<u>*WOMANIUM Quantum + AI Project*</u>

Seismic Data Analysis - A Comparative Study Using Classical and Quantum Computing Methods

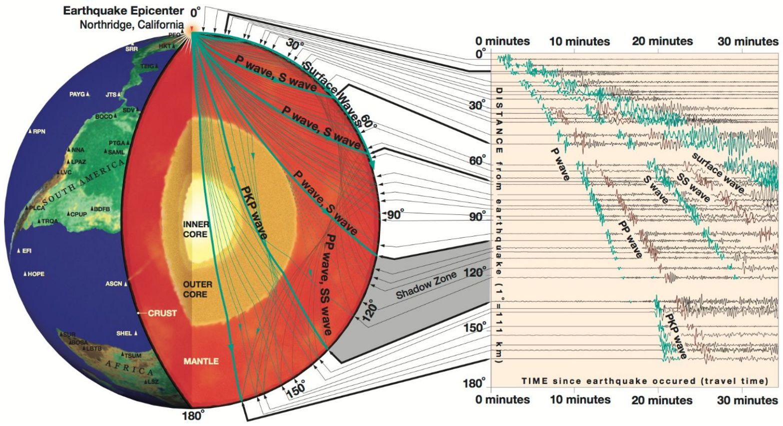

Image from IRIS Consortium - Exploring Earth through Seismology

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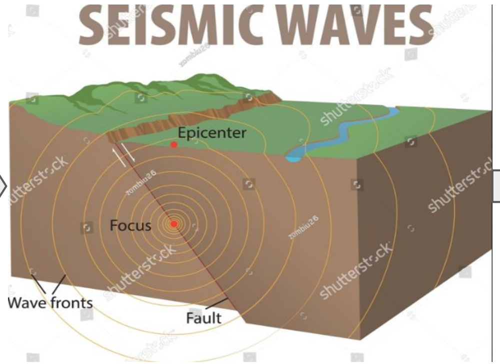
Problem Statement

Seismic data processing is essential for resource exploration and monitoring. Traditional methods often fall short in accuracy and efficiency due to complex data patterns.



Why seismic Data Analysis is necessary ?

Enhances exploration efficiency and resource management.

Improves the accuracy of environmental assessments.

Seismic Inversion Converts reflectivity data into (impedance) for subsurface analysis.

High Dimensionality issues

Noise Issues

Data Sources: Volve field measurements and synthetic data. **Ref** [1] & [2]

Objectives of the Project

Explore quantum computing for high-dimensional seismic data to improve pattern recognition and data interpretation.

Why should we use Quantum Computing ?

It can Process High-Dimensional Data Efficiently to Capture complex patterns.

Seismic Trace Reconstruction and Impedance Inversion.

Enhance accuracy and efficiency, comparing & Benchmarking with classical methods.

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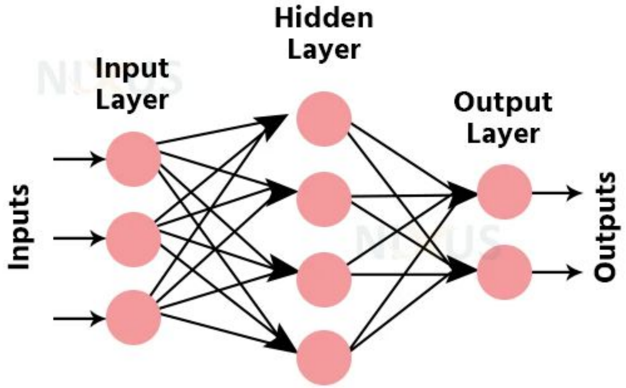
Image Reference-Illustration of Seismic waves diagram/Shutterstock

