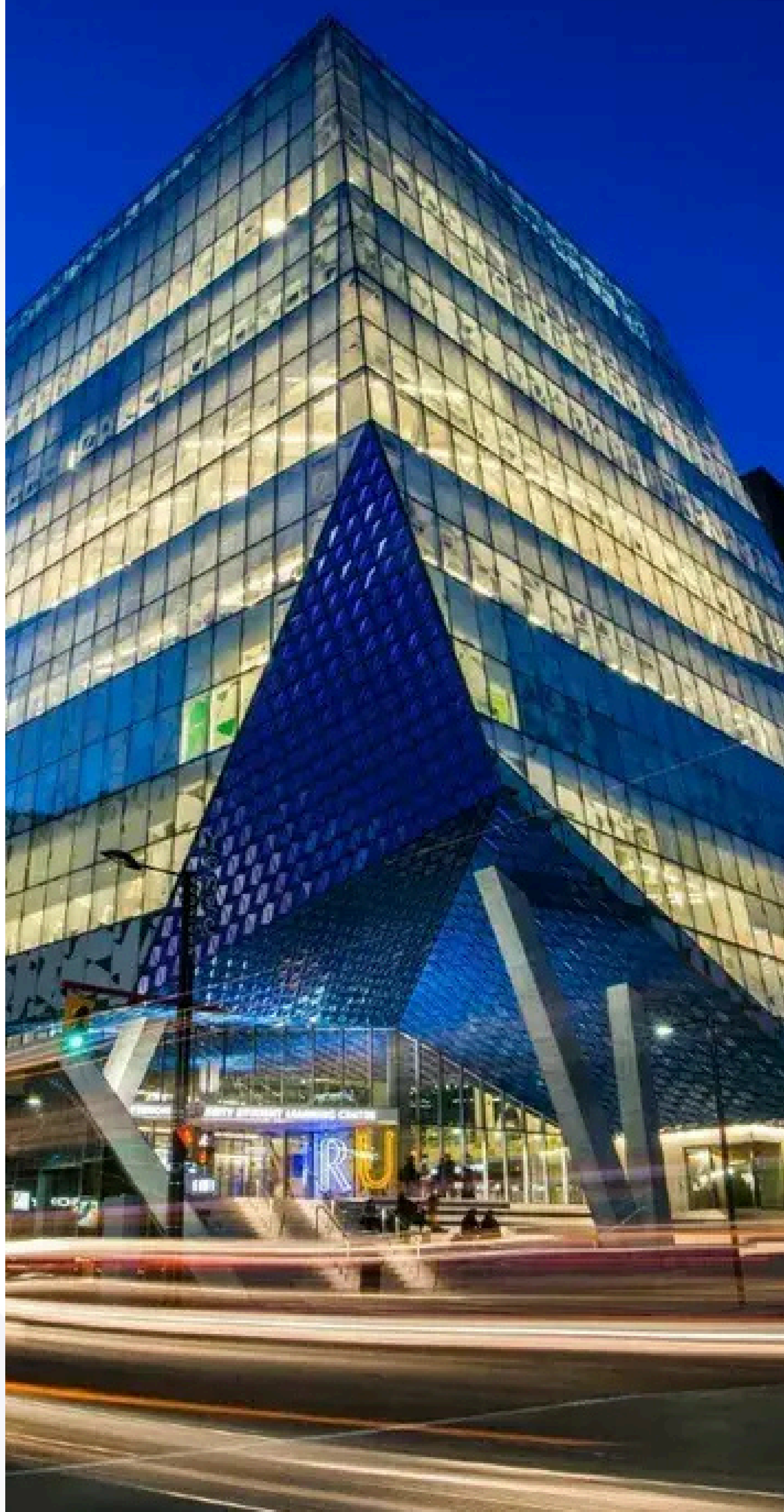
Quantum Machine Learning for Prognostics and Health Management

Presented By : Mohamed Rayen Ouni

Presentation Plan

1. **Introduction and Context**
2. **Theoretical Foundations**
3. **Quantum Machine Learning Approach**
4. **Implementation**
5. **Experimental Results**
6. **Conclusion and Perspectives**

Introduction and Context



Research Context and Environment

Canada

mitacs

Internship Program

Toronto Metropolitan University

Host institution

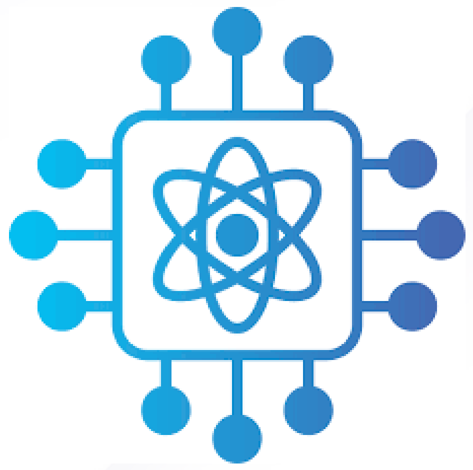
RRMR LAB

Reliability, Risk and Maintenance Research Laboratory

Research laboratory

Project Context and Industrial Motivation

Research Problem



Industrial Challenge

- Bearings fail unexpectedly → costly downtime, safety risks
- Current maintenance is reactive or preventive : **not predictive**

Limitation of Classical ML

- struggles with noisy, high-dimensional vibration data
- computationally expensive

The Quantum Opportunity

Quantum circuits can:

- Process very complex data patterns
- Do more with fewer parameters
- Learn effectively even with limited data

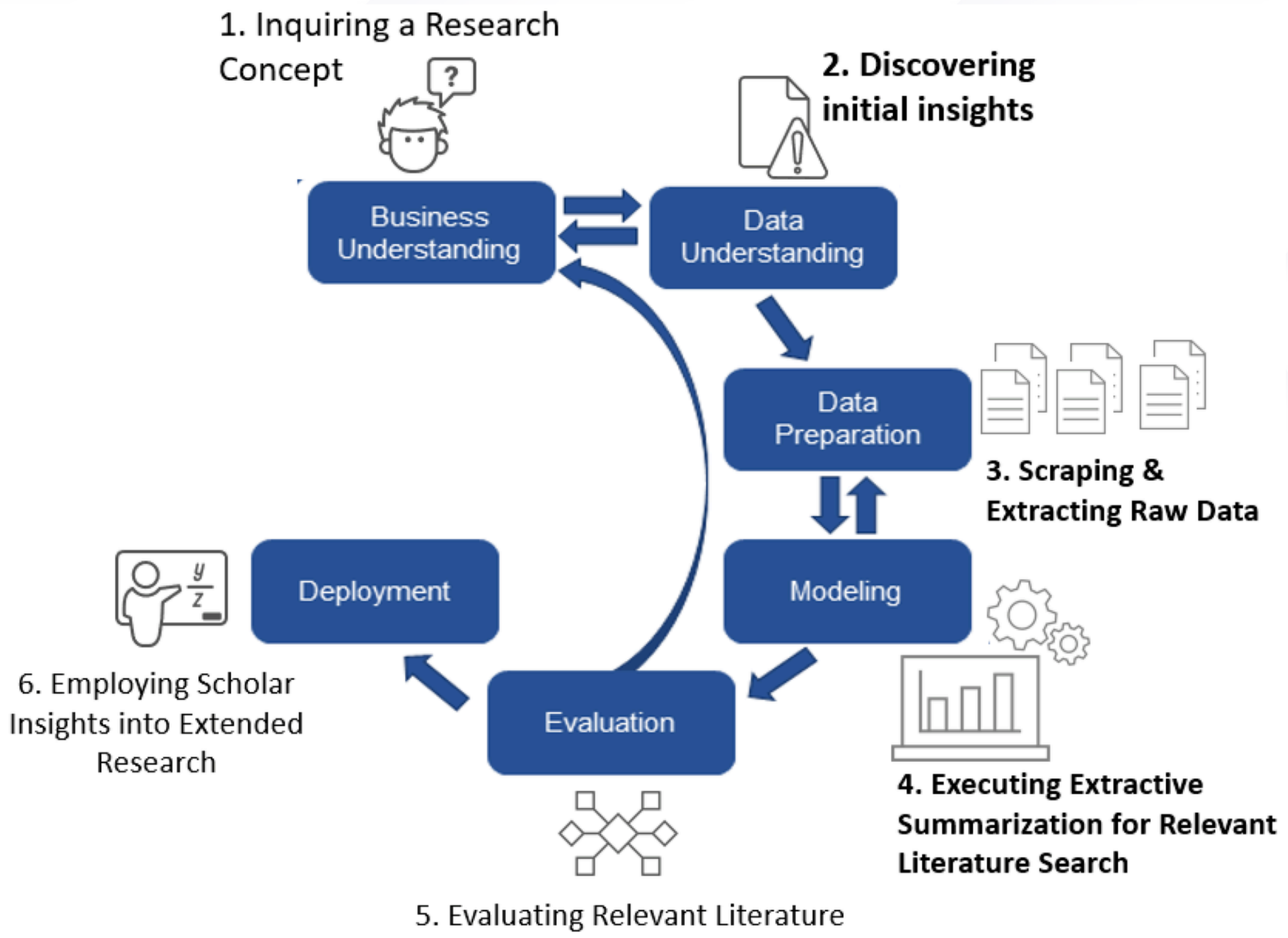
Project Objectives

A Implement and compare Variational Quantum Regressor (VQC) vs Hybrid LSTM-Quantum model using NASA IMS dataset.

