

Quantum Machine Learning Models for Acoustic Sensor Metrology

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STUDY DESIGN

DATA	60 acoustic bands
REDUCTION	PCA to 4 components
MODELS	MLP, RBF-SVM, 2 QNNs, QSVM
EVALUATION	Accuracy · P · R · F1

$$K(x,x') = |\langle \varphi(x) | \varphi(x') \rangle|^2$$

Quantum-kernel fidelity

From acoustic measurements to a four-qubit representation

COMMON INPUT PIPELINE

01 ACOUSTIC RETURN

$$\mathbf{x} \in \mathbb{R}^{60}$$

One amplitude value per frequency band.

02 STANDARDIZE

$$\mathbf{z}_j = (\mathbf{x}_j - \boldsymbol{\mu}_j) / \sigma_j$$

Training-set mean and variance define the transform.

03 PCA PROJECTION

$$\mathbf{u} = \mathbf{W}_4^T \mathbf{z} \in \mathbb{R}^4$$

The four leading components form a shared input.

04 QUANTUM STATE

$$|\psi\rangle = \mathbf{S}(\mathbf{u})|0\rangle^4$$

Angle encoding prepares four qubits.

Research question

Do quantum feature maps improve classification of non-linear sonar reflections when every model receives the same four PCA features?

Comparison: MLP and RBF-SVM baselines versus two variational QNNs and a QSVM.

Controlled input: The same standardized four-component representation is used throughout.

Scope: The experiment evaluates predictive performance and parameter efficiency; it does not claim quantum computational advantage.

Recent sensor studies evaluate shallow quantum kernels

2024

Wang et al.

Power-quality disturbance signals

QSVM feature mapping supported disturbance detection and identification and remained robust under added noise.

2024

Jeong et al.

Urban GPS reception conditions

A ZZ feature map with a fidelity kernel outperformed the reported RBF-SVM baseline; input scaling was a key implementation choice.

2026

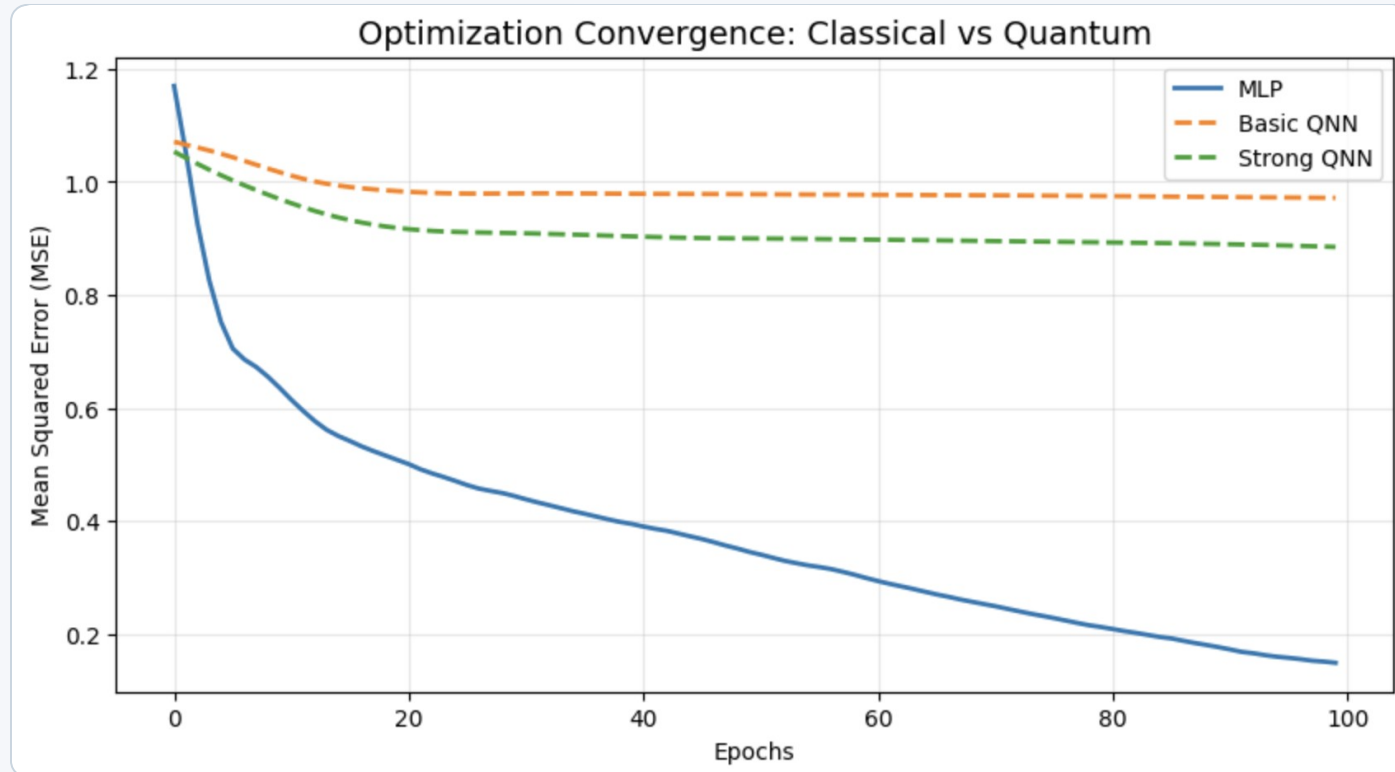
D'Amore et al.

