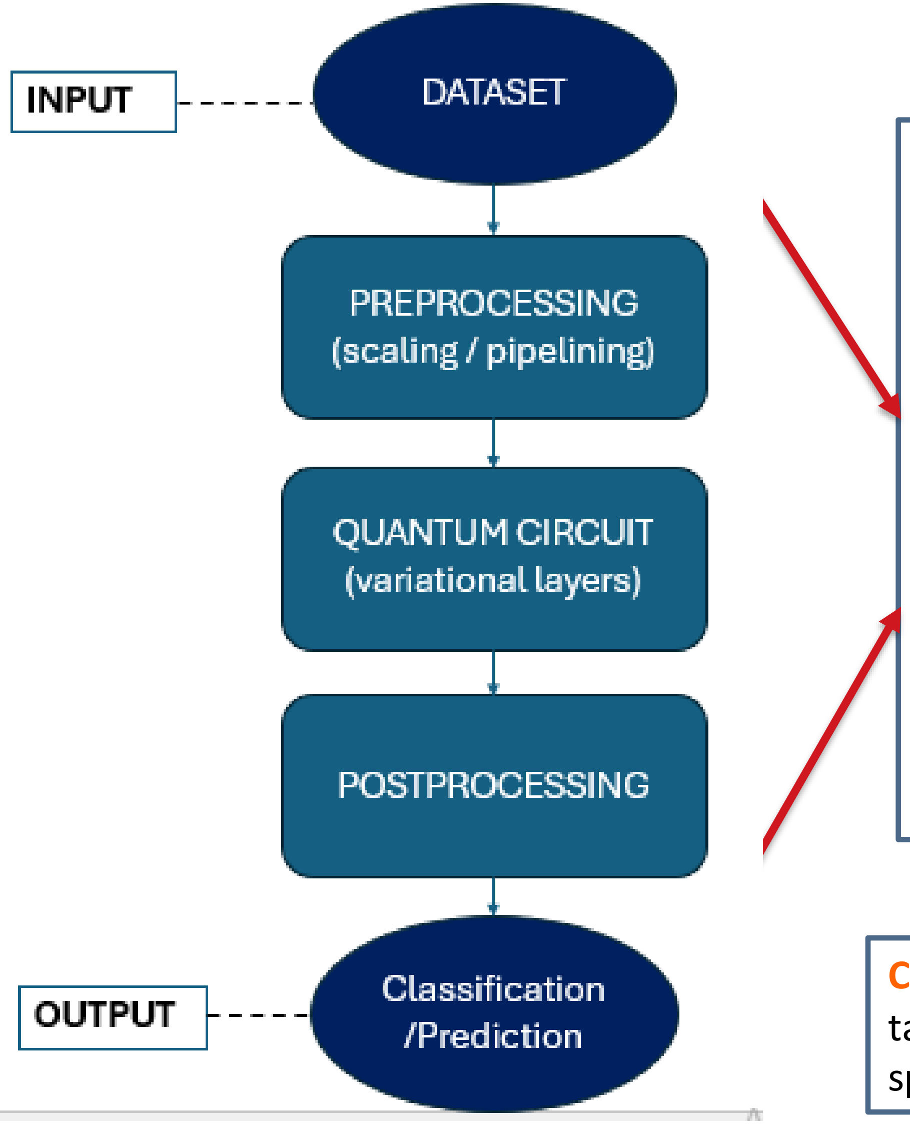
