# Anomaly Detection in ECG Signals using a Quantum Autoencoder

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# Project Goal and Approach

- The main goal was to investigate whether quantum models can meaningfully separate normal and anomalous ECG patterns.

- One-class learning - trained on normal ECG signals

- Comparison between classical, quantum-simulated and hardware-based inference

# Challenges and Motivation

- High dimensionality and noise in ECG signals
- Classical methods rely on handcrafted features or deep models that require large datasets.
- Quantum computing offers a different representation paradigm, where information is processed in high-dimensional Hilbert spaces, potentially enabling richer feature transformations

# Comparison of Approaches

- Classical Approach - Classical autoencoder trained end-to-end on real-valued ECG features, serving as a strong baseline optimized for accuracy and scalability.

- Quantum Simulator - Idealized quantum execution without noise, used to evaluate the representational capacity of the quantum autoencoder independently of hardware imperfections.

- Real IBM device - only evaluation on real IBM Quantum hardware to assess the impact of noise, limited shots, and hardware constraints.

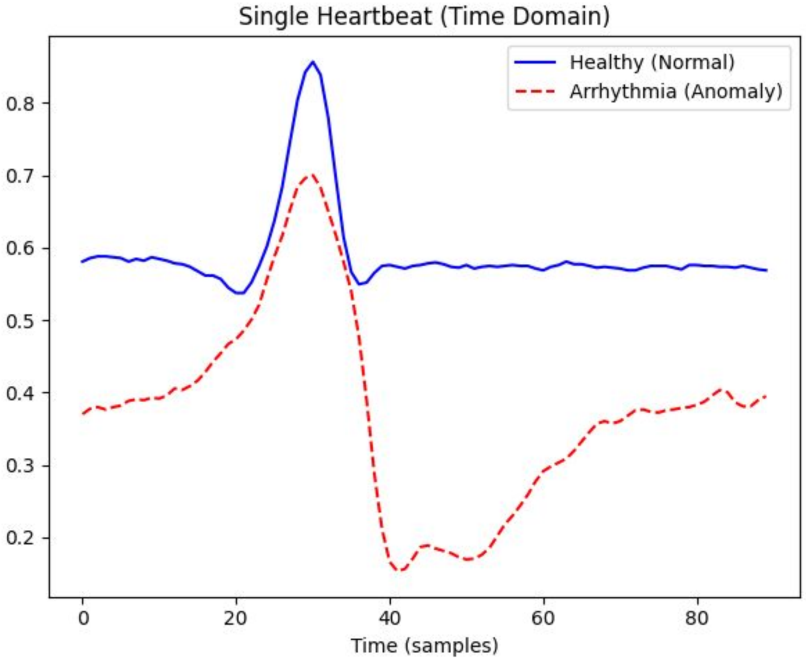
# Dataset

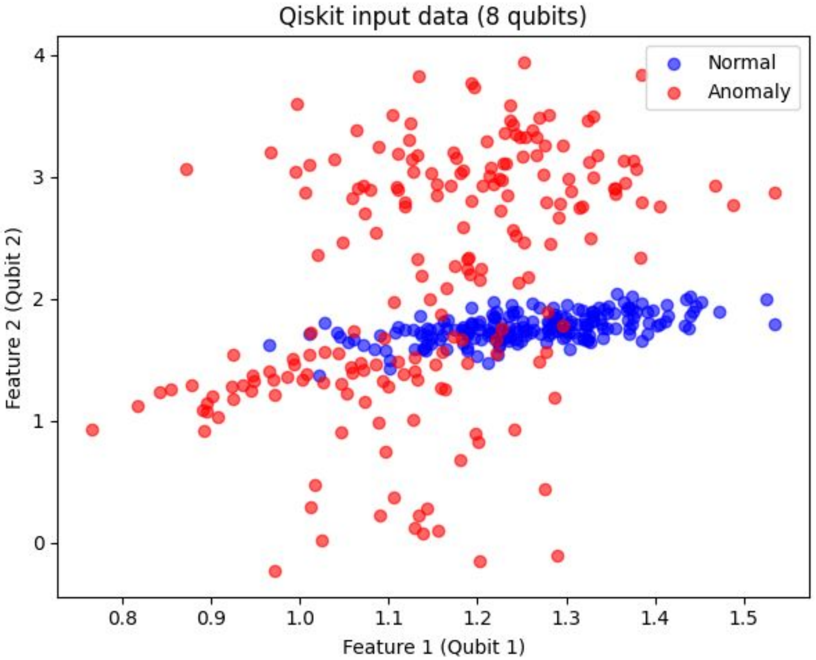
- **MIT-BIH Arrhythmia Database**

(Base Setup)