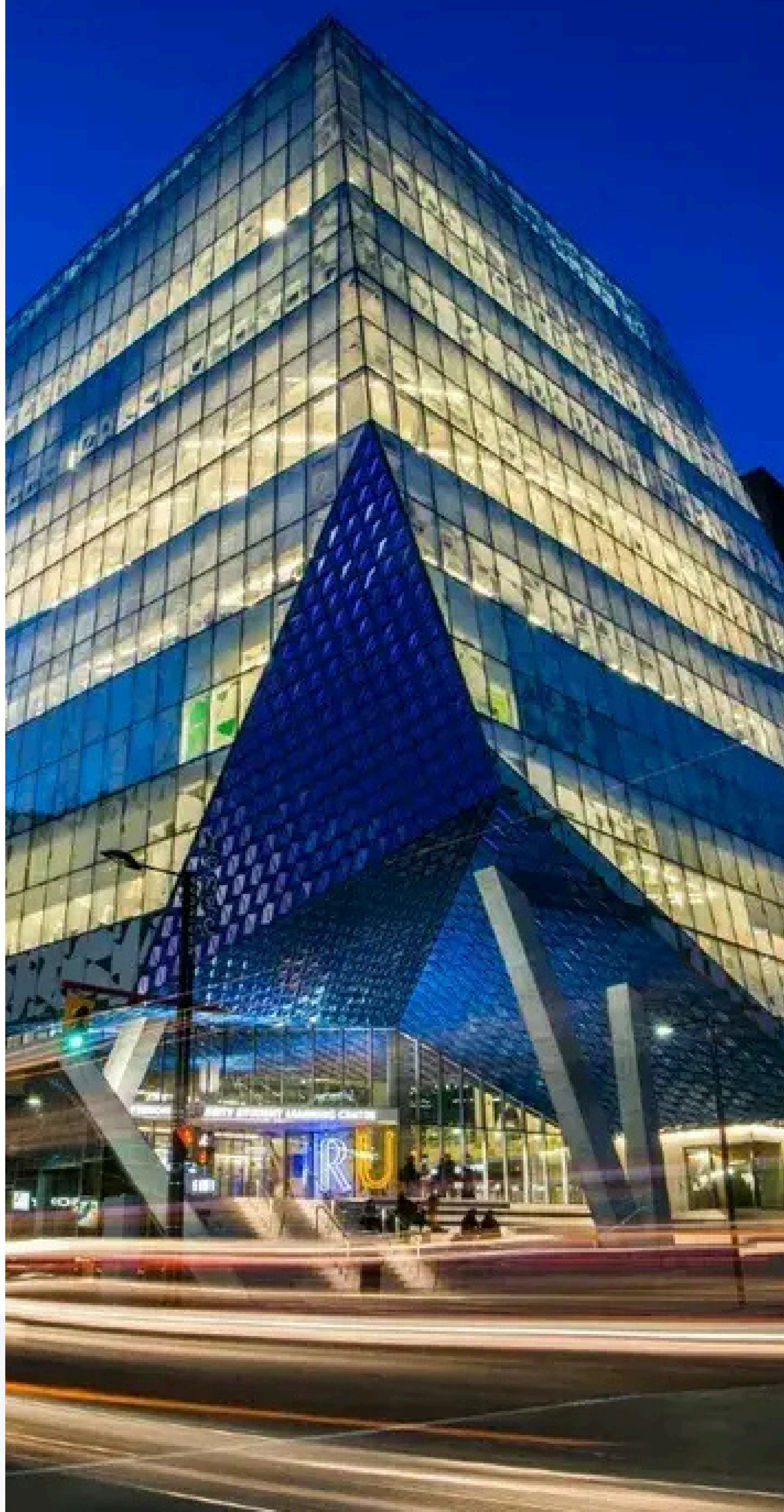
B Analyze performance vs parameter-efficiency compared to classical models.

C Identify current limitations of quantum approaches.

Methodological Framework CRISP-DM



Theoretical Foundations



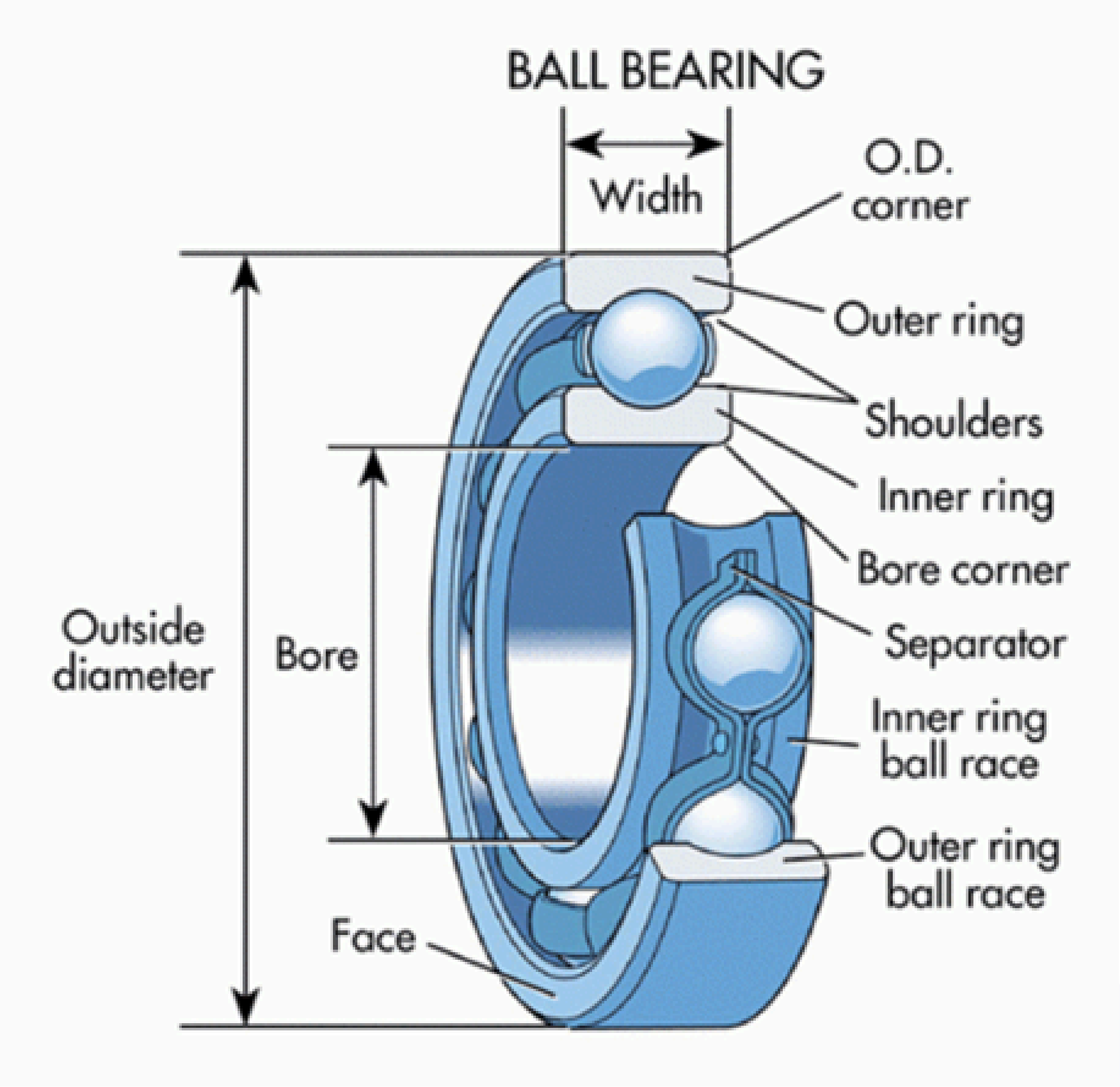
Bearing Reliability & Failure Mechanisms

Reliability & Bearing Basics

Reliability = probability a component performs without failure over time
Failure rate shows how quickly failure is likely to occur

Common Failure Mechanisms

Fatigue, contamination, lubrication issues,misalignment...
These factors accelerate wear, cracks, and surface damage



Prognostics & Health Management (PHM)

Goal of PHM

- Predict future health states of machinery and estimate Remaining Useful Life (RUL)
- Helps plan maintenance before failure occurs

Approaches to Prognostics

- Physics-based: relies on physical models
- Data-driven: uses machine learning
- Hybrid: combines physics and ML

RUL & Performance Metrics

- RUL: time remaining until component reaches a failure threshold
- Metrics to evaluate predictions: MAE, MSE, R^2

Machine Learning for Bearing Prognostics

Modeling Approaches

- Classical ML
- Deep Learning

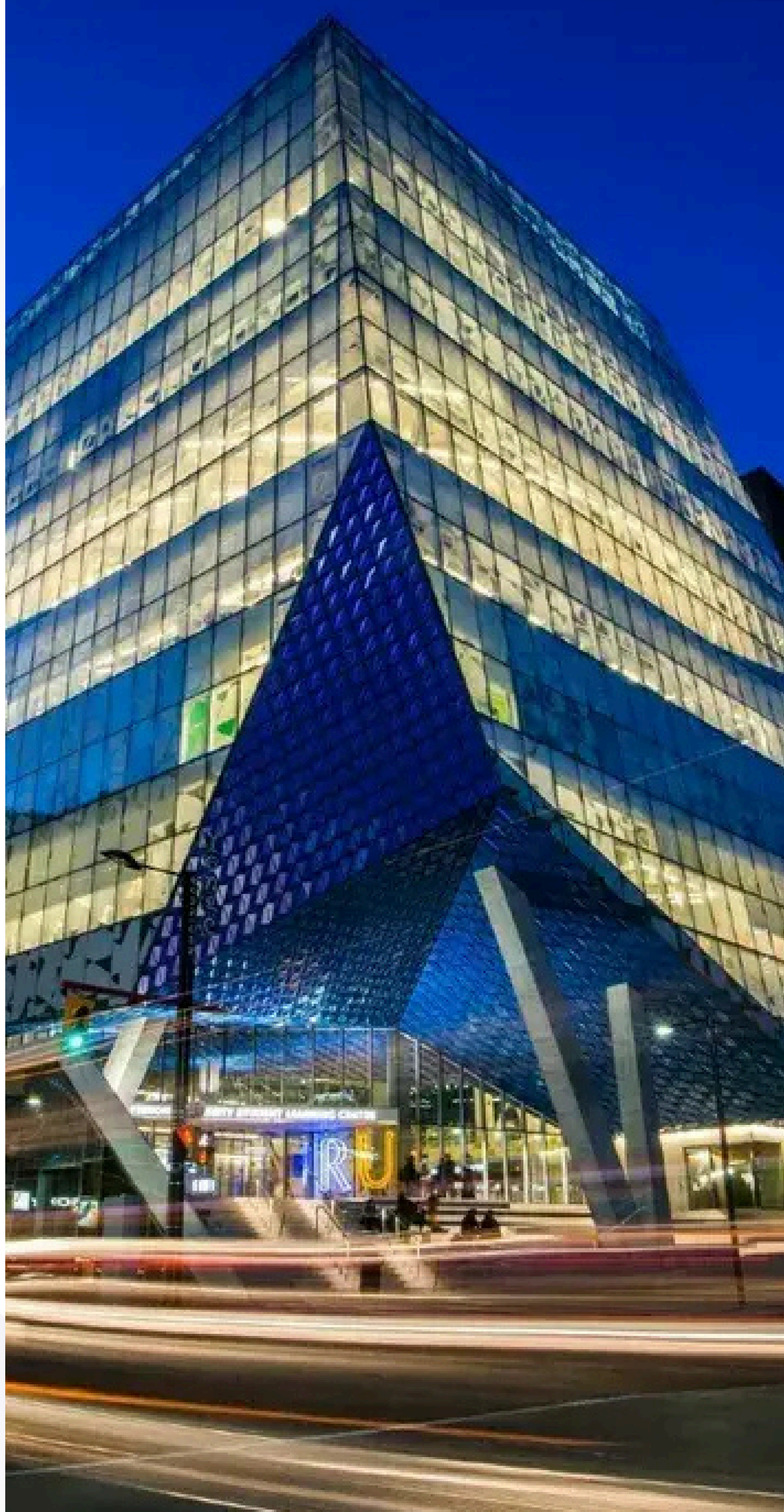
Feature Extraction

- Time-domain
- Frequency-domain
- Time–frequency

Limitations & Motivation

- High computational cost, complex optimization, many parameters
- Motivates quantum machine learning for richer representations and efficiency