IoT occupancy sensing

Projected quantum kernels matched classical methods with shallow encodings while exposing feature-map and shot-noise tradeoffs.

Gap: direct QNN-versus-QSVM benchmarking on continuous acoustic spectra remains limited.

MLP loss decreases while both QNN losses flatten early



Observed loss landscape

The MLP loss falls steadily; both QNN curves plateau near their early-epoch values.

Observed convergence: The 49-parameter MLP continues to reduce MSE across training.

Plateau signature: Both QNN losses flatten early. This is consistent with vanishing-gradient behavior, although gradient variance was not measured directly.

Model-design question: Can a fixed quantum feature map avoid variational optimization while retaining useful geometry?

PCA compresses 60 acoustic bands into four shared features

PREPROCESSING APPLIED BEFORE MODEL FITTING

01 INPUT MATRIX

$$\mathbf{X} \in \mathbb{R}^{N \times 60}$$

Each row is one sonar return; each column is an acoustic frequency band.

02 STANDARDIZATION

$$\mathbf{Z} = (\mathbf{X} - \boldsymbol{\mu})\mathbf{D}\boldsymbol{\sigma}^{-1}$$

Means and variances are estimated on the training data.

03 COVARIANCE EIGENSYSTEM

$$\boldsymbol{\Sigma}\mathbf{v}_k = \lambda_k\mathbf{v}_k$$

Principal directions are ordered by decreasing explained variance.

04 4D PROJECTION

$$\mathbf{U}_4 = \mathbf{Z}[\mathbf{v}_1 \ \mathbf{v}_2 \ \mathbf{v}_3 \ \mathbf{v}_4]$$

The same four-component representation is supplied to all five models.

One common 4D input → all five model architectures

Dataset: The Sonar benchmark represents each return with 60 continuous acoustic frequency bands.

Scaling: Standardization controls feature magnitude before angle encoding.

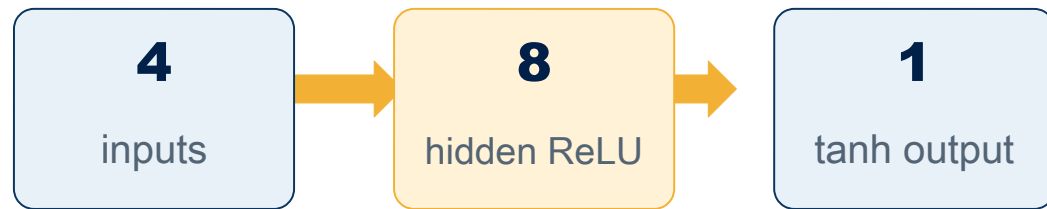
PCA: The four leading principal components define the common model input.

Hardware alignment: Four real-valued components map directly to four qubit rotations.

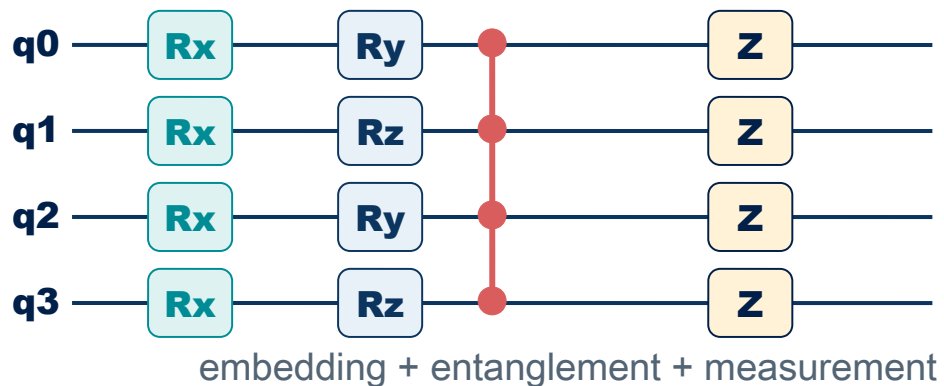
Five models compare classical, variational, and kernel learning

Comparable architectures

CLASSICAL



QUANTUM



MLP: Dense 4-8-1 baseline; 49 trainable parameters.