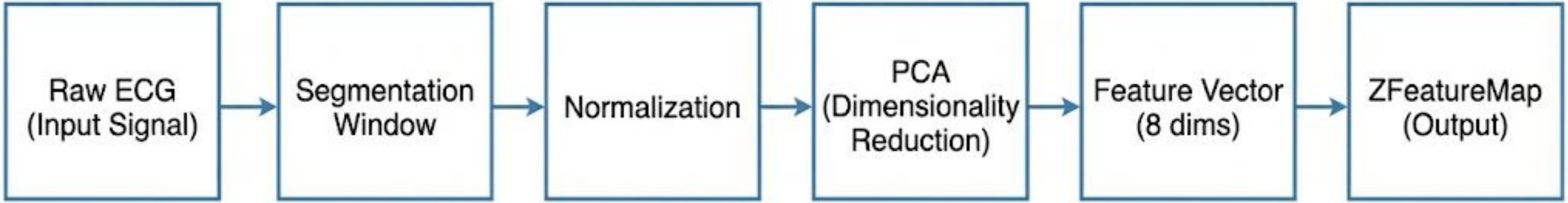
Train set - 1299 Normal

Test set - 1200 Normal, 964 Anomaly



# ECG Signal Processing Pipeline



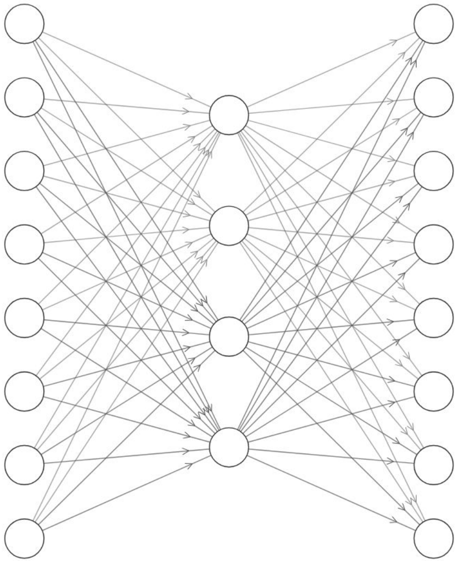

90 samples

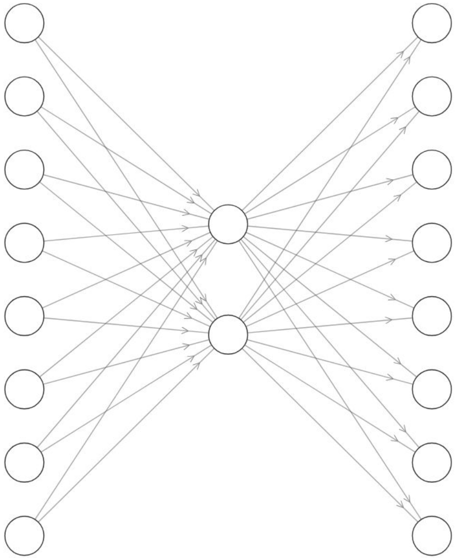
MinMaxScaler [0, π]

90 → 8 features
Retained 99.48%
information

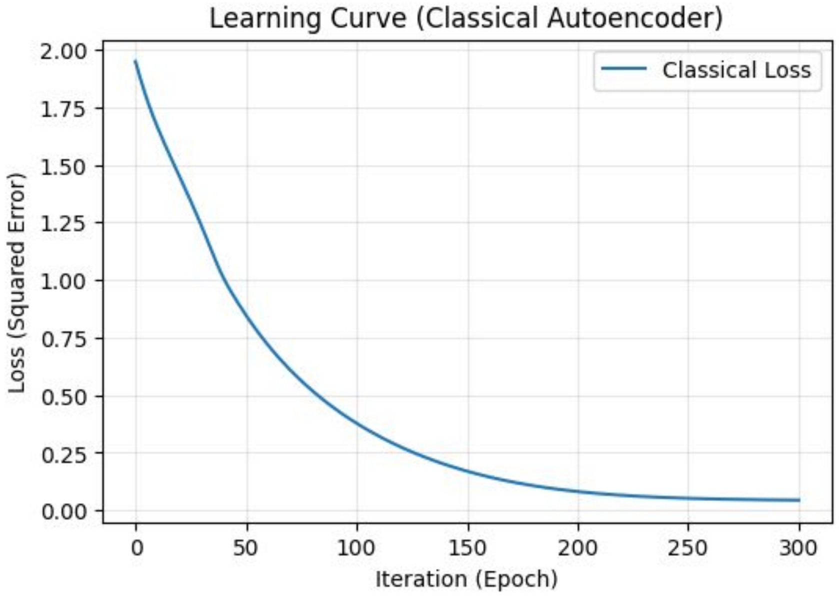
# Classical Baseline: MLP Autoencoder Architecture

