Quantum Machine Learning for Land Cover Classification: Evaluating Variational Quantum Classifiers Using Sentinel-2 Imagery

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Abstract. *Land cover classification using remote sensing data is essential for environmental monitoring and agricultural management. This study evaluates the feasibility of applying a Variational Quantum Classifier (VQC) to distinguish soybean fields from forest formations using Sentinel-2 imagery. Spectral bands B2, B3, B4 (10 m resolution) and annual mean NDVI were used as input features. The quantum model, implemented in Qiskit's simulator, was compared with a classical neural network trained on the same dataset. While the classical model achieved higher accuracy (above 90% for both classes), the quantum classifier demonstrated competitive performance, particularly for forest identification. The results highlight current limitations of quantum classifiers in complex agricultural landscapes, while indicating future potential as quantum hardware and algorithms evolve.*

1. Introduction

Land cover classification based on satellite imagery plays a central role in environmental assessment and agricultural monitoring. Classical machine learning approaches such as Random Forests and Support Vector Machines have shown high performance in vegetation mapping tasks. However, increasing data dimensionality and computational demands motivate the exploration of alternative paradigms.

Quantum computing introduces new computational frameworks capable of exploiting superposition and entanglement for complex optimization and classification tasks. Variational Quantum Algorithms, particularly the Variational Quantum Classifier (VQC), combine quantum feature encoding with parameterized circuits optimized through classical routines. Recent studies suggest that quantum-enhanced feature spaces may offer advantages in nonlinear classification problems.

This study investigates the application of a VQC to classify soybean and forest areas using Sentinel-2 data and compares its performance against a conventional neural network. The objective is to assess the practical viability of quantum machine learning in remote sensing classification tasks.

2. Material and Methods

Sentinel-2 imagery from the COPERNICUS/S2_SR collection was acquired for Rio Grande do Sul, Brazil, covering January 1 to December 31, 2020. Cloud-contaminated pixels were removed using the QA60 mask, and a median composite was generated using bands B2 (blue), B3 (green), B4 (red), and NDVI. Forest areas exhibited low reflectance in visible bands and high NDVI, whereas soybean fields showed contrasting spectral behavior (Figure 1).

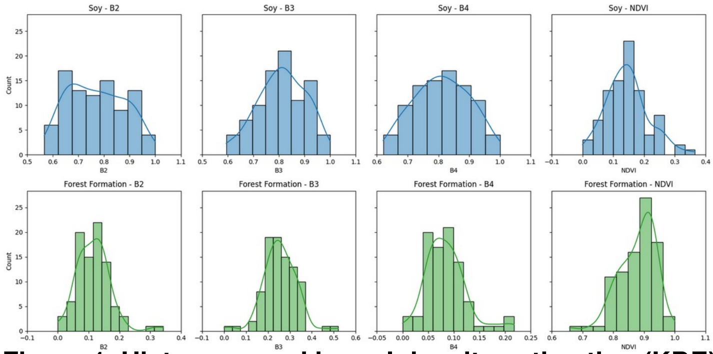

Figure 1. Histogram and kernel density estimation (KDE)

Representative sampling points for soybean and forest were manually selected in Google Earth Engine (GEE). Points were labeled (1 = soybean, 2 = forest), and spectral values were extracted at 10 m resolution. The dataset was exported as CSV, normalized using Min-Max scaling in Python, and divided into stratified training (80%) and testing (20%) subsets.

Classical Neural Network

A feedforward neural network was implemented in TensorFlow/Keras using the four normalized spectral features as input. The architecture consisted of two hidden layers with 64 and 32 neurons (ReLU activation) and a two-neuron softmax output layer. Training was conducted for 50 epochs with batch size 32, using the Adam optimizer and sparse categorical cross-entropy loss. Predictions were reclassified into original labels (1 and 2) and exported for spatial analysis.

Variational Quantum Classifier

The quantum model was implemented using Qiskit Machine Learning on a simulator. Feature encoding employed a ZZFeatureMap with four qubits (q_0–q_3), each representing one spectral variable (B2, B3, B4, NDVI). The feature map embedded nonlinear relationships via ZZ entangling operations(Figure 2).

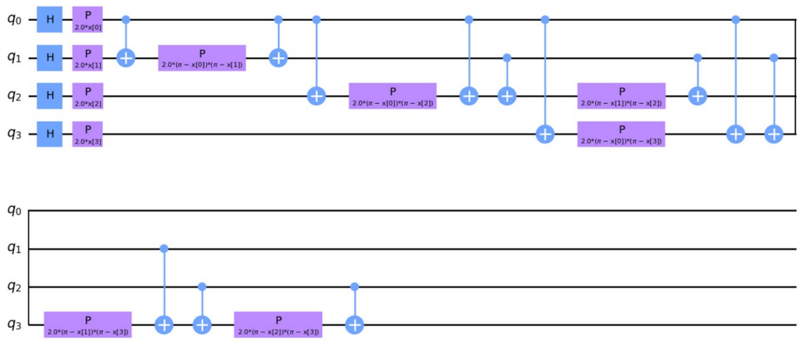

Figure 2. ZZFeatureMap

The ansatz consisted of a RealAmplitudes circuit with four qubits and three repetitions (reps = 3), including parameterized RY rotations and CNOT entanglement layers to ensure expressive state exploration (Figure 3). Circuit parameters were optimized using the COBYLA algorithm over 80 iterations. (Figure 3).