Quantum Machine Learning Approach

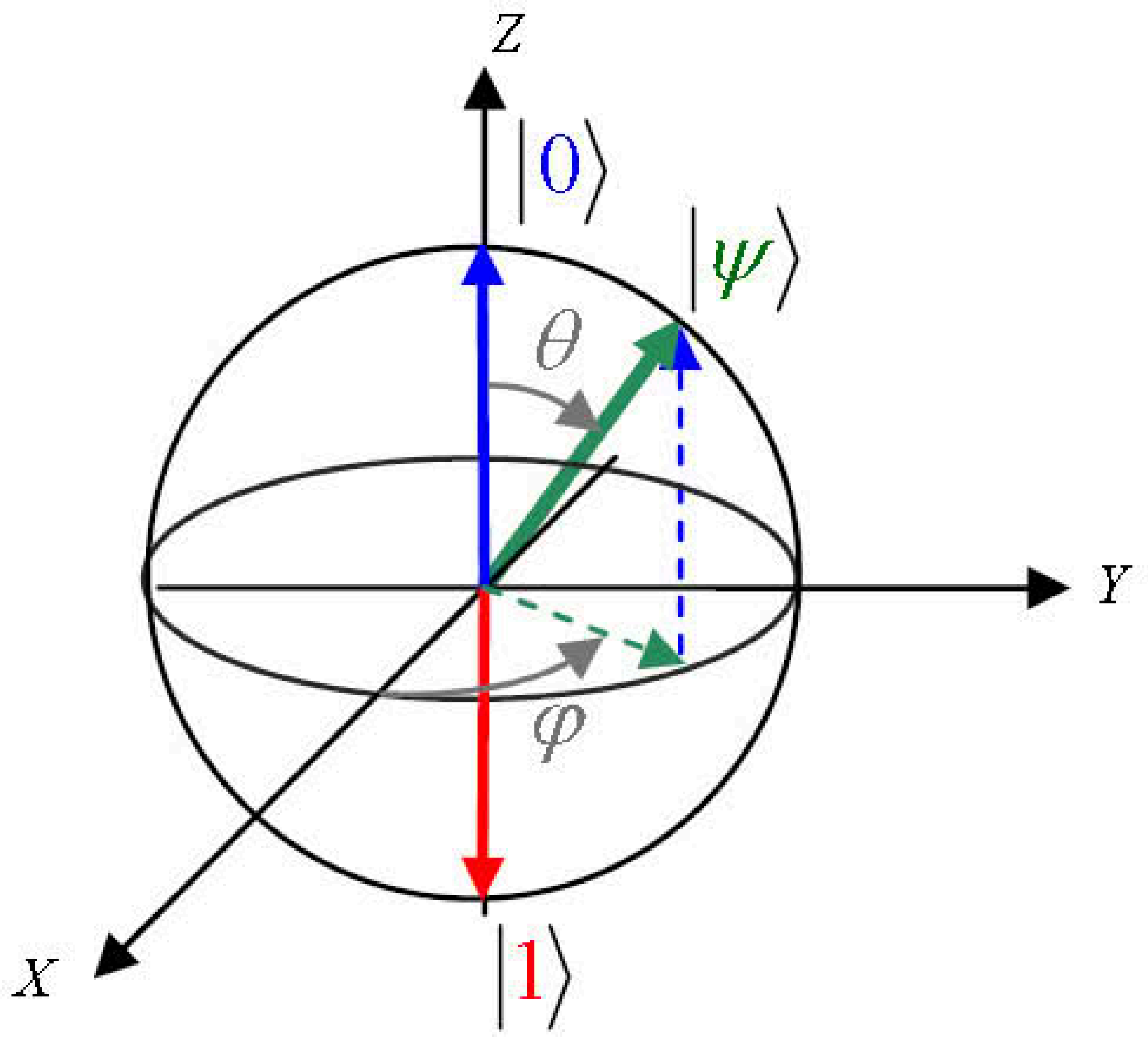


Quantum Computing Fundamentals

Superposition
The ability of a qubit to exist in a linear combination of |0\ and |1\ until it is observed.

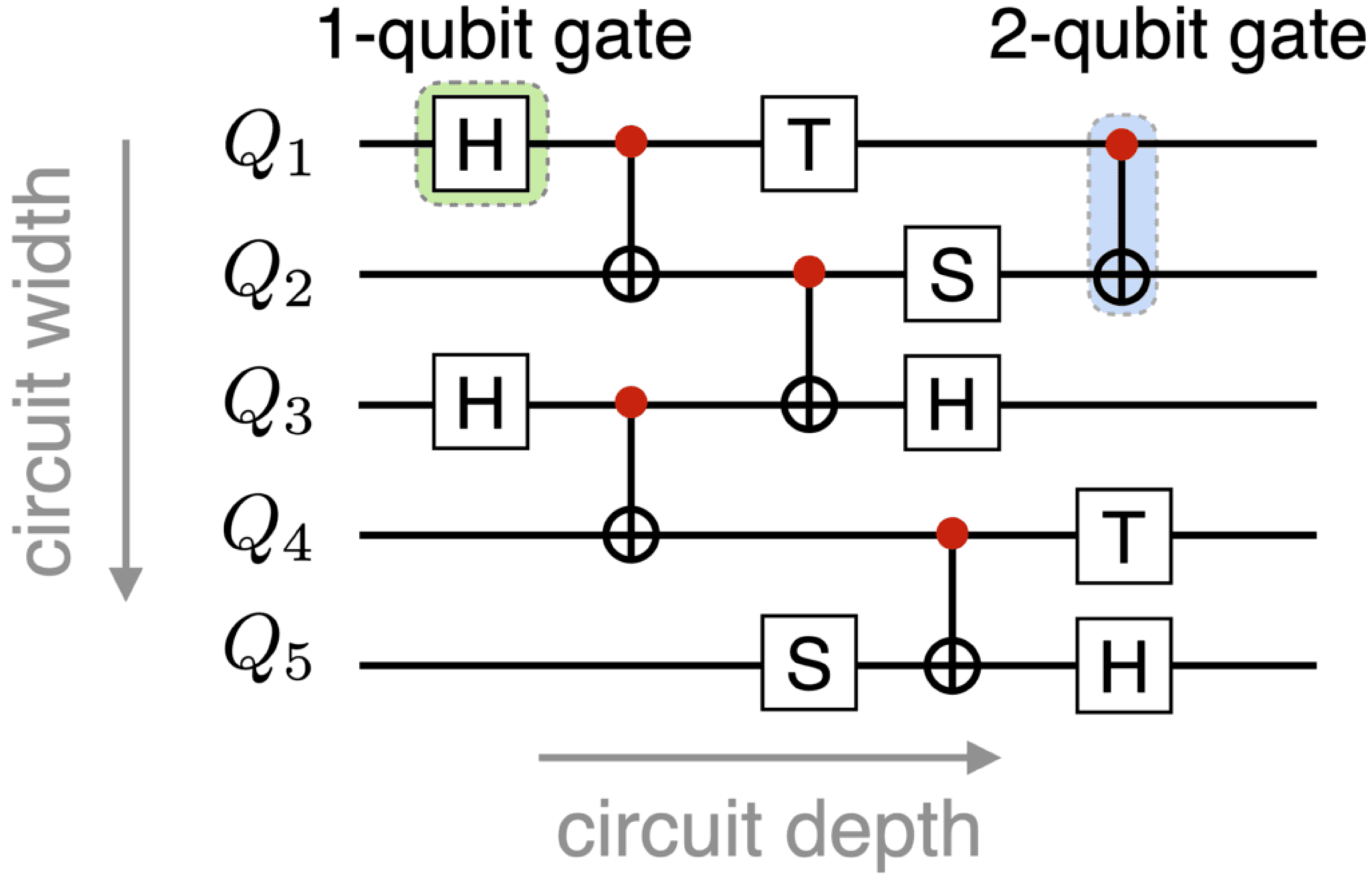
Quantum Measurement
The process of collapsing a quantum state into a classical bit (0 or 1) based on probability amplitudes.