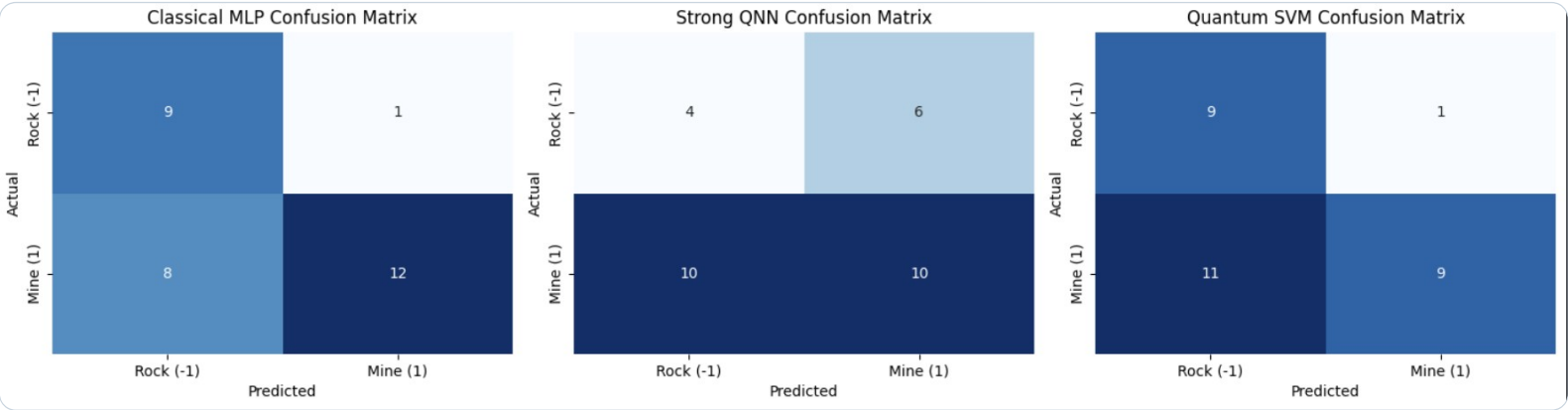
RBF-SVM: Classical non-linear margin benchmark.

Basic QNN: Two entangling layers; 8 trainable parameters.

Strong QNN: Three-axis rotations; 24 trainable parameters.

QSVM: Fixed quantum kernel; zero trainable quantum parameters.

Classical baselines lead; QSVM matches MLP on Rock specificity



Test-set confusion matrices

70.00%

MLP accuracy

21 / 30

MLP correct

9 TN

QSVM Rock hits

The same 9 true negatives appear for MLP and QSVM; QSVM loses recall on Mines rather than collapsing the Rock class.

Evaluation: Accuracy plus macro-averaged precision, recall, and F1 are derived from the test confusion matrices.

MLP leader: 70.00% accuracy with 0.6970 F1.

RBF-SVM: 66.67% accuracy with 0.6606 F1.

Interpretation: Within this test split, the MLP gives the best balance of Mine and Rock classification.

QSVM leads the quantum models in this experiment

Model	Acc.	Macro P	Macro R	Macro F1
Classical MLP	70.00%	0.7262	0.7500	0.6970
RBF-SVM	66.67%	0.6786	0.7000	0.6606
Basic QNN	46.67%	0.4306	0.4250	0.4258
Strong QNN	46.67%	0.4554	0.4500	0.4444
Quantum SVM	60.00%	0.6750	0.6750	0.6000

Accuracy and macro-averaged metrics from the supplied experiment

Variational result: Both QNNs reach 46.67% accuracy, consistent with the flat loss curves.

QSVM result: 60.00% accuracy and 0.6000 F1 outperform both trainable quantum circuits.

Mechanism: Quantum transition fidelities create the feature geometry; the margin is optimized classically.

Parameter result: The QSVM uses zero trainable quantum parameters.

Quantum kernels outperform the tested variational circuits

EMPIRICAL RESULT	QUANTUM RESULT	INTERPRETATION
MLP remains the overall leader 70.00% accuracy and 0.6970 F1 on the reported test split.	QSVM is the strongest quantum model 60.00% accuracy and 0.6000 F1, with no trainable quantum parameters.	The tested QNNs do not optimize effectively Both variational circuits reach 46.67% accuracy and show early loss flattening.

LIMITATIONS AND NEXT TESTS

Inference boundary: This simulator benchmark does not establish quantum computational advantage.

Validation: A single 70/30 split and PCA to four components limit claims about generalization.

Next tests: Use repeated stratified splits, gradient-variance diagnostics, shot-noise analysis, and physical hardware.

References

- [1]** Q.-L. Wang et al., “An advanced quantum support vector machine for power quality disturbance detection and identification,” *EPJ Quantum Technology*, vol. 11, Art. no. 70, Oct. 2024, doi: 10.1140/epjqt/s40507-024-00283-5.

- [2]** S. Jeong, S. Kim, and J. Seo, “Quantum Support Vector Machine-Based Classification of GPS Signal Reception Conditions,” in *Proc. IEEE Int. Conf. Quantum Computing and Engineering (QCE)*, vol. 2, Montreal, Canada, 2024, pp. 530–531, doi: 10.1109/QCE60285.2024.10390.

- [3]** F. D’Amore et al., “Assessing projected quantum kernels for the classification of IoT data,” *Array*, vol. 29, Art. no. 100695, Mar. 2026, doi: 10.1016/j.array.2026.100695.