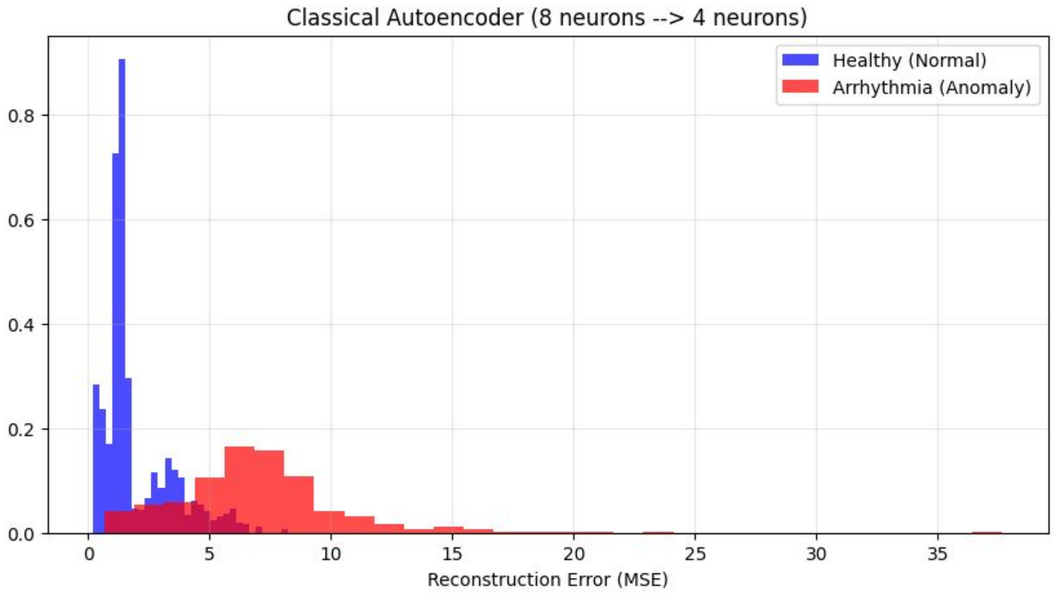
- Feed-forward Neural Network (Multi-Layer Perceptron).
- Structure: 8 (Input) → 4 (Latent Space) → 8 (Output).
- Objective: Identity mapping (f(x)≈x) with dimensionality reduction.
- Mechanism: Information Bottleneck forces the model to learn robust features.
- Optimization: Further compression to 2 neurons yielded higher accuracy.





# Results & Analysis



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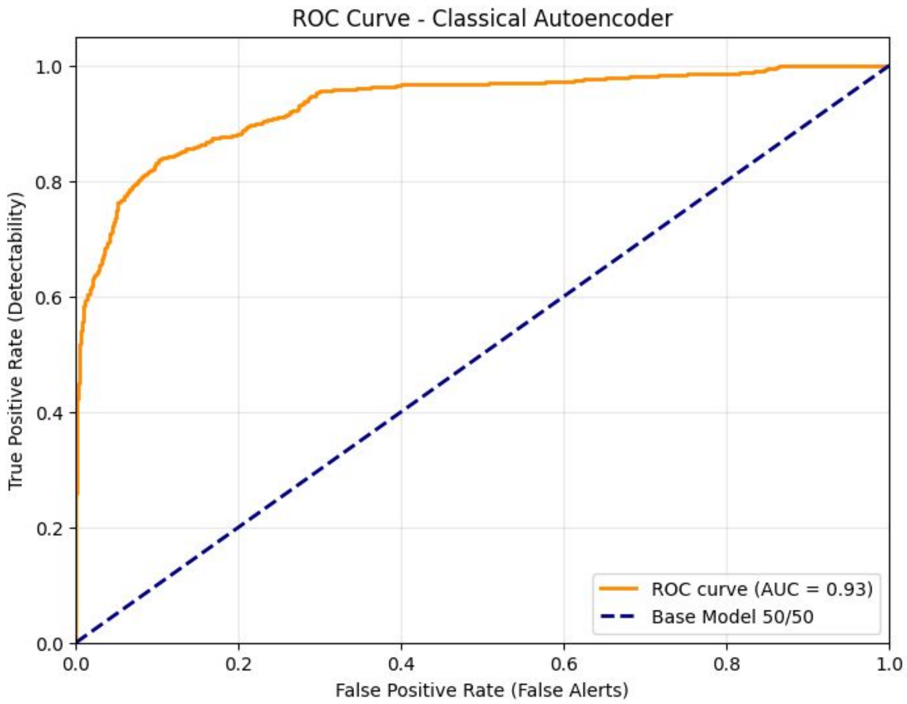
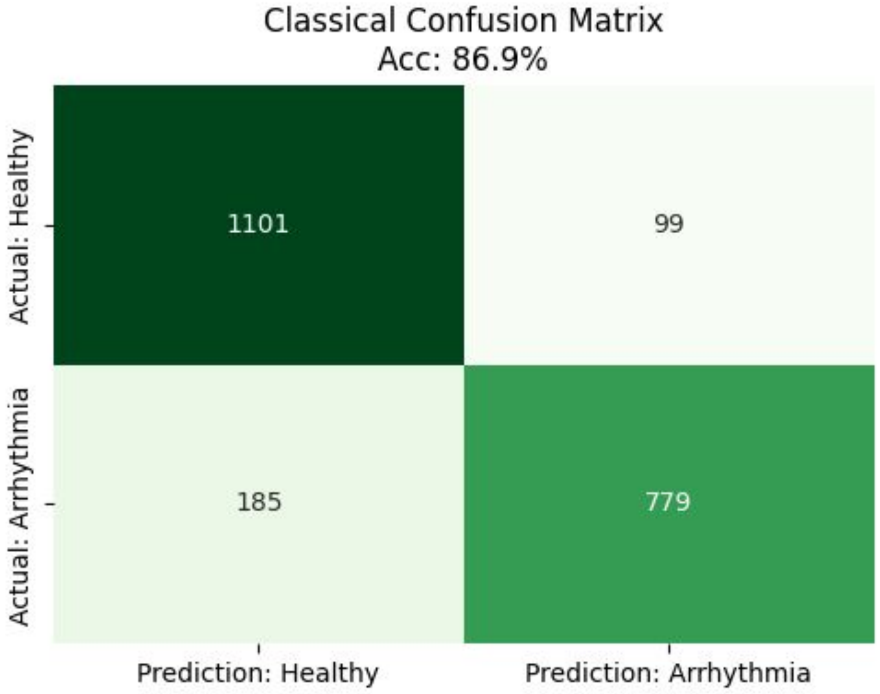


