Advancing EEG Signal Analysis with Quantum Machine Learning

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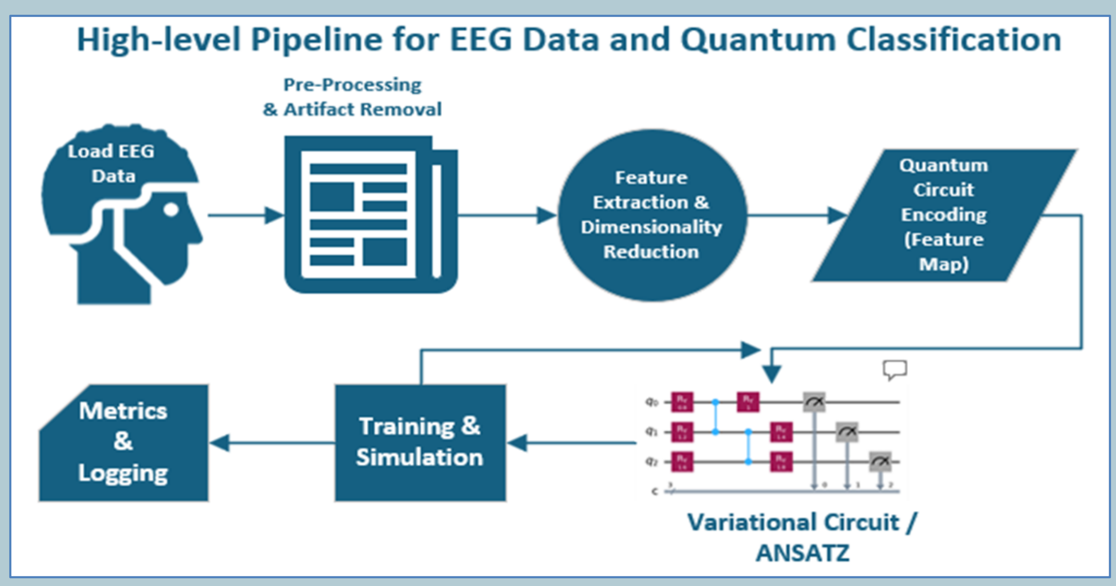
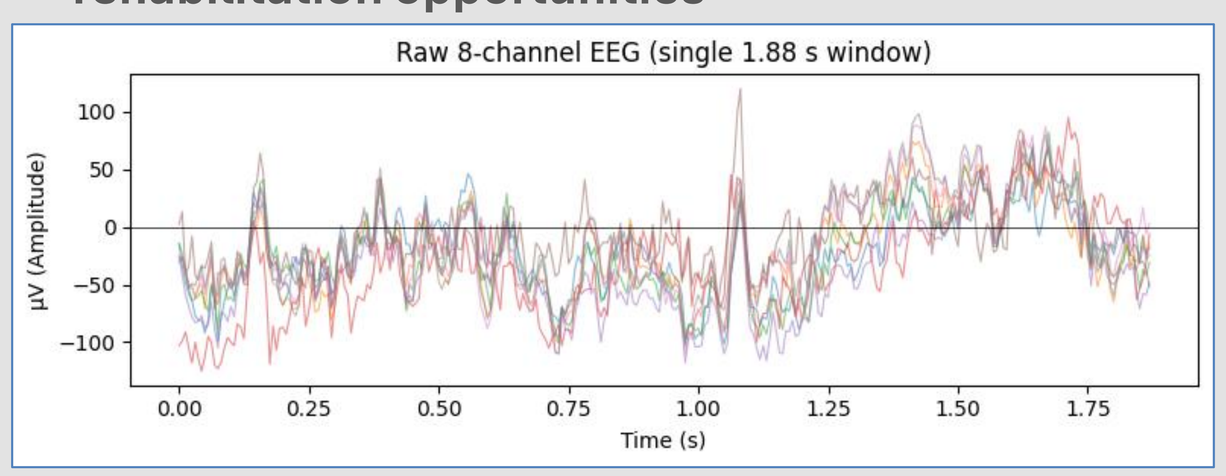
Abstract