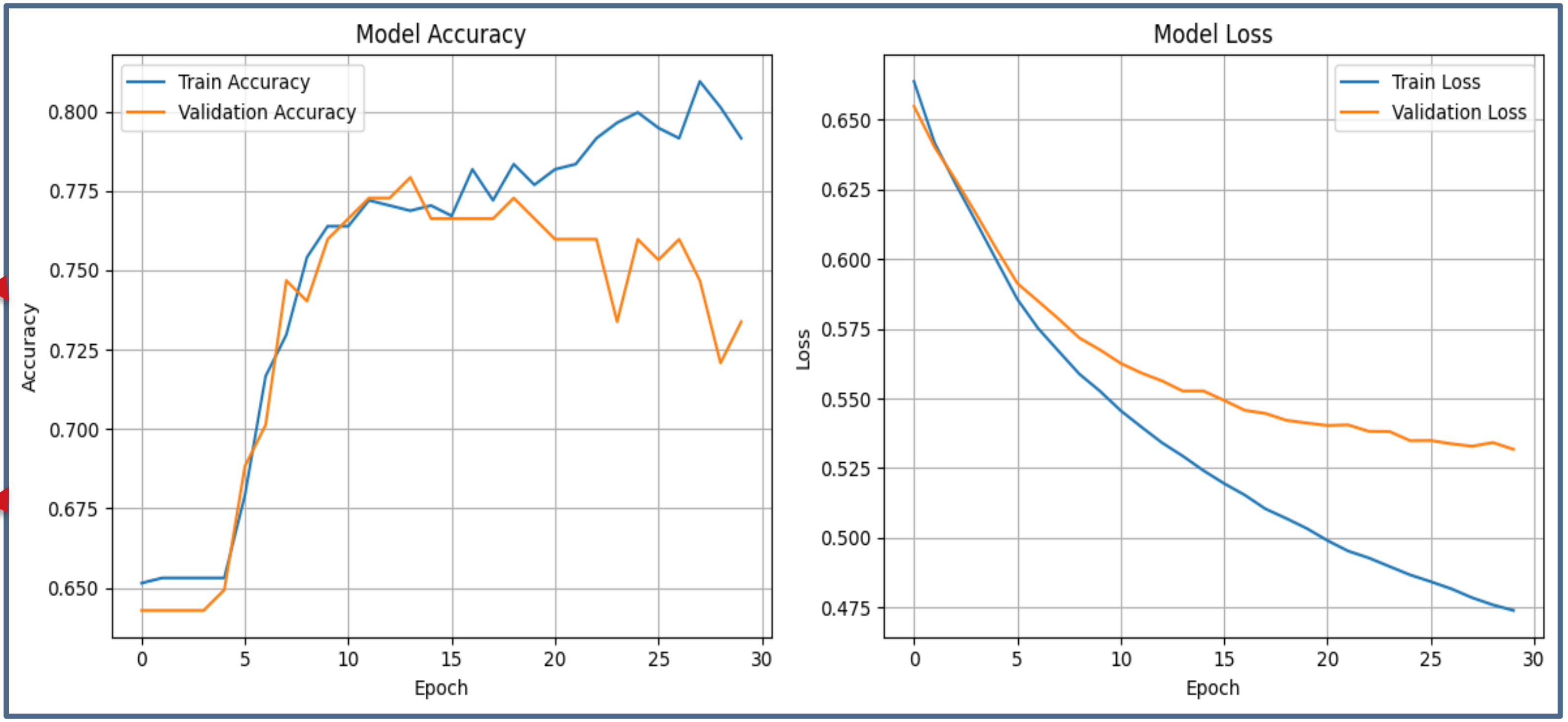
RESULTS