Entanglement
The unique correlation between qubits that allows for exponential scaling of the computational workspace.



$$|\psi\rangle = \cos\left(\frac{\theta}{2}\right)|0\rangle + e^{i\phi}\sin\left(\frac{\theta}{2}\right)|1\rangle$$

Quantum Gates and Circuits

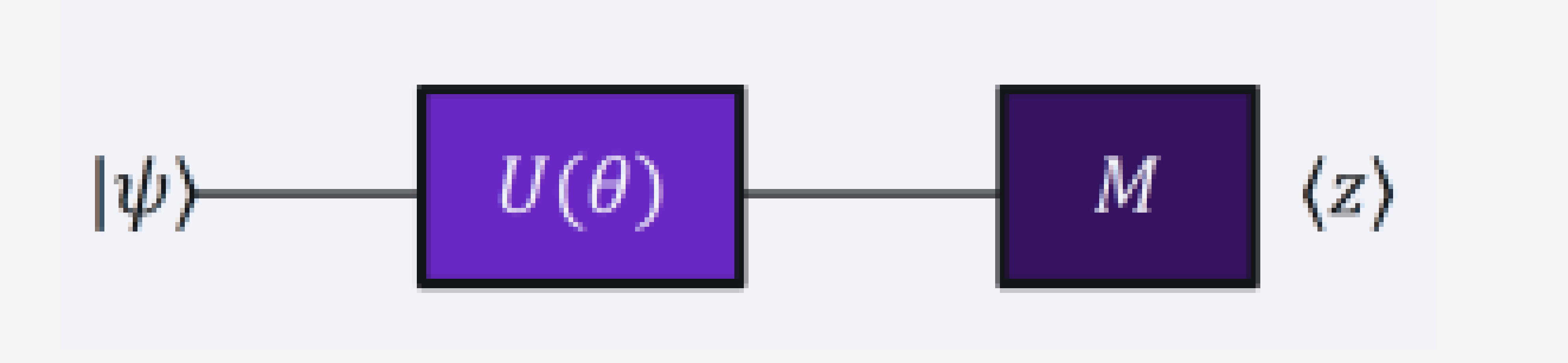


Variation Circuit For ML

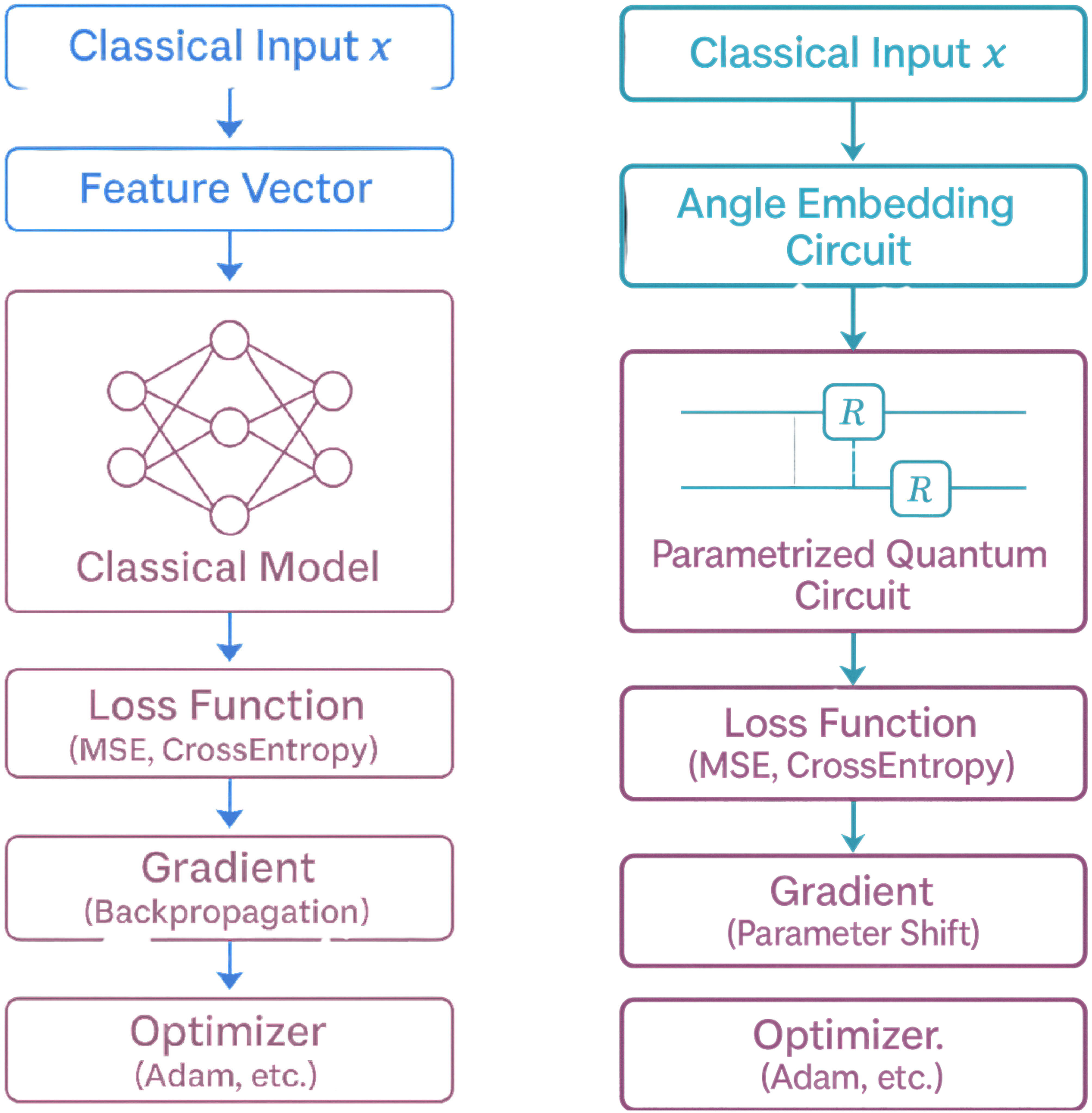
DATA: X

Model: f(X; θ)

