Quantum Machine Learning Project 2 Report

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1. Experiments

1.1 Setup

A 2-qubit Variational Quantum Classifier (VQC) was implemented using PennyLane. The circuit uses AngleEmbedding with Y rotations followed by L variational layers. Each layer consists of RX, RY, RZ rotations and entangling CNOT gates.

Training was performed using three different optimizers: Adam, Nesterov, and Adagrad. Loss was computed using Mean Squared Error (MSE) and evaluated over 50 epochs. The best configuration was selected based on f1 and test accuracy.

1.2 Optimizer Comparison

The choice of optimizer significantly affects convergence and performance. The following table summarizes results for different layer depths and optimizers.

Layers	Optimizer	Best Test Acc	Epoch	Precision	Recall	F1
1	Adam	0.725	12	0.800000	0.60	0.685714
1	Nesterov	0.725	11	0.695652	0.80	0.744186
1	Adagrad	0.750	21	0.692308	0.90	0.782609
2	Adam	0.950	11	1.000000	0.90	0.947368
2	Nesterov	0.950	14	1.000000	0.90	0.947368
2	Adagrad	0.950	23	0.950000	0.95	0.950000
3	Adam	0.950	5	1.000000	0.90	0.947368
3	Nesterov	0.950	9	0.950000	0.95	0.950000
3	Adagrad	0.925	12	0.947368	0.90	0.923077

1.3 Best Trial

The model's loss and accuracy over 50 epochs are shown below for the best configuration (3 layers, Nesterov optimizer).

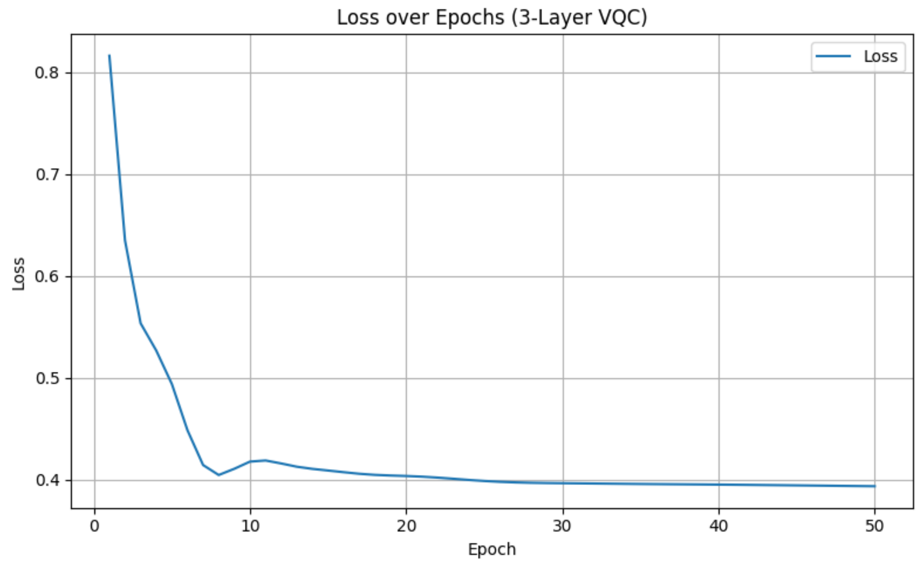

Figure 1: Loss over epochs.

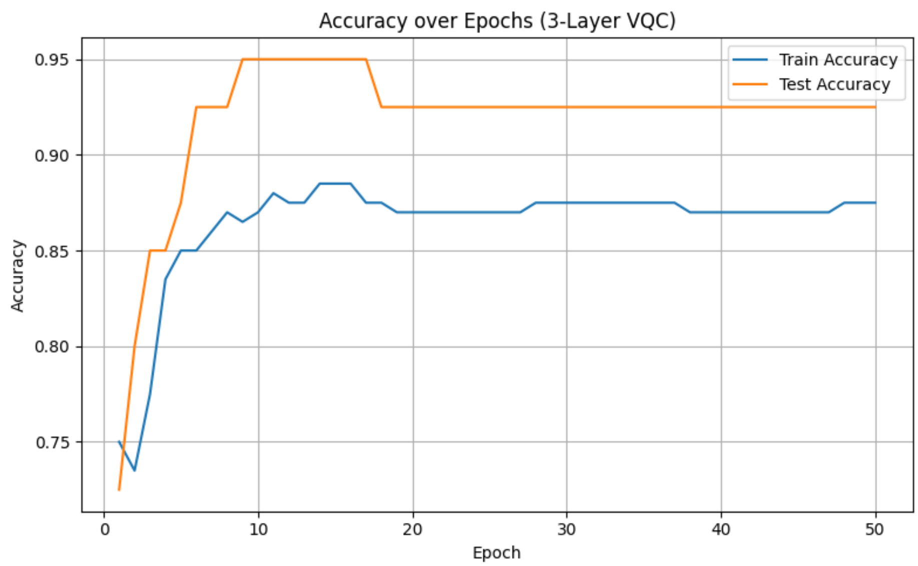

Figure 2: Train and test accuracy over epochs. Best test accuracy of 0.950 was reached at epoch 9.