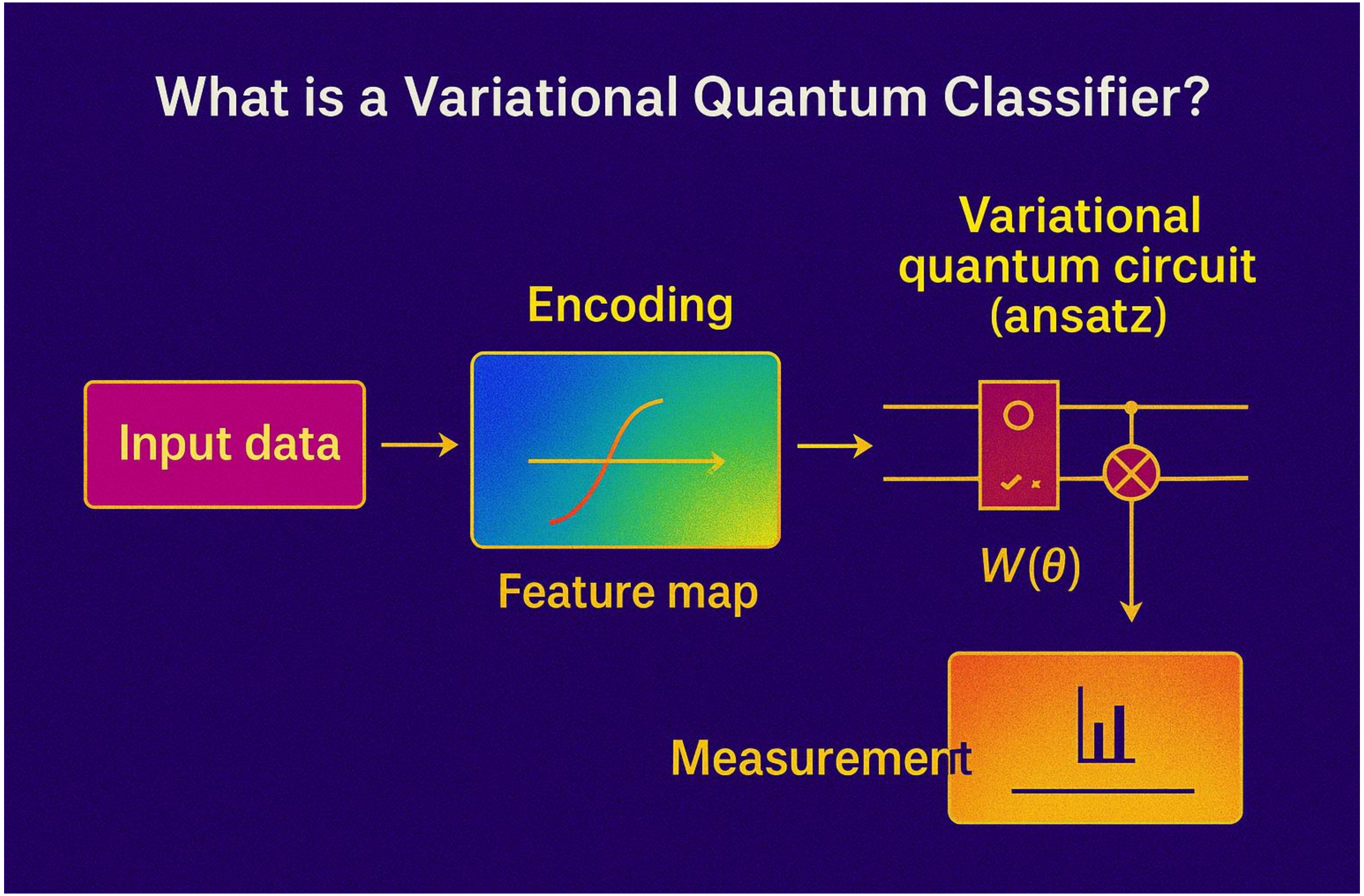
Evaluation Metrics



CONCLUSION:QNN model achieved >80% accuracy, proving its potential in real-world ML tasks. Unlike CNNs, QNNs can leverage quantum parallelism, offering future advantages in speed, scalability, and solving problems beyond classical limits.

How VQC Works

- ✓ A VQC is a hybrid quantum-classical model for supervised classification.
- ✓ VQC is like a regular classifier but uses a quantum circuit to find patterns.