Methods Used

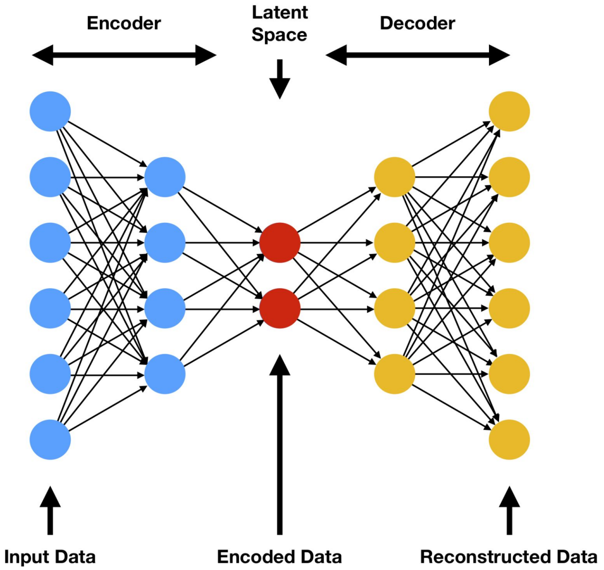
Category	Method	Description	Application
Classical Machine Learning	Artificial Neural Network	Classical fully connected neural net that processes data through a single hidden layer.	Seismic Impedance Inversion
	Autoencoder	A type of neural network which compresses and reconstructs data.	Seismic Trace Reconstruction
Quantum Machine Learning	Variational Quantum Hybrid Neural Network	Quantum convolutional neural network integrating quantum convolutional layers with classical feed forward layers.	Impedance Inversion
	Quantum Autoencoder	Quantum version of classical autoencoder.	Trace Reconstruction
	Quantum Kernel PCA with RBF Kernel	Quantum kernel principal component analysis with radial basis function kernels.	Dimensionality Reduction, Seismic Feature Analysis
Quantum Algorithms	Quantum Phase Estimation (QPE)	Estimates eigenvalues of unitary operators	Estimating Parameters for Seismic Data

Classical Models

Artificial Neural Network



Autoencoder



Images retrieved from:
https://nixustechnologies.com/artificial-neural-network-in-machine-learning/
https://www.compthree.com/blog/autoencoder/

Quantum Methods

Quantum Auto-Encoder

Encoder: Maps classical data to quantum state.
Gates:

$$R_Y(\theta), \quad R_X(\phi), \quad \text{CNOT}$$

Decoder: Reconstructs classical data from quantum state.
Gates: Inverse of encoder gates, measure with Z operators.

Quantum Kernel PCA

Dimensionality reduction using Kernel PCA with RBF kernel .

- Apply Kernel PCA on standardized data.

Kernel:

$$K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$$

VQCNN

VQCNN for Seismic Data: Quantum Layer: Applies parameterized gates:

$$U(\theta) = R_z(\theta_1) \cdot R_y(\theta_2) \cdot \text{CNOT}$$

Pooling: Classical max pooling of quantum measurements.Process and normalize seismic data. Train using quantum and classical optimizers. **Optimization:** Minimizes loss:

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Quantum Phase Estimation (QPE)

Quantum Phase estimation For seismic data:
Estimates the phase of a unitary operator using:

- Gates: Hadamard H, Phase Shift R_ϕ, Inverse QFT QFT^{-1}.
- Load and normalize seismic data.
- Define QPE circuit components.

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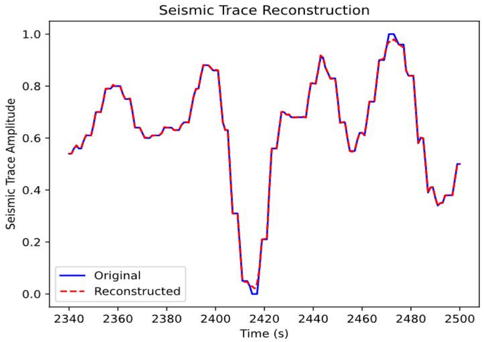
Comparison between Models

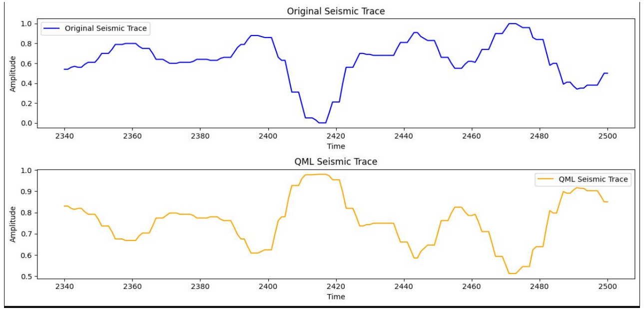
Models	MSE (Mean Squared Error)	MAE (Mean Absolute Error)	R2 Score (R-squared)
VQC Hybrid Neural Network	0.0521	0.2056	0.0247
Quantum Autoencoder	0.0031	0.0414	
Classical Neural Network	1.60E-04	0.0099	0.9969
Classical Autoencoder	3.68E-05	0.003	