# Quantum Architecture Overview

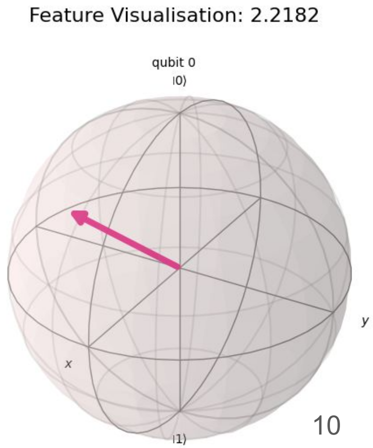
## The model consists of two main components:

- **Data encoding circuit**

  Classical ECG features are embedded into a quantum state using a feature map.

- **Trainable quantum ansatz**

  Ansatz transforms this state before measurement producing probabilistic outputs used for anomaly scoring



# Experimental Setup

- The model is trained exclusively on normal ECG segments

- Evaluation is performed on separate test sets containing both normal and anomalous samples

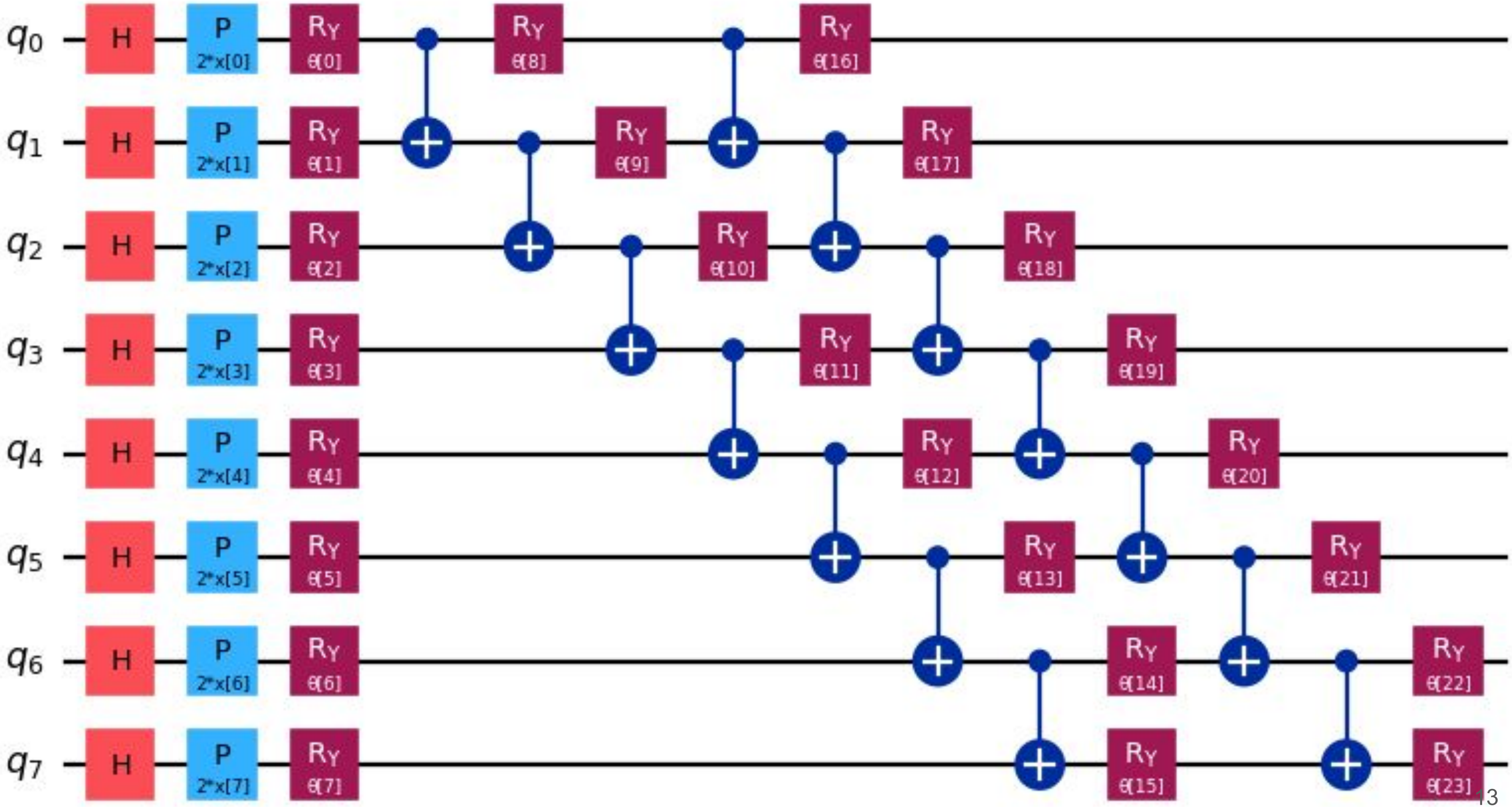
- Identical preprocessing steps are applied across all experiments to ensure fair comparison