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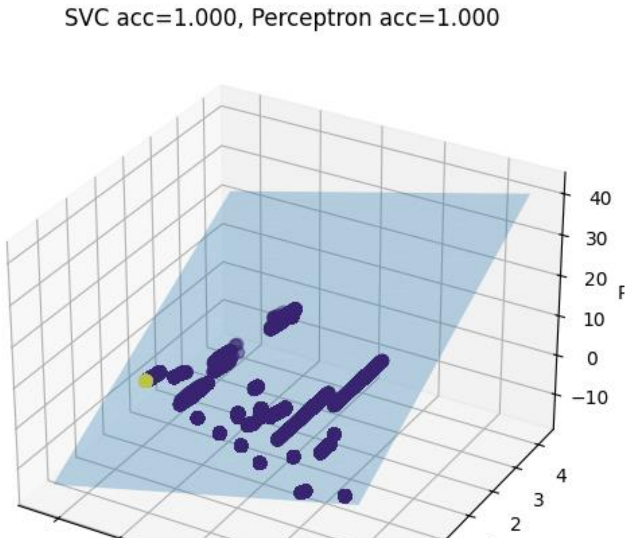
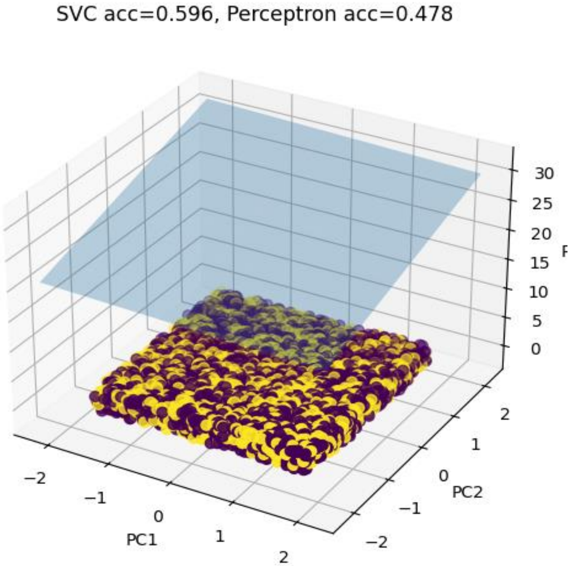
VQC vs SVM on 2 Use Cases in the Automotive domain:

Dataset A: CAN Bus Intrusion Detection (Linearly Separable)



- The Controller Area Network (CAN) bus enables efficient ECU communication but lacks security. Thus, vehicle intrusion detection systems require high accuracy, as limited attack signatures and false positives could endanger driver safety.
- This dataset captures Controller Area Network (CAN) bus traffic from a real vehicle, simulating both normal driving scenarios and Denial of Service cyberattacks.

Dataset B: Engine Fault Detection (Non Linearly Separable)



- This dataset is designed for the purpose of detecting and classifying engine fau
- It contains data representing sensor readings collected during various operatir conditions of an engine, including normal, minor fault, and critical fault states.