2. Bloch Sphere Visualization

To better understand how the VQC transforms input data, the quantum states were visualized on the Bloch sphere for qubit 0 both before and after training. Each point represents the reduced state of a sample encoded and (optionally) processed by the circuit.

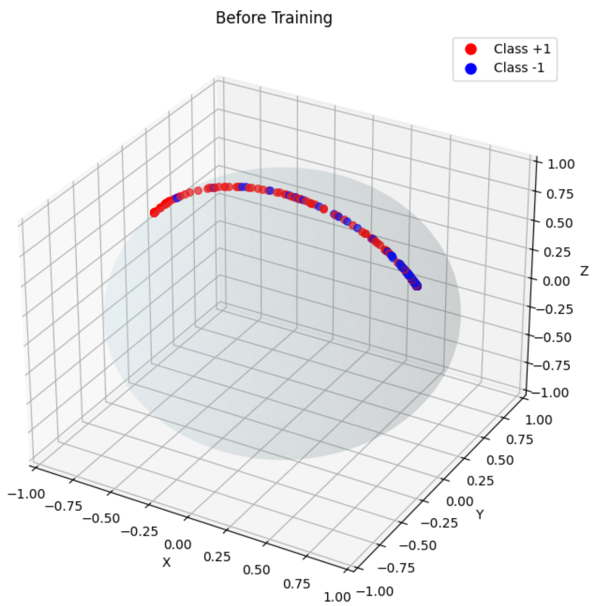

Figure 3: Bloch Sphere **Before Training**: The quantum states of class +1 (red) and class -1 (blue) are intermingled, indicating no learned separation. Only AngleEmbedding has been applied.

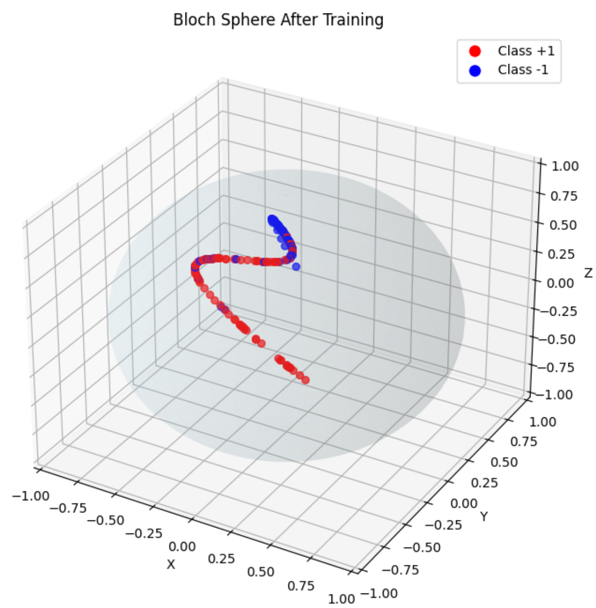

Figure 4: Bloch Sphere **After Training**: The VQC has transformed the input states such that the classes are now more distinguishable on the Bloch sphere, aiding classification.

3. Classical Baseline: Support Vector Machine

A classical Support Vector Machine (SVM) with an RBF kernel was trained on the same dataset for comparison. The SVM serves as a strong benchmark in binary classification tasks. Its performance metrics are shown below:

- **Test Accuracy**: 0.98
- **Precision**: 0.97
- **Recall**: 0.97
- **F1-Score**: 0.97

The SVM slightly outperformed the VQC in terms of accuracy, but both models achieved strong F1-scores, indicating good overall performance.

4. Conclusions

The Variational Quantum Classifier achieved an F1-score of 0.95, demonstrating that shallow quantum circuits can be effectively trained to solve simple classification problems. The comparison of optimizers showed that Nesterov momentum consistently led to faster and more stable convergence.

Bloch sphere visualizations revealed how the circuit learns to transform the input space into more distinguishable quantum states, particularly for qubit 0. While the classical SVM had a slight performance edge, the quantum model performed comparably well and highlighted the potential of quantum-enhanced learning for small-scale data.