- $L(\theta) \; = \; E_{x \sim Dnormal}[P_{\theta}(anomaly \mid x)]$

# Implementation details

- **Entire pipeline is implemented in Jupyter Notebook**
  - Ansatz - RealAmplitudes
  - Optimizer - SPSA
  - Feature map - ZFeatureMap

- **Libraries used during the project:**
  - Qiskit 2.3.0 - Quantum Circuit
  - Qiskit algorithms 0.4.0 - Optimizers
  - IBM runtime 0.45.0 - Connecting to the real IBM device
  - Scikit-learn 1.8.0 - Preprocessing, Decomposition



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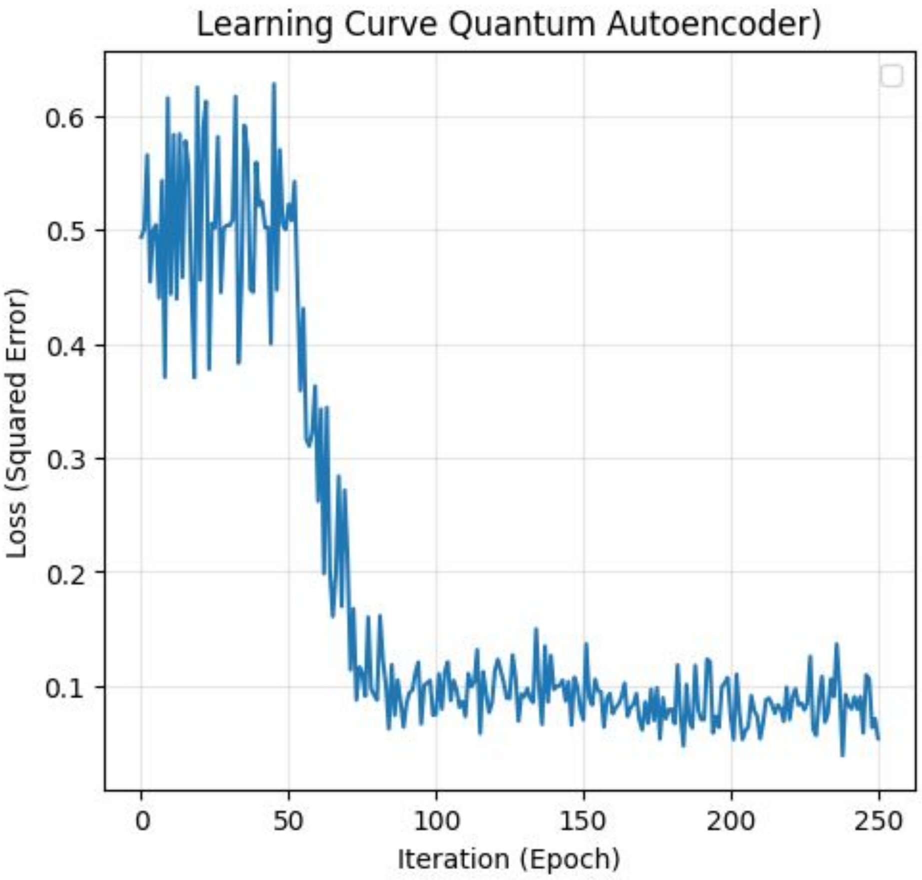
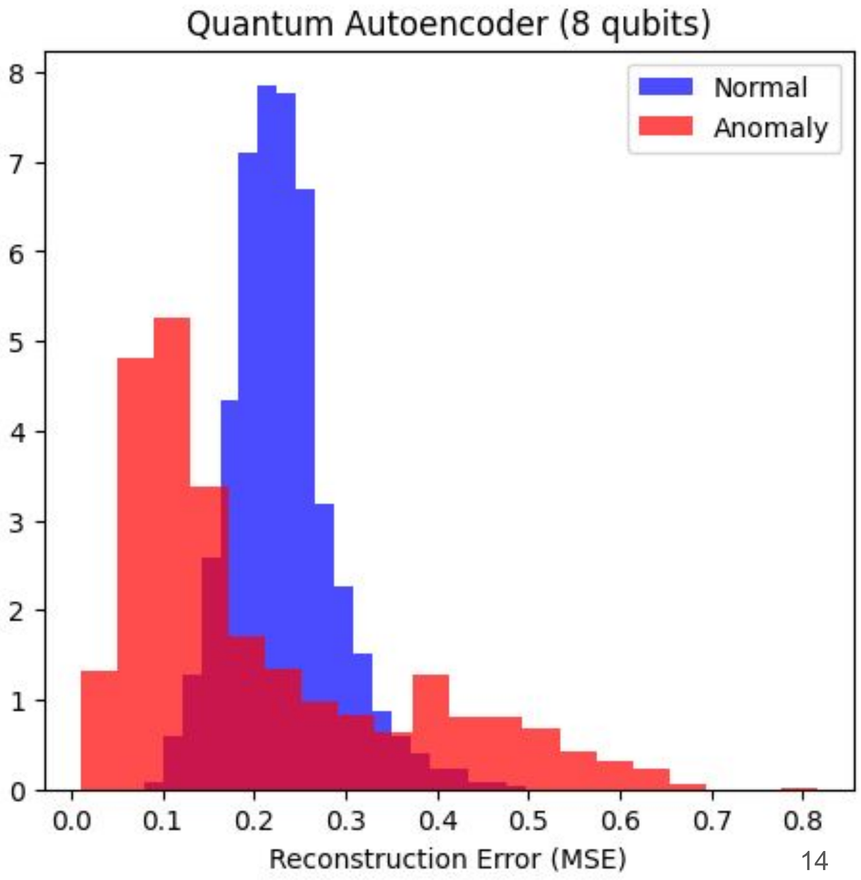
# Results and Analysis