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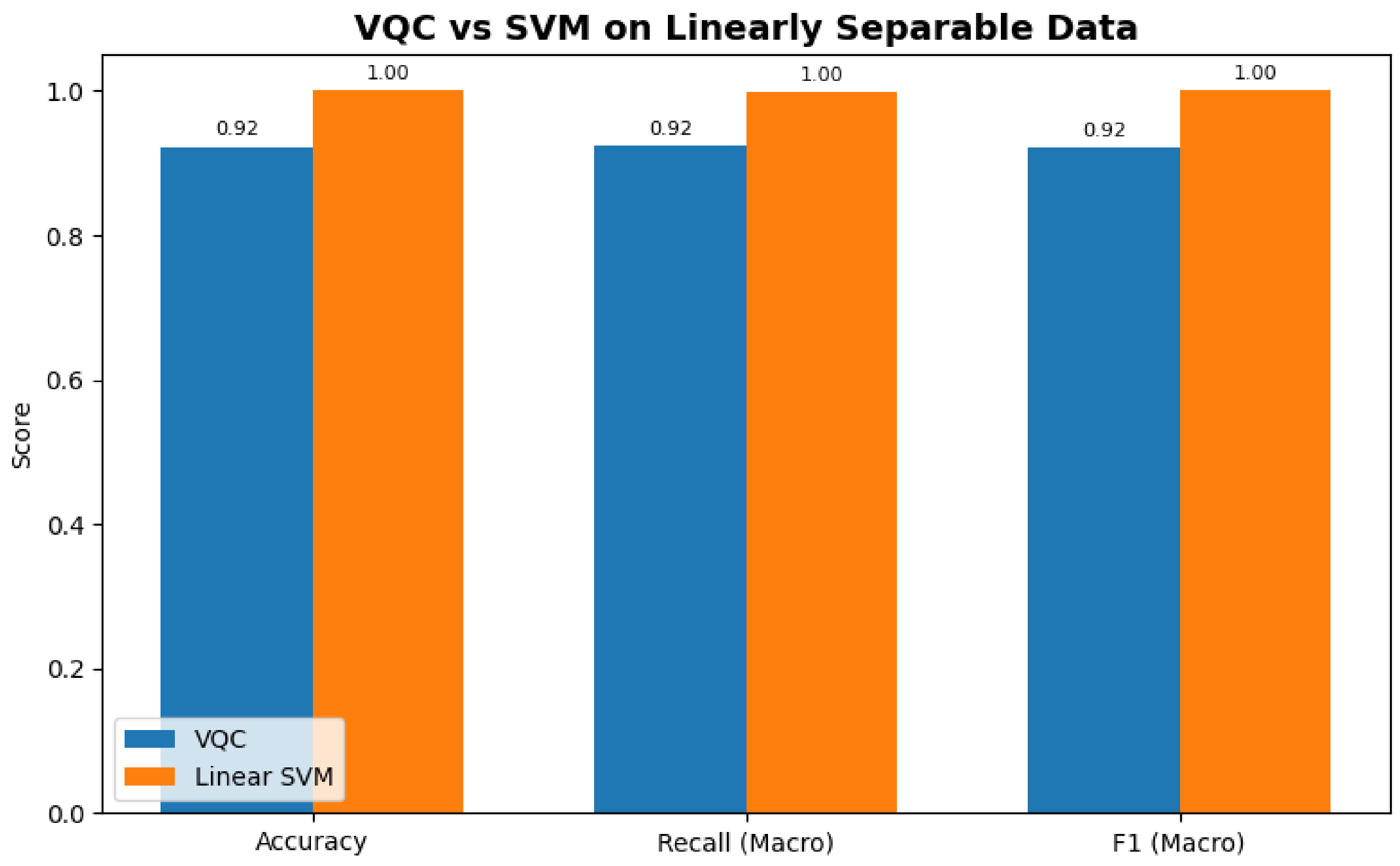
Dataset A: SVM vs VQC on Linear Data

- Linear SVM achieves perfect accuracy, proving best for linearly separable data.

- VQC performs well but misclassifies, highlighting current quantum model limitations.

- VQC offers quantum advantage potential but is currently limited by noise, circuit depth, and optimization instability, whereas SVM provides stable and reliable performance.