- ❑ Electroencephalography (EEG) signals are noisy and hard to classify
- ❑ Classical ML using PCA + CSP + Random Forest) effective but misses cross-channel structure
- ❑ Quantum ML using Variational Quantum Classifier (VQC) embeds features in high-dimensional Hilbert space to capture richer patterns
- ❑ Goal: Determine if a 10-qubit VQC can match or exceed Classical ML approach classification



Introduction

- ❑ Brain–computer interfaces (BCIs) translate neural signals into device control, aiding with rehabilitation opportunities

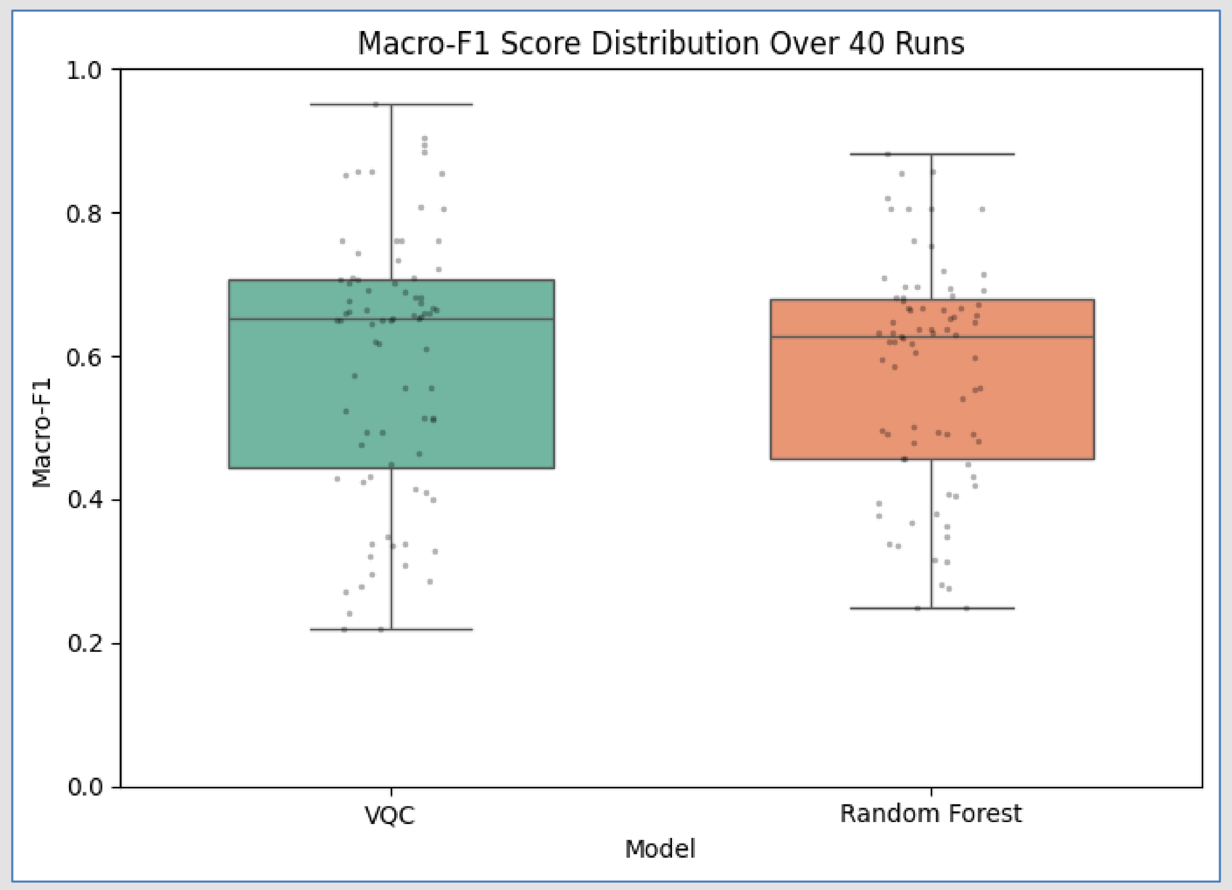


Example 1.88-second raw EEG window from the 8 motor-area channels selected for this study (subset of 64-channel PhysioNet dataset).