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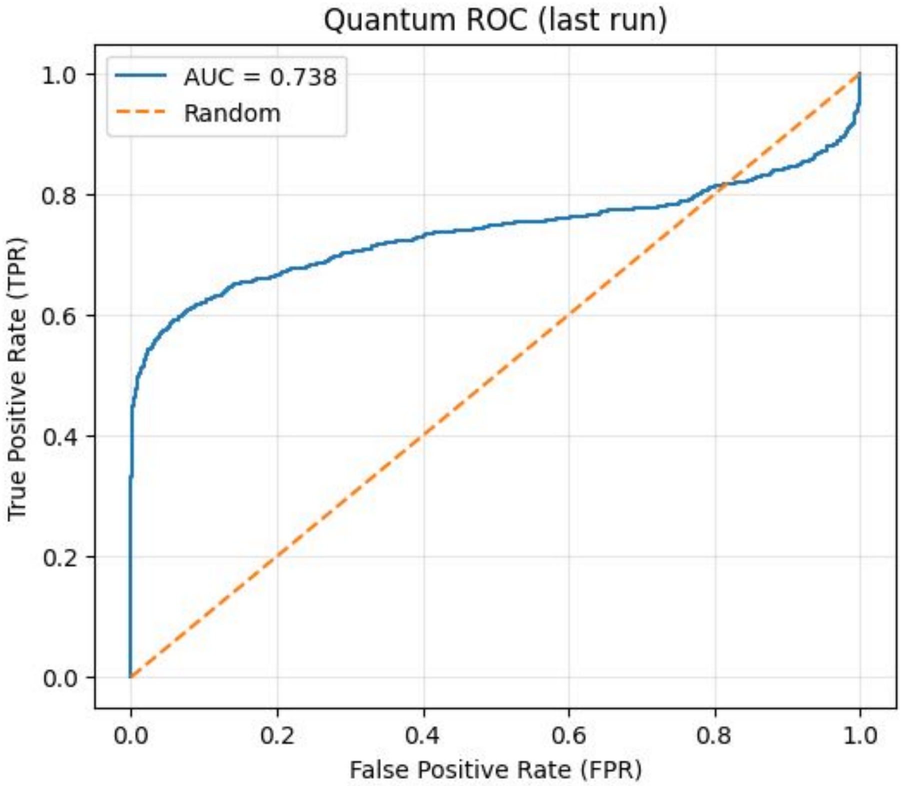
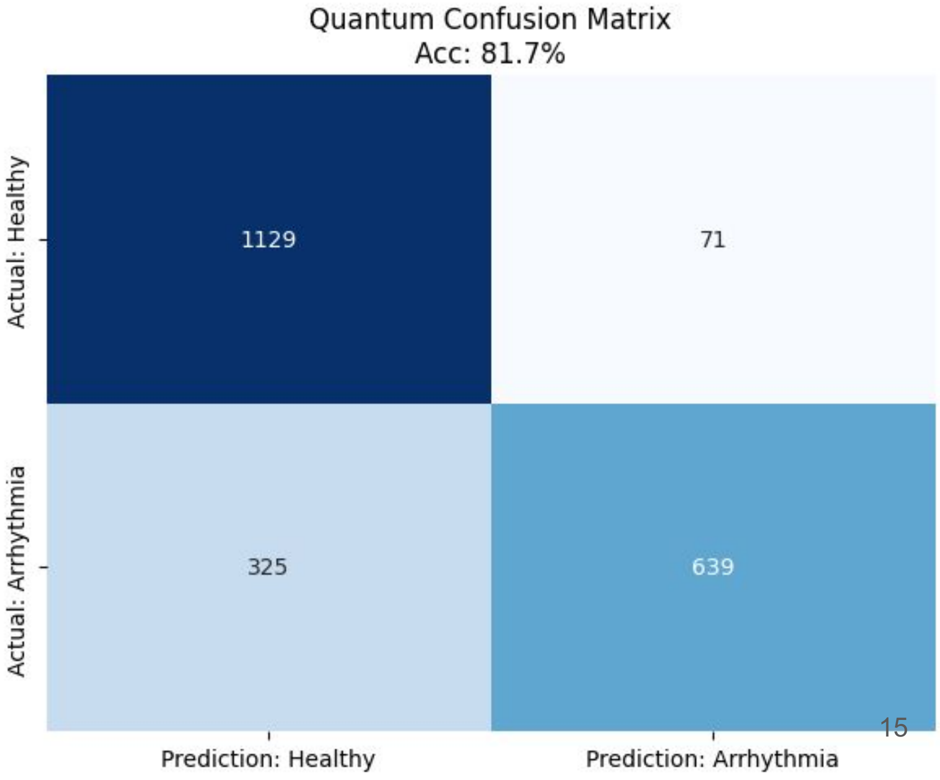