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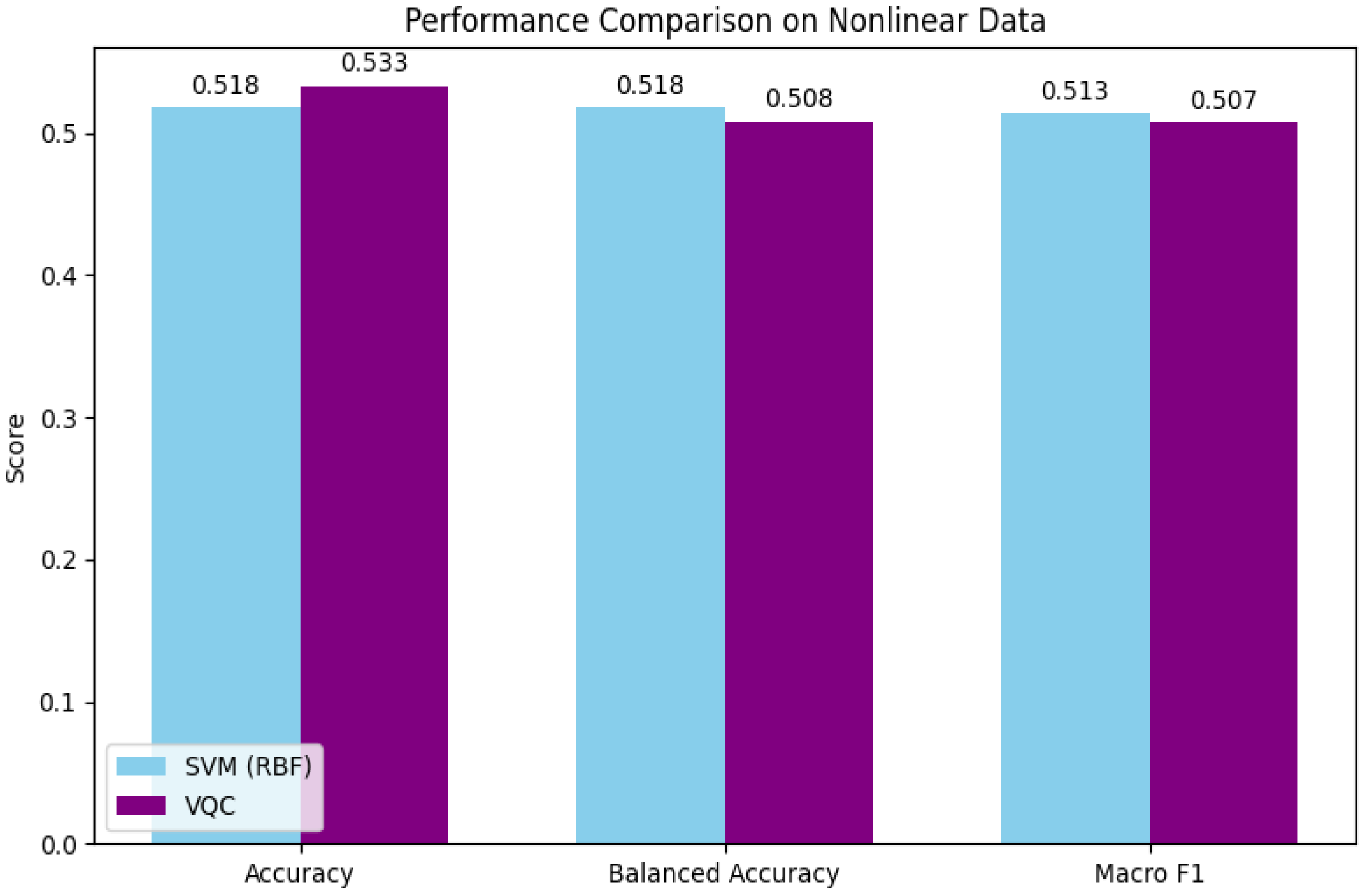
Dataset B: VQC vs SVM on Non Linear Data



- VQC slightly surpasses Kernel SVM in overall accuracy, showing strong promise.
- Quantum circuits capture nonlinear structure effectively, despite modest recall trade-offs.
- Results highlight VQC's potential as quantum hardware and optimizers mature.

Results and Discussion

Approach	Key Results	Conclusion
CNN vs QCNN	**CNN** → Higher training time, better for complex datasets due to adaptability **QCNN** → Faster training, More efficient on simple datasets	QCNNs need deeper circuits and more qubits to handle complex datasets, adaptable quantum circuits would improve performance on varying datasets
VQC vs SVM	**VQC** →Not yet faster than SVM on Linear data, but has the potential to outperform on Non-Linear Data **SVM** → Faster training Strong for Linear data	VQC is still new but shows promise for Non-Linear Cases, but is currently limited by noise, circuit depth, and optimization instability
QNN vs CNN	**QNN** → Shows faster learning on small and complex data **CNN** → CNN works best for image dataset	CNNs are reliable for large image datasets, while QNNs show faster learning and efficiency on smaller or more complex datasets but require scalable circuits and hardware maturity.