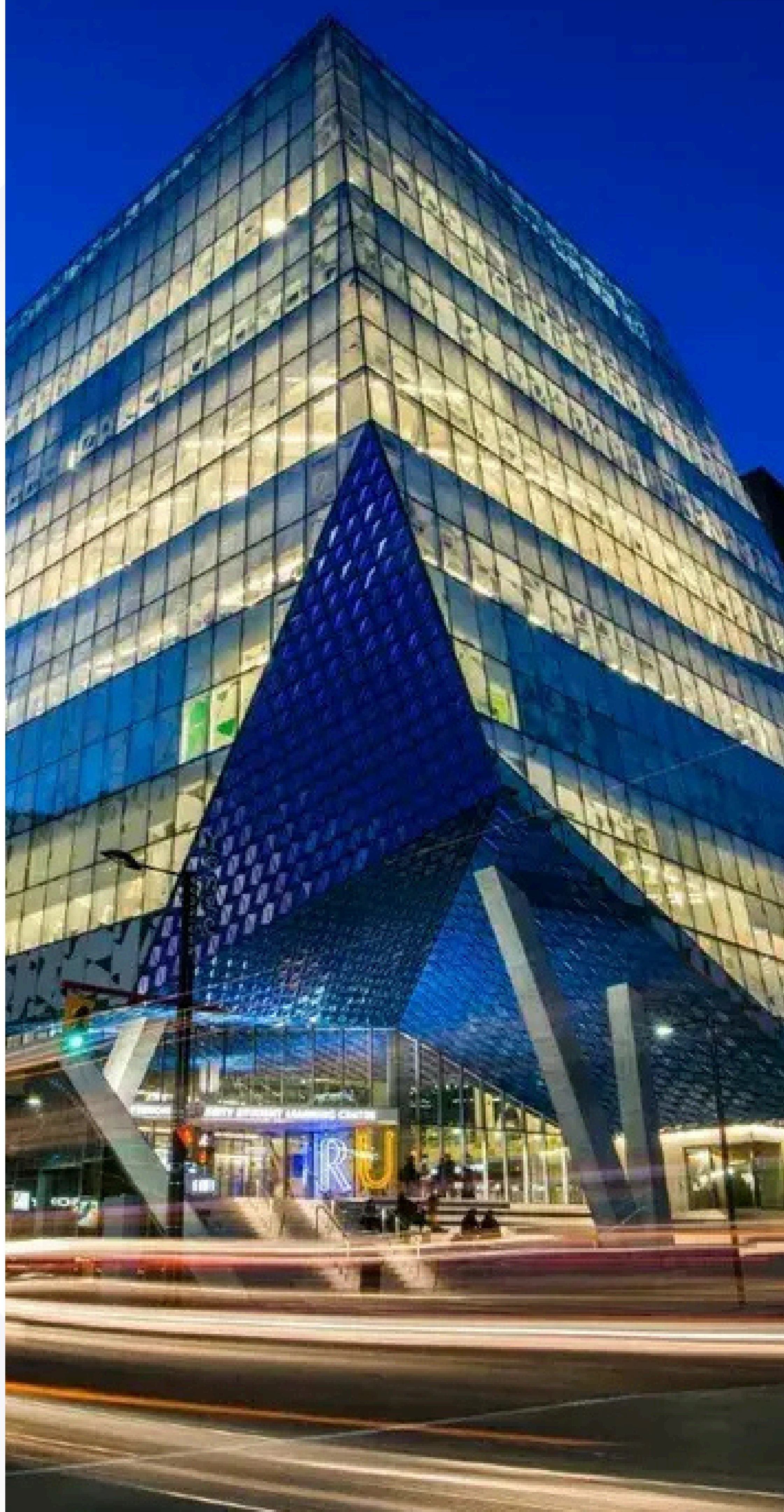
Get a prediction/answer/label



Structure of QML vs classical



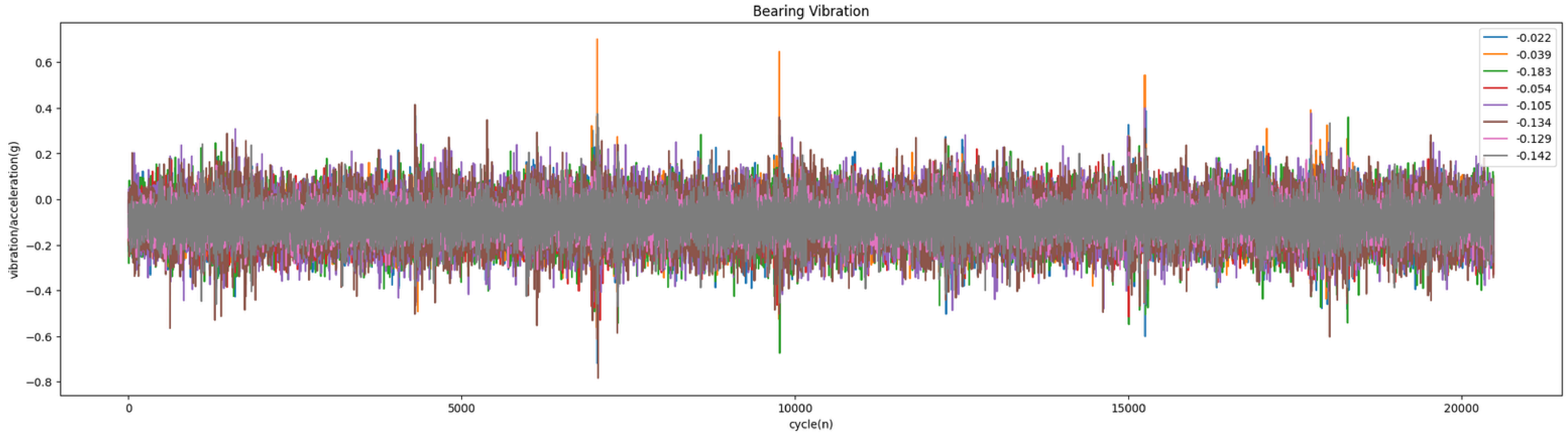
Implementation



Overview and Dataset

NASA IMS Bearings

sensor



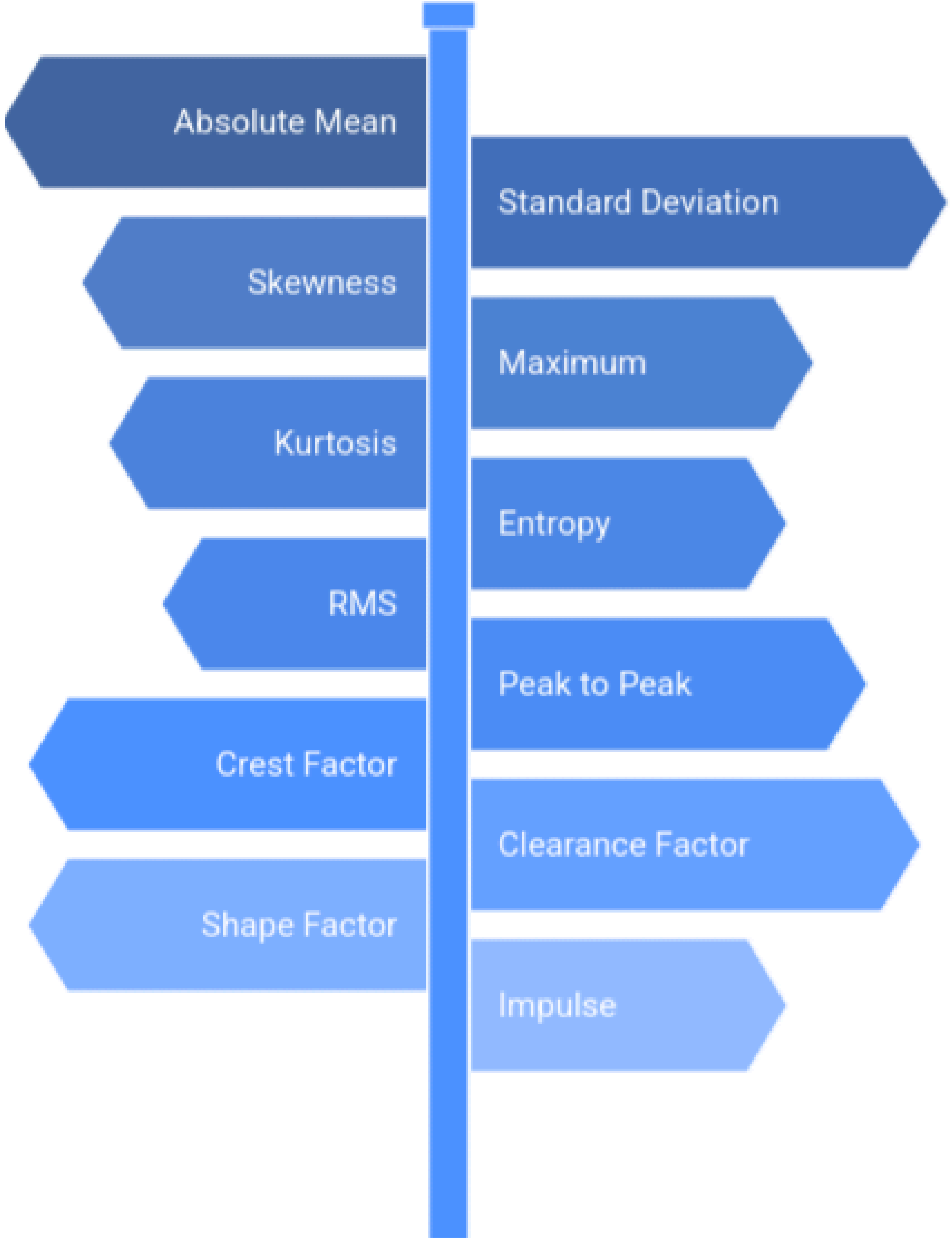
vibrational signals

Feature Engineering

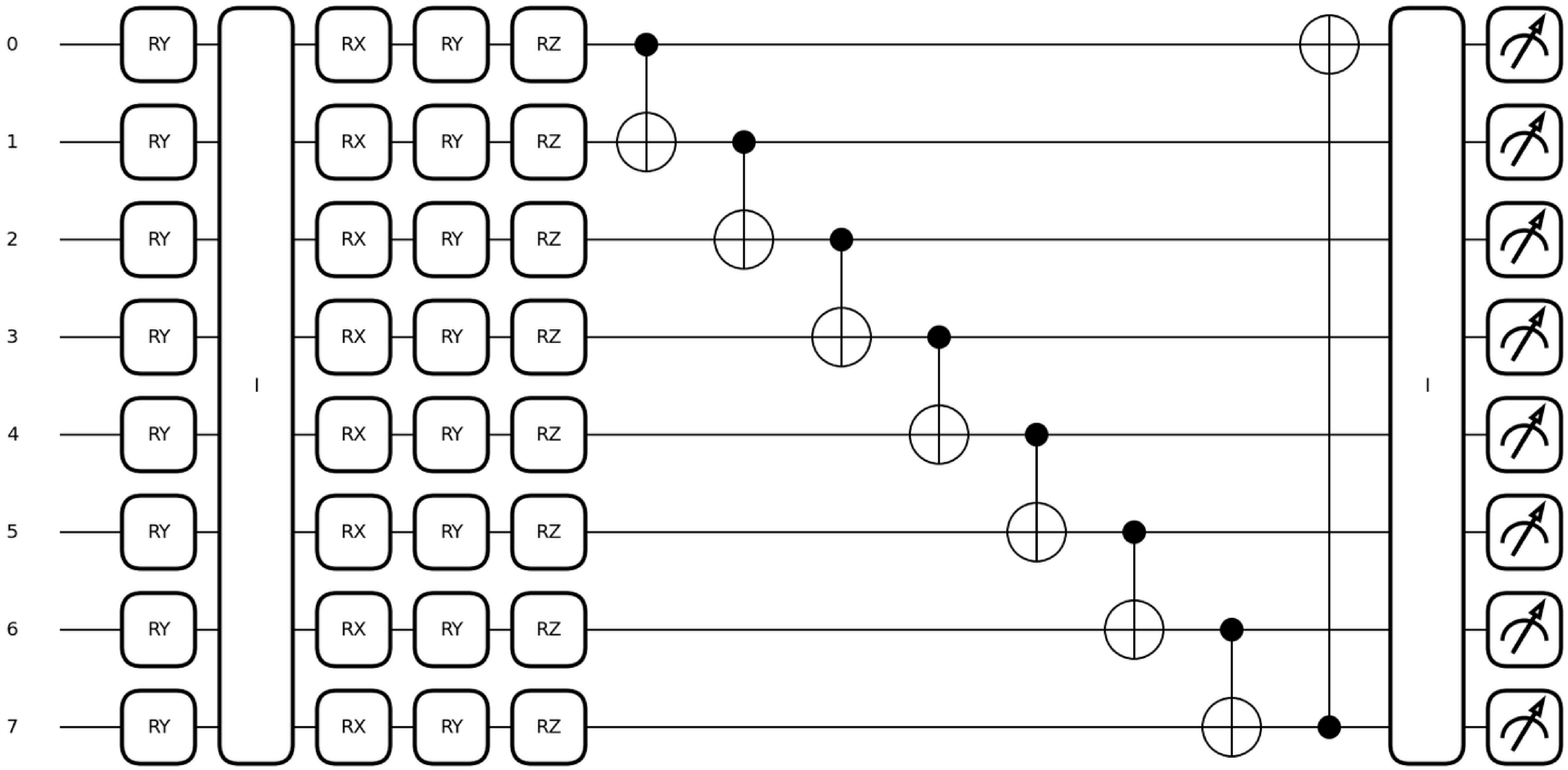
144 Features Total: 12 time-domain stats × 12 channels

VQC (8-qubit):
Random Forest ranking → Selected top 8 predictive features for efficient, low-redundancy quantum encoding.

Hybrid QLSTM (8-qubit):
PCA reduction of 144 → 8 PCs, matching qubit count while keeping degradation signals.