# Scalability Analysis: Dataset Size & Generalization

- **Two scalability axis were tested independently:**
    - Sample per patient: 200 → 600
    - Number of patients: 1→2→3→5

- **For each configuration we measured:**
    - Reconstruction loss
    - Detection accuracy
    - ROC AUC
    - Total number of samples

# Scalability Analysis

| Hidden Layer Neurons | Number of Patients | Sample Limit / Patient | Summed Samples | Loss | Accuracy | ROC AUC |
|---|---|---|---|---|---|---|
| 4 | 1 | 200 | 200 | 0.038846 | 81.24 | 0.9946 |
| 4 | 1 | 600 | 600 | 0.033613 | 81.56 | 0.9957 |
| 4 | 2 | 200 | 400 | 0.046569 | 80.36 | 0.9917 |
| 4 | 2 | 600 | 1200 | 0.048084 | 80.64 | 0.9955 |
| 4 | 3 | 200 | 600 | 0.074402 | 80.22 | 0.9818 |
| 4 | 3 | 600 | 1800 | 0.060584 | 80.96 | 0.9897 |
| 4 | 5 | 200 | 800 | 0.079987 | 77.63 | 0.9762 |
| 4 | 5 | 600 | 2062 | 0.06673 | 77.87 | 0.9838 |

Classical

Quantum

| Qubits | Number of Patients | Sample limit/patient | Summed samples | Loss | Accuracy | ROC AUC |
|---|---|---|---|---|---|---|
| 8 | 1 | 200 | 200 | 0.261204 | 0.5175 | 0.506906 |
| 8 | 1 | 600 | 600 | 0.200252 | 0.678373 | 0.703147 |
| 8 | 2 | 200 | 400 | 0.14366 | 0.7725 | 0.838231 |
| 8 | 2 | 600 | 1200 | 0.122035 | 0.859519 | 0.88273 |
| 8 | 3 | 200 | 499 | 0.18057 | 0.75375 | 0.778138 |
| 8 | 3 | 600 | 1299 | 0.037794 | 0.766636 | 0.677064 |
| 8 | 5 | 200 | 862 | 0.273116 | 0.755 | 0.769144 |
| 8 | 5 | 600 | 2062 | 0.138173 | 0.744455 | 0.729215 |

# Optimizing Classical Architecture

- **Observation:**
  - 4 neurons: Slightly better for single-patient data, but performance degrades as patient diversity increases (overfitting to noise).
  - 2 neurons: Demonstrated superior robustness. Accuracy remained stable (~81%) event with 5 heterogeneous patients.
  - Sample Saturation: Increasing training samples from 200 to 600 per patient yielded diminishing returns (<0.5% accuracy gain). The model converges quickly.
  - In general more samples translate into better accuracy and a smaller loss function result.
- **Conclusion:** The ECG signal features are highly compressible. A tighter bottleneck forces the model to learn universal features rather than patient-specific noise. High compression (2 latent neurons) in classical autoencoder is essential for a subject-independent model.

| Number of Patients | Latent Neurons = 2 | Latent Neurons = 4 | 2vs4 accuracy difference |
|---:|---:|---:|---:|
| 1 | 81.05 | 81.56 | -0.51 |
| 2 | 80.45 | 80.64 | -0.19 |
| 3 | 80.91 | 80.96 | -0.05 |
| 5 | 80.91 | 77.87 | 3.04 |

# Optimizing Quantum Autoencoder

- **Observation**
  - Gains are visible for small patient sets (1–3 patients), while benefits diminish for higher diversity.
  - Increasing the number of qubits from 4 to 8 improve performance and stability
- **Sample saturation**
  - Similarly to classical case sample increase yields limited accuracy gains
  - This suggests that data diversity dominates over data quantity