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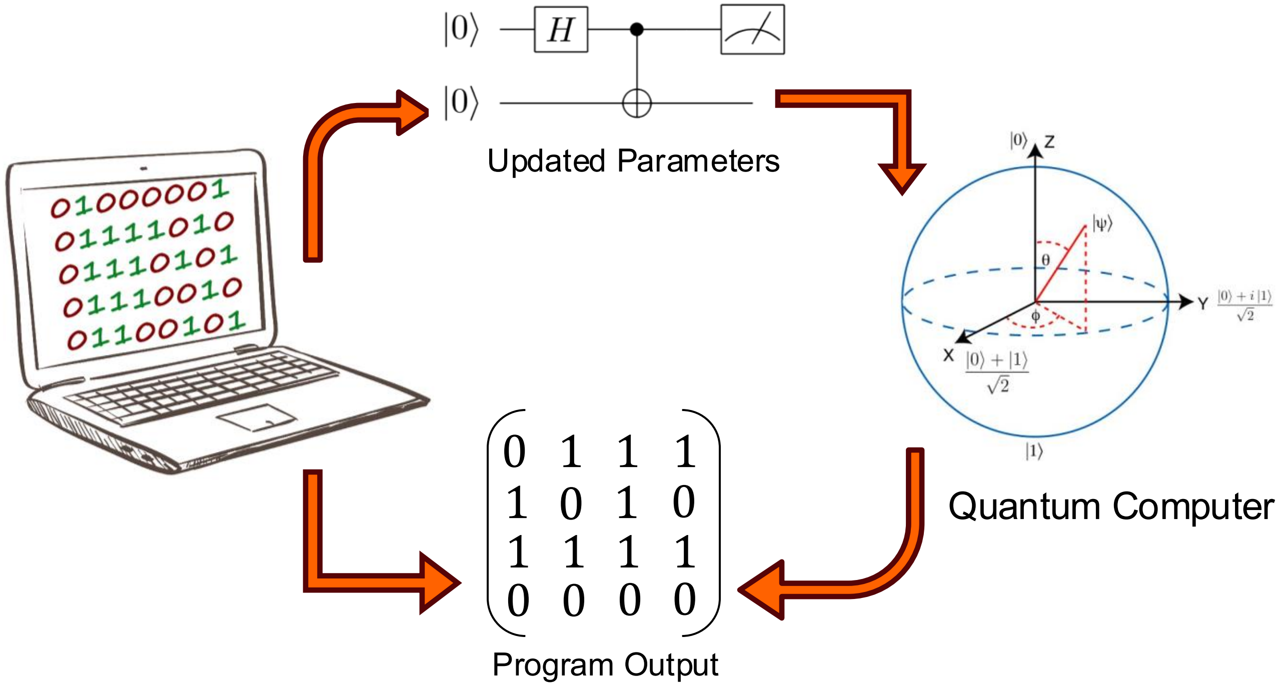
Conclusion and Future Outlook

- Foundational insights highlight both current limitations and niche strengths of QML.
- The research demonstrates that hybrid architectures can serve as bridges to practical quantum advantage.

Next Steps:

- Extend benchmarking to specialized industrial use cases.
- Move towards scalable, deployable hybrid systems aligned with industry needs.



RL vs QRL in Robotic Path Planning

Motivation / Problem

1. Path planning is critical for robotics (navigation, obstacle avoidance).
2. Classical RL works well but can be slow, unstable.
3. Quantum RL promises faster convergence and higher stability.
4. **Goal**: Compare both approaches for robot path tracing.

Use Cases

1. Automotive Assembly
2. Factory Palletizing
3. Welding Automation
4. Healthcare Robotics

Trajectory Patterns for Robot Motion

1. Shapes include circle, triangle, square, pentagon, star, Figure-8, U-shape, zig-zag, spiral.
2. These cover turns, loops, crossings and sharp edges.

Experimental Setup and Evaluation Metrics

1. Robot: Kuka Robot Arm Environment
2. Models: Classical RL, Quantum RL
3. Training: 20000 steps, Testing: 4000 steps
4. Metrics: Reward, Time, Memory, Convergency, Stability.

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Comparative Analysis

Metric	Classical RL (Test)	Quantum RL (Test)
Average Reward	11.06	10.68 (-4%)
Training/Test Time (s)	642.05	343.01(+46.5%)
Latency (s/step)	0.160512	0.171505(+7%)
Memory Consumed (MB)	829.66	928.43(+11.91%)
Stability (Reward Std)	43.68	42.37(+3%)

** Quantum RL is faster and more efficient than classical RL but needs advanced quantum hardware.

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Thank you for being Patient!

Dr. – Ing Muhammad Saeed
Research Coordinator

muhammad.saeed@arena2036.de

+49 155 60070608

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- **Ateeqa Siddiqui (Student):** Foundational work in QML and VQCs
- **Kanak Pandit (Student): For Laying down the QRL foundations**

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