- ❑ Classical ML (PCA + CSP + Random Forest) effective, yet can miss subtle dependencies
- ❑ Quantum ML (QML) offers a fundamentally different approach by embedding features in high-dimensional Hilbert spaces
- ❑ Quantum ML (10-qubit VQC) offers an alternative, benchmarked here against Random Forest (RF)

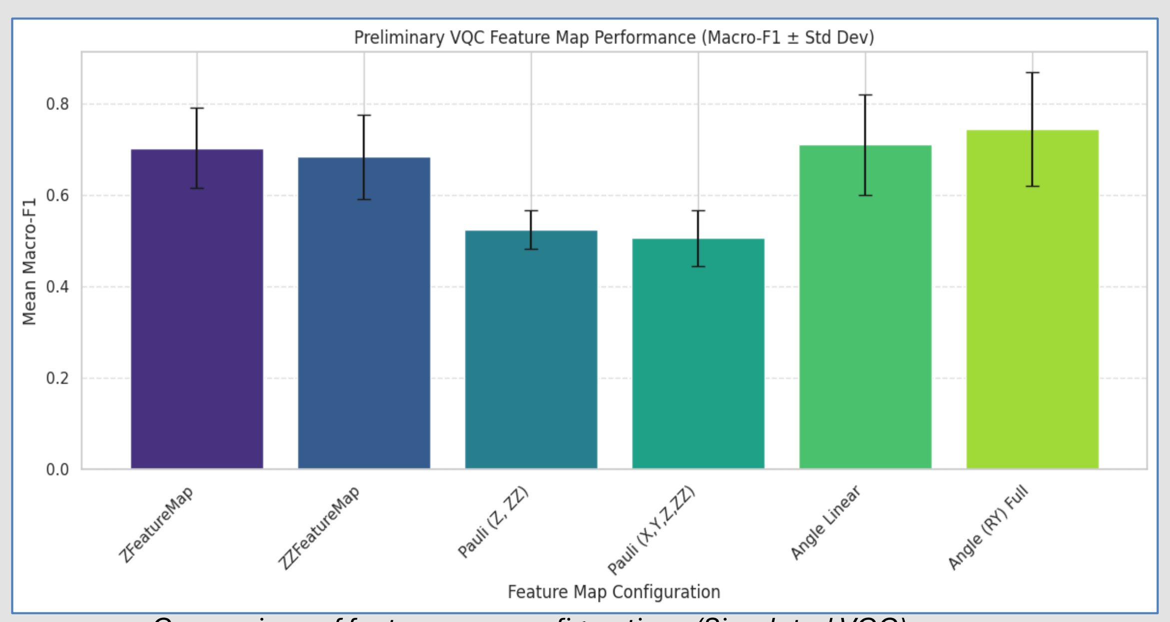
Results

- ❖ 2-class problem "movement" vs. "rest"
- ❖ Best Simulated Run (Angle + COBYLA): Macro-F1 = 0.95, AUROC = 0.83, Accuracy ≈ 0.76.
- ❖ RF Baseline: macro-F1 = 0.70, AUROC 0.75
- ❖ Simulated VQC improved precision (+17 pts) and recall (+19 pts) on "movement" class ($p < 0.001$; very large effect sizes)
- ❖ Across 40 runs: VQC averaged Macro-F1 ≈ 0.75, showed higher variance than RF but stronger best-case performance.



Macro-F1 score distribution across 40 runs. Simulated VQC shows higher variance than Random Forest but achieves stronger best-case performance.