VQC

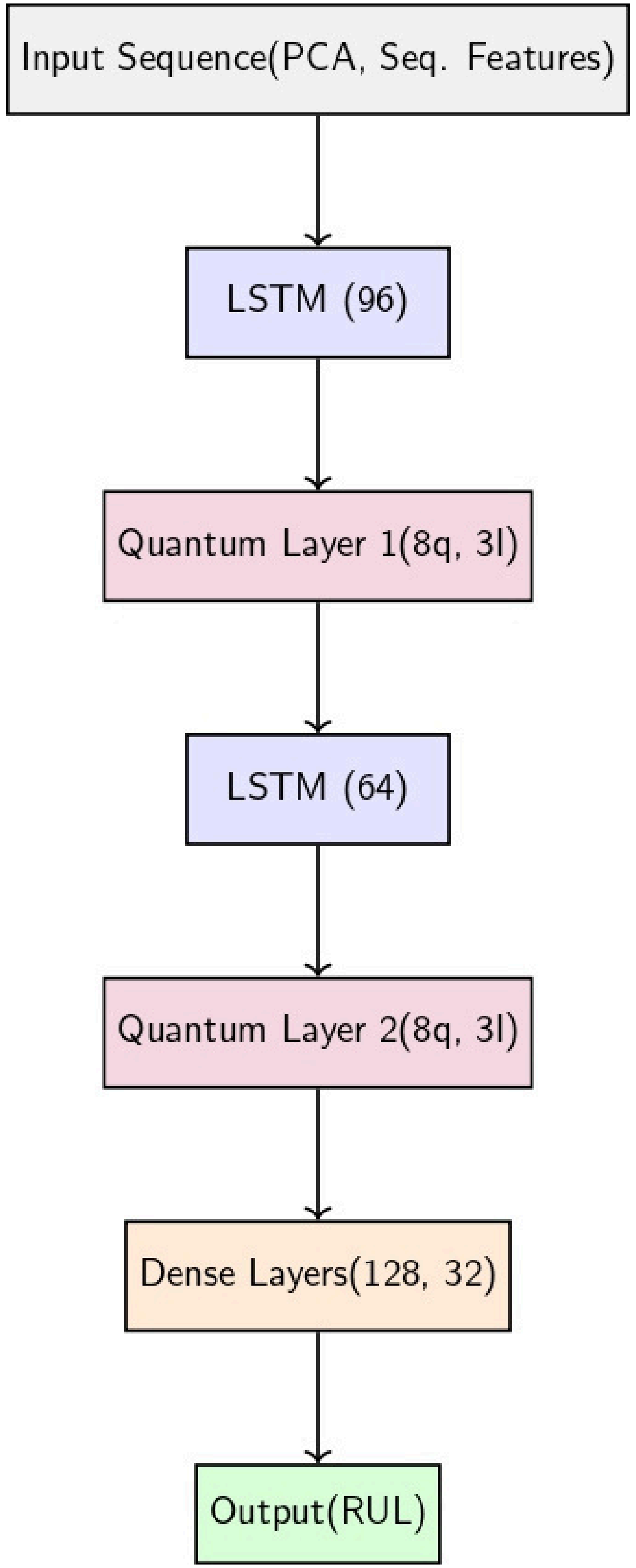


QLSTM

1. LSTM Layer: Extracts temporal dependencies from sequential vibration features.

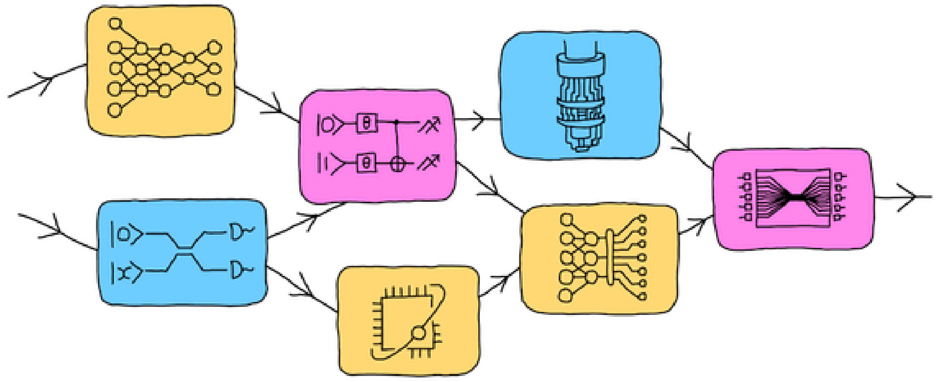
2. Quantum Layer: Projects classical features into high-dimensional quantum space for richer representations.

3. Dense Layers: Map quantum outputs to Remaining Useful Life (RUL) regression.

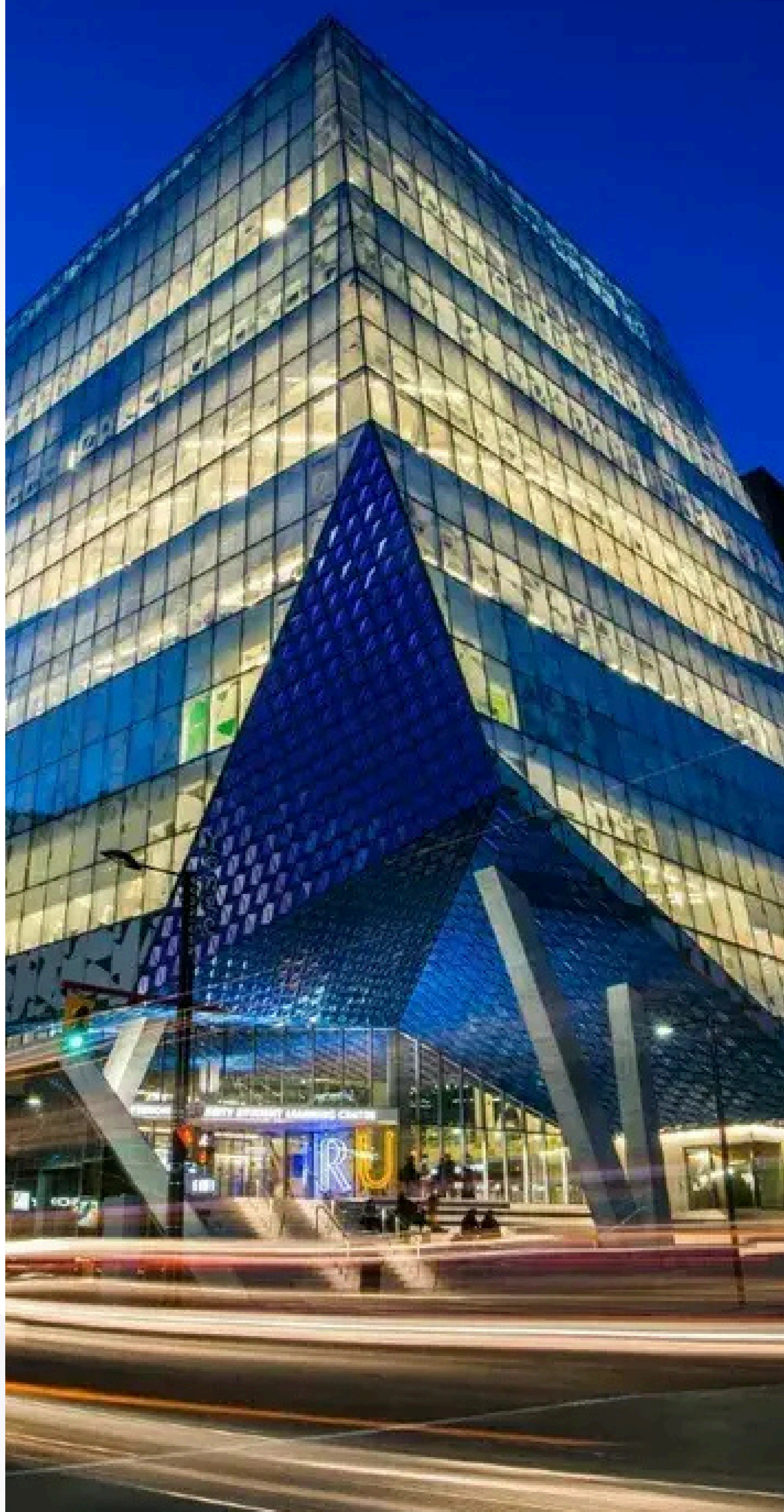


Setup and Configuration

Parameter	VQC Model	Hybrid Model
Total Data Points	3,140	3,130 sequences
Training Split	70% (2,198)	80% (2,504)
Testing Split	30% (942)	20% (626)
Input Features	8 (selected)	8 (PCA reduced)
Sequence Length	N/A	10 time steps
Original Features	144	144