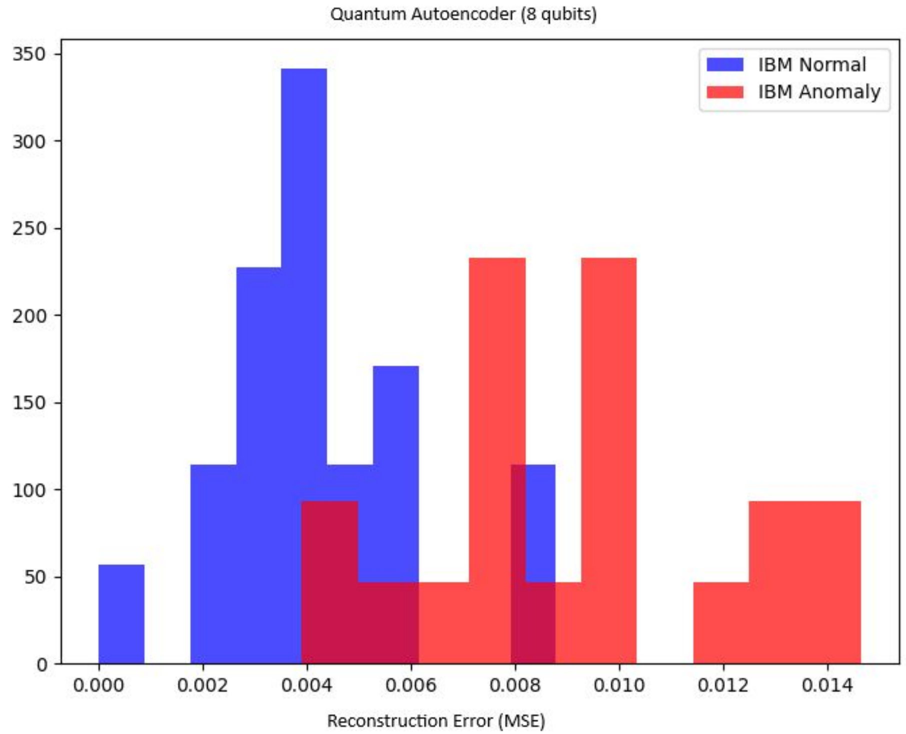
| Number of Patients | Qubits = 4 (Accuracy %) | Qubits = 8 (Accuracy %) | 4 → 8 Accuracy Difference |
|---|---|---|---|
| 1 | 67.01 | 67.84 | +0.83 |
| 2 | 83.83 | 85.95 | +2.12 |
| 3 | 72.37 | 76.66 | +4.29 |
| 5 | 74.49 | 74.45 | −0.04 |

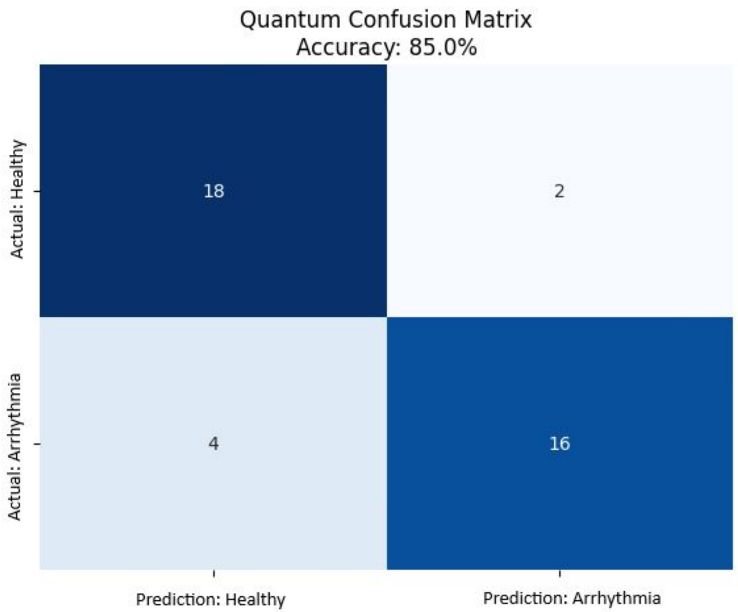
# Real IBM QPU

**Experimental setup and constraints:**

- Execution on real IBM Quantum hardware (QPU)
- 40 ECG samples executed within a single quantum job
- Inference-only run (training performed on simulator)
- Limited sample size due to hardware access and noise constraints

# Results and Analysis



# Key Findings

- **Feasibility of Quantum Anomaly Detection**
    - Successfully implemented a hybrid pipeline using an 8-qubit autoencoder.
    - Demonstrated that quantum circuits can learn structured representations of ECG signals.

- **Anomaly Separation Capability**
    - The quantum autoencoder achieved measurable separation between normal and anomalous ECG segments.
    - Performance exceeded random baseline, as confirmed by ROC analysis.

- **Scalability Trends**
    - Stable behavior observed across different dataset sizes.