- ❖ Feature maps: Angle encoding > Z, ZZ, Pauli
- ❖ Optimizers: COBYLA most stable; SPSA & GD less reliable
- ❖ Variability: Higher run-to-run variance, but VQC reached stronger top-end



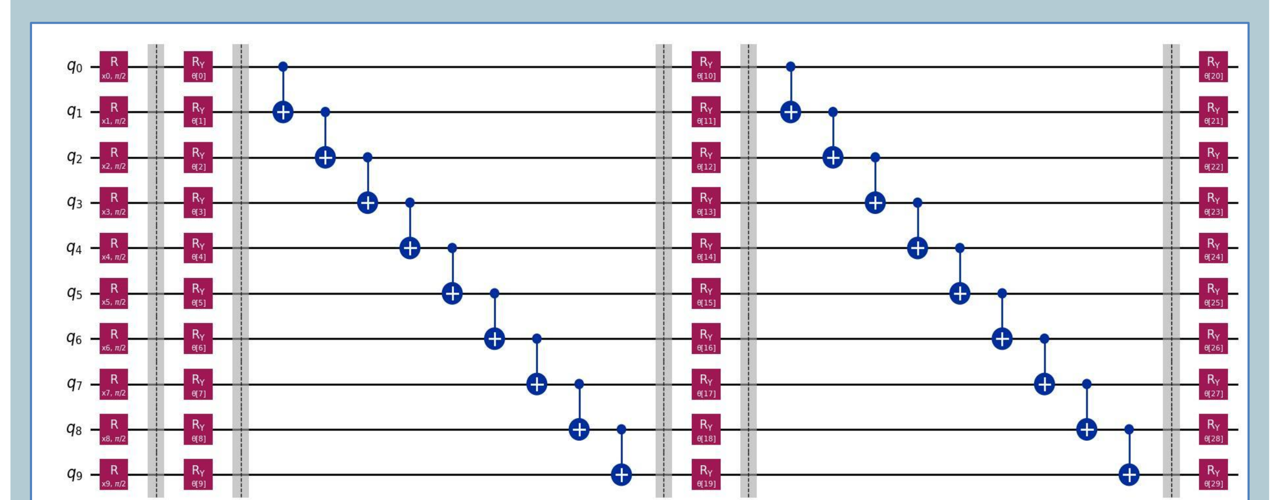
Comparison of feature map configurations (Simulated VQC).

Data & Tools

- ❑ **Dataset:** PhysioNet EEG Motor Movement/Imagery (curated, labeled subset)
- ❑ **≈1,333 windows** (1.88 s) from ≈26 subjects; "Relax" vs "Hand-Movement"
- ❑ **8 motor-area channels** (C3, C4, Cz, FC5, FC6, CP3, Fz, C1)
- ❑ **Environment**: Python + scikit-learn; Qiskit for quantum simulation/hardware
- ❑ **Hardware:** NVIDIA A100 GPU (simulation), IBM Quantum cloud backend

Methods

- ❑ **Filtering:** Band-pass 8–30 Hz (retain µ, β; suppress drift/noise)
- ❑ **Segmentation:** Non-overlapping 1.88 s (300-sample) windows
- ❑ **Features:** 7 time-domain stats to PCA (6) + CSP (4) to 10-D feature vector
- ❑ **Balancing:** SMOTE oversampling in feature space
- ❑ **Models:**
  - Random Forest (300 trees, tuned params)
  - 10-qubit VQC (Angle encoding + RealAmplitudes ansatz, 2 reps)
- ❑ **Training:** COBYLA optimizer, 80/20 split, 40 runs
- ❑ **Evaluation:** Macro-F1, AUROC, precision & recall (Move class)



Ten-qubit Variational Quantum Classifier circuit with Angle feature map and RealAmplitudes ansatz (2 reps, linear entanglement). Results shown are from simulated runs.

Conclusion

- ❖ A 10-qubit VQC matched or exceeded Random Forest when paired with strong preprocessing (PCA + CSP)
- ❖ Strongest gains were in movement-class precision and recall; macro-F1 improvements were modest
- ❖ Angle encoding + RealAmplitudes (linear entanglement) gave best results.

Key Takeaways

- ❖ QML is already viable for small-scale EEG classification
- ❖ Preprocessing is critical for both classical and quantum pipelines
- ❖ Further optimization is needed to reduce variability and test cross-subject generalization

Future Work

- ❖ Cross-subject validation for generalization
- ❖ Expanded features: frequency & hybrid time–frequency
- ❖ Robustness tuning: adaptive optimizers, initialization
- ❖ Real-time feasibility: latency, streaming, calibration

References

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