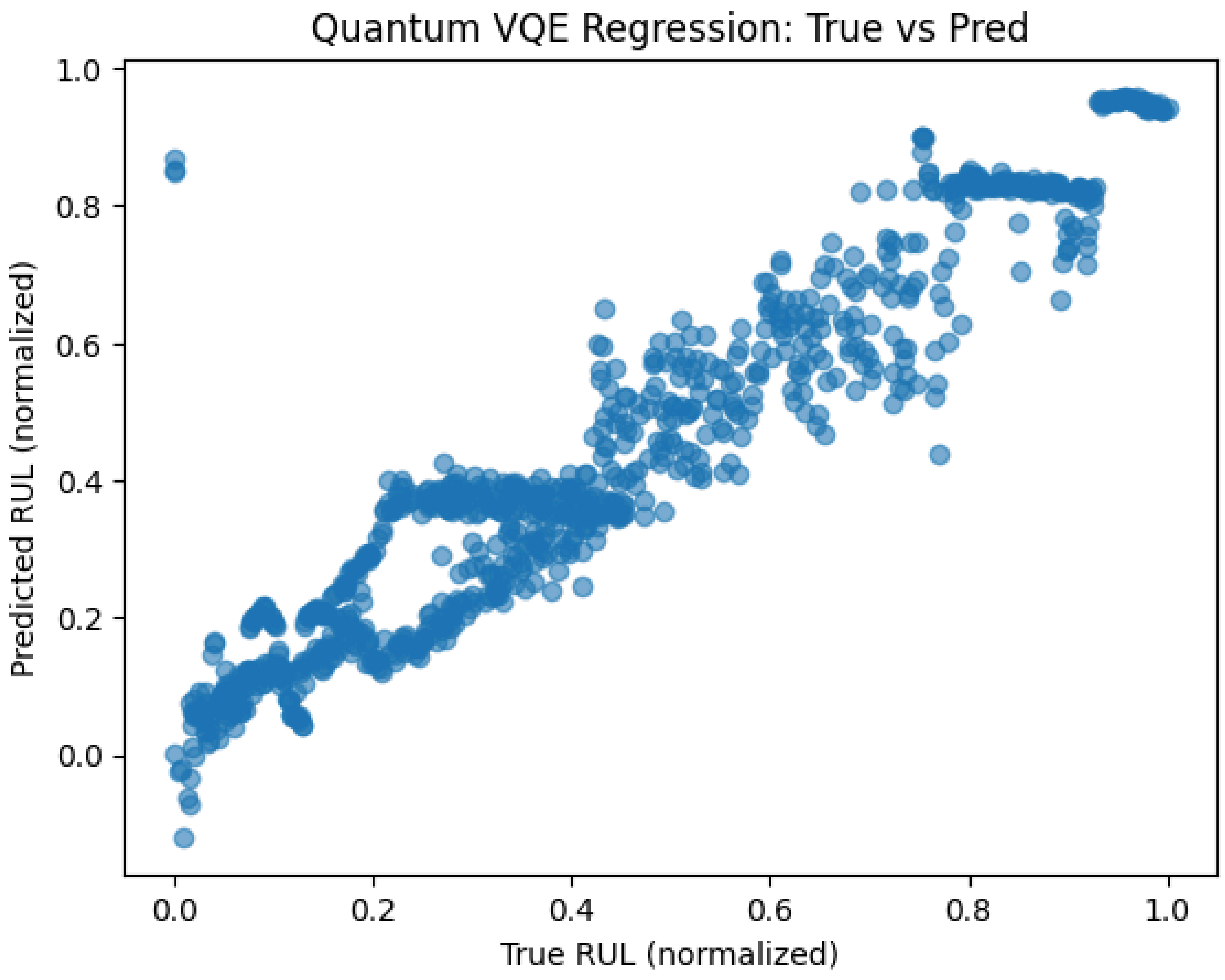


Experimental Results



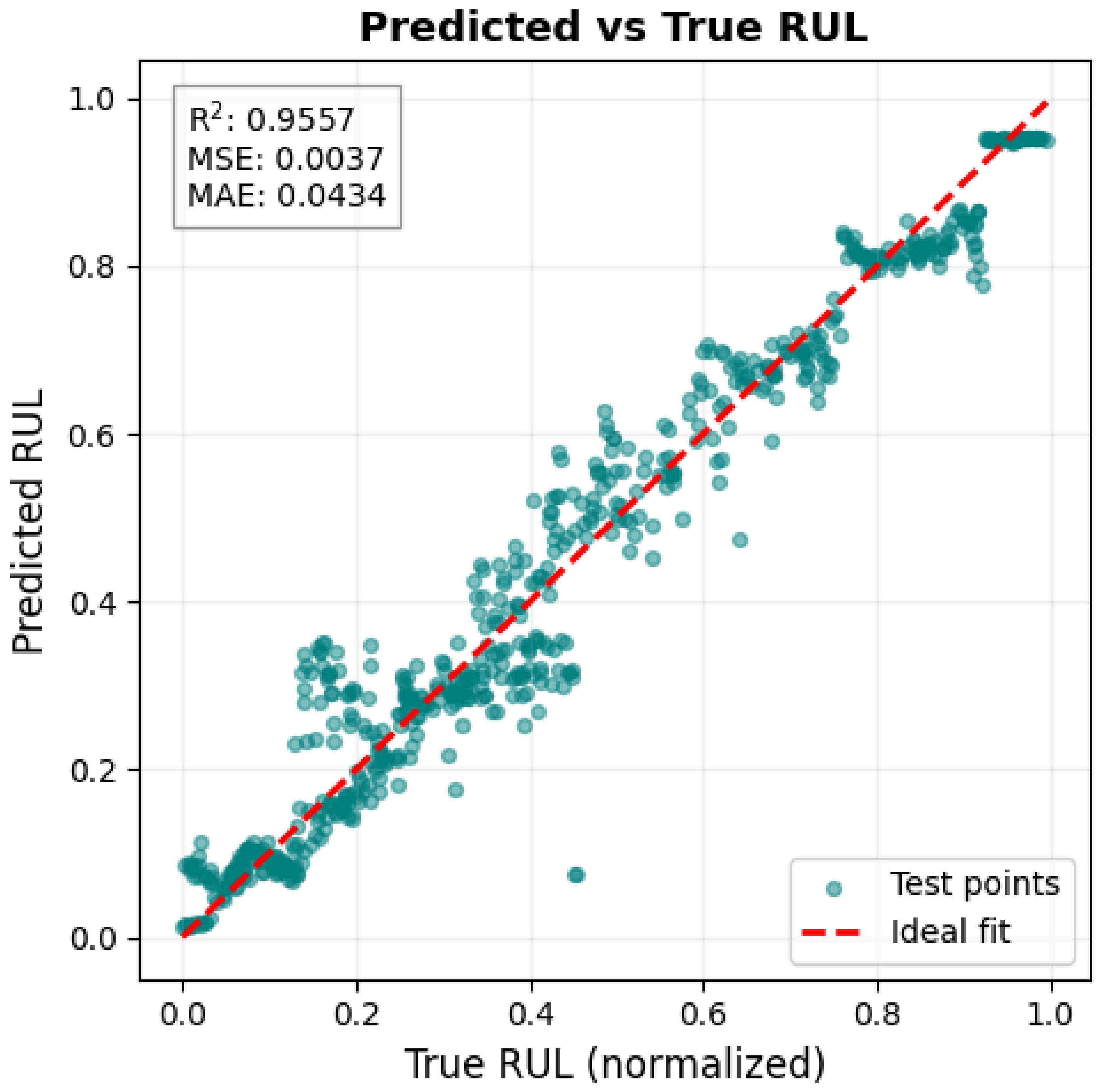
VQC RESULTS

Metric	Normalized RUL
Mean Squared Error	0.007902
Mean Absolute Error	0.062233
R^2 Score	0.901641



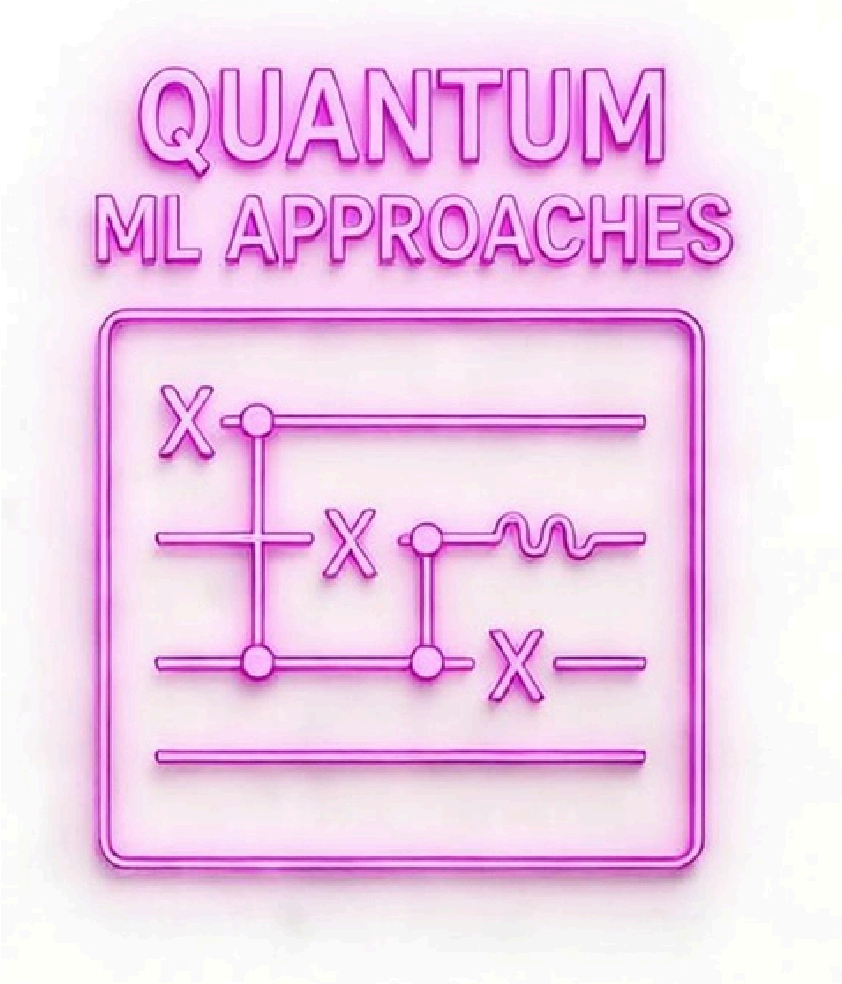
QLSTM RESULTS

Metric	Normalized RUL
Mean Squared Error	0.003704
Mean Absolute Error	0.043374
R^2 Score	0.955714



Comparisons and Advantages

Characteristic	VQC (8-qubit)	Hybrid QLSTM (8-qubit)	Classical MLP
Accuracy (%)	90.16	95.57	96.06
Parameters	729	~10,000	~15,000