Comparison between Models (Trace Reconstruction)

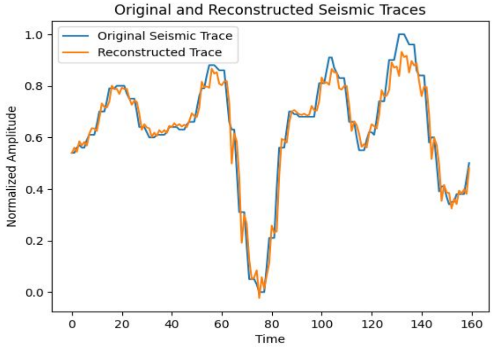
Classical Autoencoder



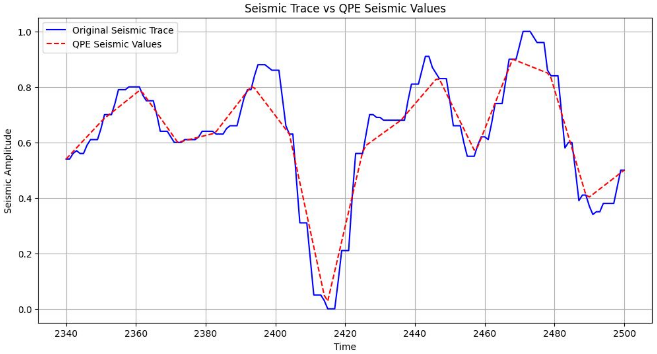
Quantum Kernel PCA



Quantum Autoencoder



Quantum Phase estimation (QPE)



Success metrics

Improved Seismic Trace Reconstruction: The Quantum Autoencoder (QAE) model significantly enhanced accuracy, with Mean Squared Error (MSE) dropping from 0.271 to 0.003 and Mean Absolute Error (MAE) from 0.450 to 0.042.

Effective Dimensionality Reduction: Kernel PCA with an RBF kernel identified two clusters, achieving a Silhouette Score of 0.47, indicating good clustering.

Efficient Data Processing: Quantum methods improved handling and optimization of high-dimensional seismic data.

Enhanced Feature Space and Visualization: Quantum models provided clearer feature space distinction and better visualization of processed seismic data.

Comprehensive Metrics: Error histograms, MSE, and R-squared were used to assess quantum-enhanced seismic data processing quality.

Advanced Data Normalization: Applied sophisticated normalization and preprocessing techniques for quantum-enhanced seismic analysis.

Quantum Phase Estimation (QPE): Implemented QPE for estimating seismic-related phases, a novel application in seismic data analysis.

Future Scope

- Extend to larger datasets.
- Explore more advanced quantum circuits and architectures for potentially better results.
- Investigate other hybrid techniques and algorithms to further optimize performance.

Current Limitations

- Computational resources
- Refinement of model complexity and quantum circuit design

References

[1] Equinor. Volve Field Dataset, 2018. Retrieved from https://www.equinor.com/energy/volve-data-sharing

[2] V. Das and A. Pollack. Convolutional neural network for seismic impedance inversion. Geophysics, 84:R869–R880, 2019.

[3] Employing gate-based quantum computing for traveltime seismic inversion, June 2022

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[4] An Application of Quantum Annealing Computing to Seismic Inversion, Front. Phys., 18 January 2022

[5] Mustafa, A.; Alfarraj, M.; AlRegib, G. Estimation of Acoustic Impedance from Seismic Data using Temporal Convolutional Network. In Expanded Abstracts of the SEG Annual Meeting; Society of Exploration Geophysicists: Houston, TX, USA, 2019; pp. 15–20.

[6] PennyLane: Automatic differentiation of hybrid quantum-classical computations

[7] https://pennylane.ai/qml/demos/tutorial_learning_from_experiments/

[8] A Note on Quantum Phase Estimation, Yao-Ting Lin

Thank You!