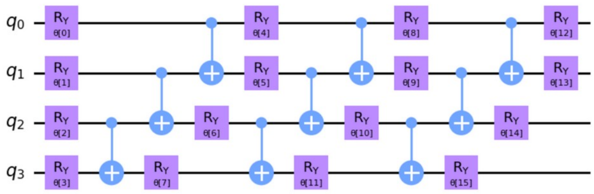

Figure 3. ansatz

Final predictions from both models were rasterized and spatially analyzed in GEE.

3. Results and Discussion

An area of approximately 44.1 hectares in Júlio de Castilhos, Rio Grande do Sul, Brazil, was selected for validation (Figure 4). Reference labels were obtained from MapBiomas Collection 9 (30 m resolution), distinguishing soybean and forest classes (Figure 5).

Figure 4. Area Selected

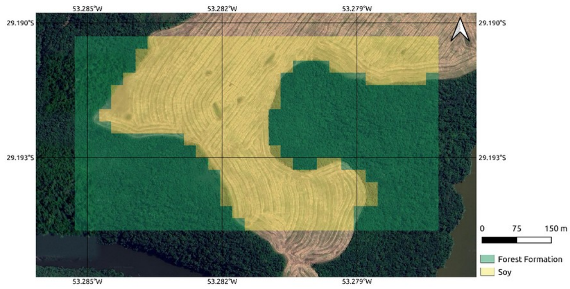

Figure 5. MapBiomas

Two 10 m resolution rasters were generated: one from the classical neural network (Figure 6) and one from the VQC (Figure 7).

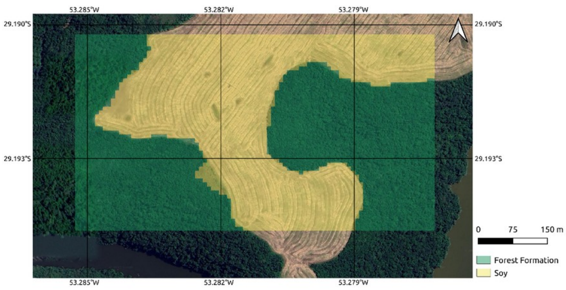

Figure 6. Classical Neural Network

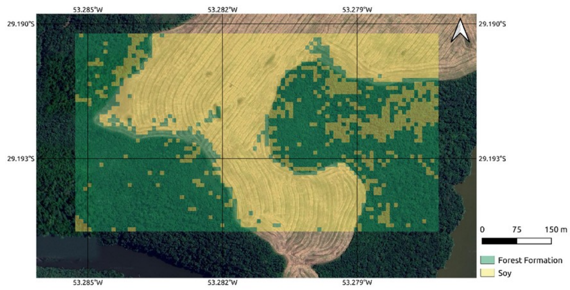

Figure 7. VQC

Model performance was assessed against the MapBiomas raster.

The classical neural network achieved:

Soybean: 92.23% correctly classified (1,910 pixels), 7.77% false positives (161 pixels).
Forest: 94.70% correctly classified (2,215 pixels), 5.30% false positives (124 pixels).

The quantum classifier achieved:

Soybean: 76.58% correctly classified (1,769 pixels), 23.42% misclassified (541 pixels).
Forest: 87.57% correctly classified (1,839 pixels), 12.43% false positives (261 pixels).

Figure 8 summarizes the comparative classification performance.

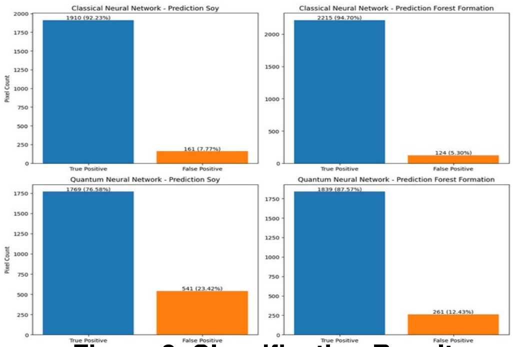

Figure 8. Classification Results

The classical neural network outperformed the VQC in both classes, particularly for soybean detection. The lower quantum performance may reflect current limitations in circuit expressivity, parameter optimization, and simulator-based constraints. Nevertheless, the VQC demonstrated relatively strong performance for forest classification (87.57%), indicating that quantum-enhanced feature encoding can capture relevant spectral relationships.

These findings suggest that classical models remain more robust for high-resolution agricultural mapping under current technological conditions. However, continued improvements in quantum hardware, circuit design, and noise mitigation may narrow this performance gap.

4. Conclusions

This study compared a classical neural network and a Variational Quantum Classifier for soybean and forest classification using Sentinel-2 imagery. The classical model achieved superior accuracy, exceeding 90% for both classes, whereas the VQC reached 76.58% for soybean and 87.57% for forest.

Although quantum performance was lower, the results demonstrate the feasibility of applying quantum machine learning to remote sensing problems. Future work should focus on optimizing quantum circuit architectures, exploring alternative feature maps, implementing noise mitigation strategies, and testing on real quantum hardware. Such developments will be essential to evaluate the long-term applicability of quantum computing in large-scale environmental classification tasks. The source code is available at: *https://github.com/kikosmoura/quantum_simulator*.

References

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24-31.

Biamonte, J., et al. (2017). Quantum machine learning. Nature, 549(7671), 195-202.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80(1), 185-201.

Havlíček, V., et al. (2019). Supervised learning with quantum-enhanced feature spaces. Nature, 567(7747), 209-212.

MapBiomas. (2022). Coleção 9 da Série Anual de Mapas de Cobertura e Uso do Solo do Brasil. MapBiomas. Retrieved from https://mapbiomas.org

Zhang, L., et al. (2016). Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, 4(2), 22-40.

Chollet, F. (2021). Deep Learning with Python (2nd ed.). Manning Publications.