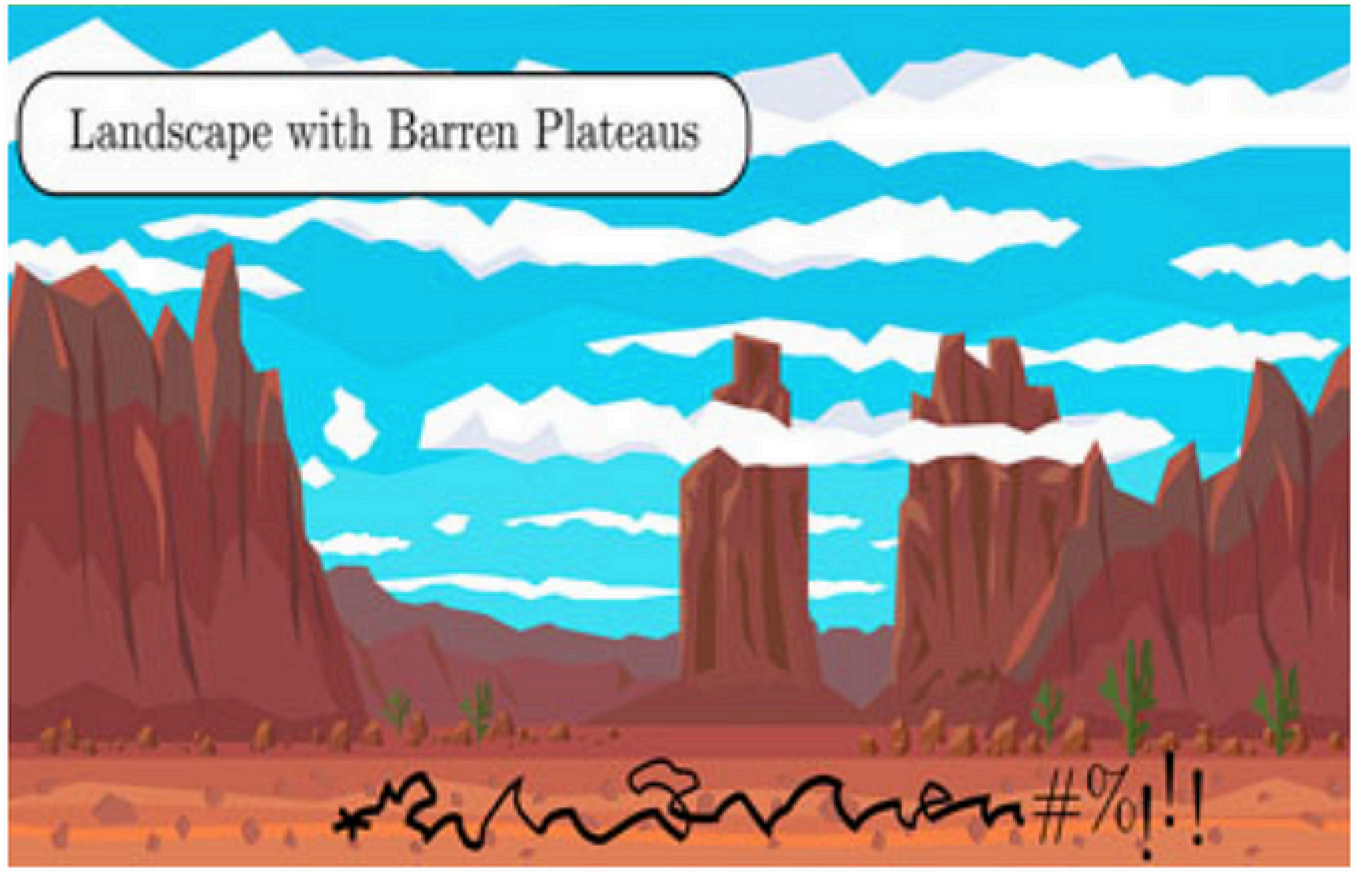


Limitations

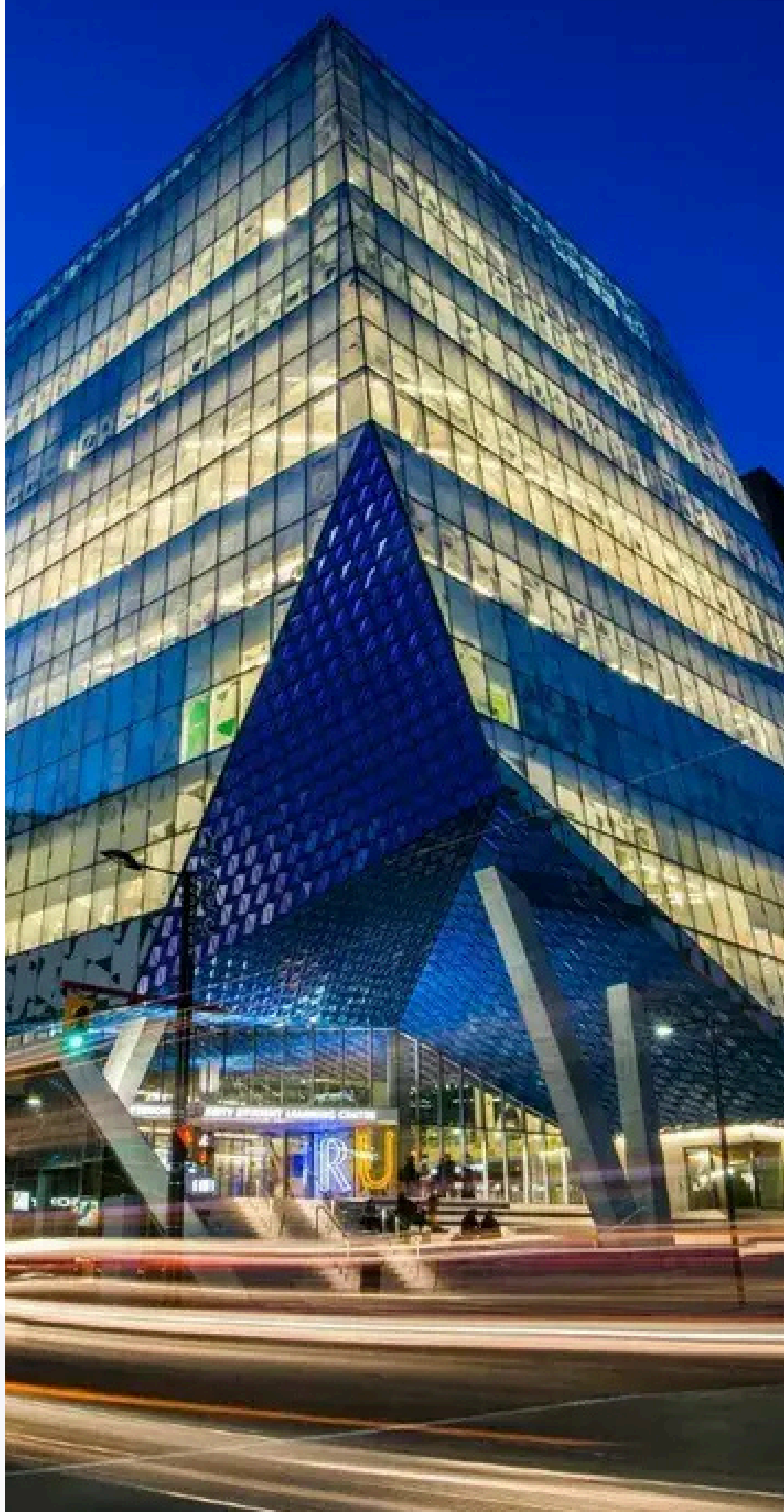
Hardware Constraints
Limited to 8 qubits → aggressive feature reduction; shallow circuits for stability; high simulation cost; real hardware adds noise/decoherence.

Algorithmic Challenges
Sensitive initialization/hyperparameters; parameter-shift gradients slow training; risk of barren plateaus; non-convex loss landscapes.

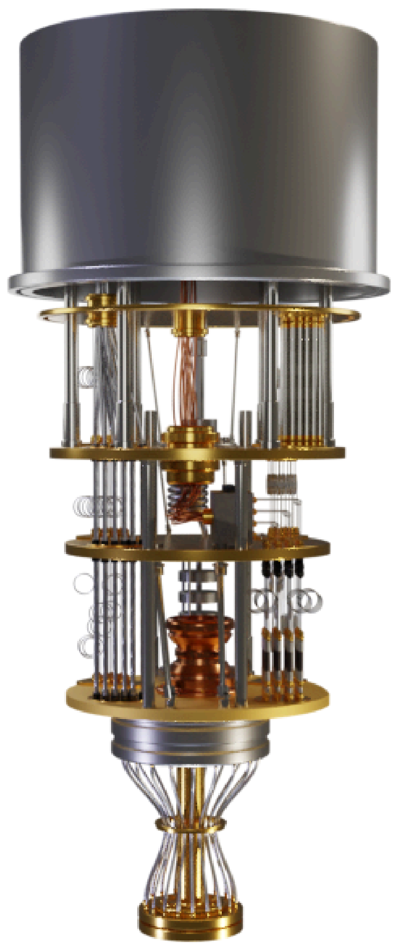
Generalization Issues
lab conditions only; sensitive to sensor setup, load/temperature variations.

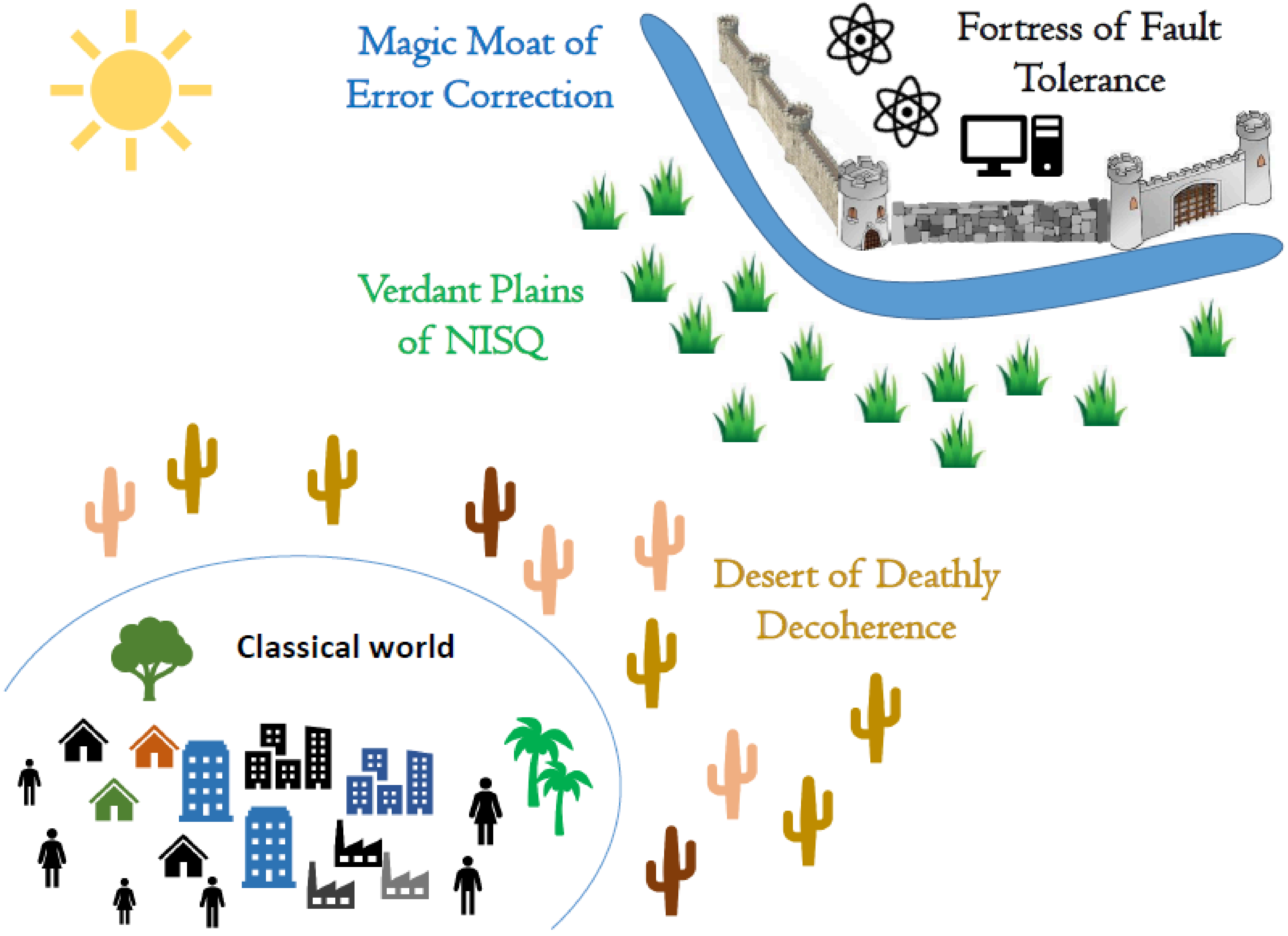


Conclusion and Perspectives



Quantum Potential





Betting on the future!

Thank You