

Hybrid Quantum-Classical CMB Pattern Classification Using Ramanujan-Inspired Feature Compression

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Abstract—This paper presents a hybrid quantum-classical framework for cosmic microwave background (CMB) pattern classification using Ramanujan-inspired feature compression and a variational quantum classifier. A dataset of 100,000 WMAP-derived local patches was formed, and each length-9 patch was assigned to cold, neutral, or hot classes through percentile-based labeling. Classical baselines achieved 99.96% accuracy for logistic regression, 99.58% for an RBF-SVM, and 97.25% for random forest on the full three-class task. The compressed classical branch reduced the feature count from 9 to 4 while preserving 99.88% accuracy. The quantum branch used four compressed features, angle encoding on a 4-qubit circuit, and a 3-layer PennyLane variational model trained on a balanced subset of 400 training and 120 test samples. The best quantum configuration achieved 99.17% accuracy, 0.99 precision, 0.99 recall, 0.99 F1-score, and a confusion matrix of [[59, 1], [0, 60]]. These results support feasible low-qubit hybrid learning for cosmology.

Index Terms—quantum machine learning, cosmic microwave background, variational quantum circuit, PennyLane, feature compression, hybrid learning

I. INTRODUCTION

Quantum machine learning (QML) has become an important direction for scientific classification, feature learning, and compact inference under near-term quantum constraints [1], [2], [4]. In parallel, cosmological datasets are natural application targets because sky-map measurements are structured, high-dimensional, and rich in subtle nonlinear patterns. Recent 2026 studies show that hybrid QML is increasingly judged through robustness, feature efficiency, and hardware awareness rather than through claims of quantum advantage alone [5], [6].

This work studies a hybrid quantum-classical pipeline for CMB pattern classification using a public WMAP map. The full task is a three-class problem over cold, neutral, and hot local temperature patches, while the quantum experiment focuses on a balanced binary subset of cold and hot patches for simulation feasibility. The project combines classical pre-processing, Ramanujan-inspired feature compression, and a compact four-qubit variational quantum model.

The main contributions are as follows. First, the work constructs a 100,000-sample CMB patch benchmark from a public sky map. Second, it develops a hybrid pipeline

combining structured feature compression, angle encoding, and variational quantum inference. Third, it reports classical and quantum behavior through accuracy, loss, confusion analysis, and baseline comparison. Fourth, it presents the study in IEEE paper format with explicit methodology, workflow, environmental setup, and discussion sections.

II. REVIEW OF LITERATURE

Recent 2026 literature shows that QML research is increasingly centered on practical model design and benchmarking. Yang *et al.* studied quantum classification for new-physics search and emphasized careful comparison against strong baselines [1]. Jabeen *et al.* showed that classical-to-quantum mappings can remain effective when representations are normalized and dimensionally aligned [2]. Jha *et al.* demonstrated that feature-map design materially affects quantum kernel quality and decision boundaries [4].

Feature engineering and reduction remain especially relevant for hybrid learning. Alotaibi *et al.* demonstrated that quantum-inspired feature engineering can preserve explainability while improving classification quality [3]. Lopatkin *et al.* highlighted the importance of hybrid feature selection when qubit budgets are limited [9]. Franco *et al.* combined SHAP-driven feature selection with quantum phase classification and showed that interpretable low-dimensional features can support strong quantum performance [10]. Montalba'n *et al.* further argued that the geometry of classical data strongly affects the usefulness of quantum representations [7].

Application-oriented studies also support compact hybrid pipelines. Bravo-Montes *et al.* analyzed hybrid QML architectures under quantum noise and showed that hardware effects must be part of evaluation [5]. Singh *et al.* benchmarked QML on real quantum hardware for MedMNIST datasets [8]. These findings motivate the present work's focus on compression, fair benchmarking, and cautious interpretation.

III. METHODOLOGY

A. System Architecture

The proposed system begins with the public WMAP seven-year internal linear combination map and converts it into a

local patch dataset. The original CMB map contains 3,145,728 values, which were reduced to 196,608 values using `healpy` downsampling with `nside=128`. From the valid reduced map, overlapping patches of length 9 were constructed. A total of 100,000 patches were retained for modeling, and percentile thresholds on patch means were used to create three classes: cold, neutral, and hot, with class counts of 33,000, 33,000, and 34,000, respectively.

The hybrid system contains data acquisition, patch extraction, percentile-based labeling, standardization, classical baseline learning, feature compression, and quantum inference. The classical branch uses all 9 standardized patch values, while the quantum branch uses four compressed descriptors derived from Ramanujan-inspired arithmetic and periodic grouping rules. For quantum feasibility, the compressed data are filtered to a balanced binary subset consisting of 200 cold and 200 hot training samples and 60 cold and 60 hot test samples.



Fig. 1. System architecture of the proposed hybrid quantum-classical CMB pattern-classification framework.

B. Model Setup

The quantum model uses a 4-qubit angle-encoding circuit followed by trainable rotation layers and nearest-neighbor entanglement. Let $\mathbf{x} \in \mathbb{R}^9$ denote the standardized patch. Ramanujan-inspired compression maps the original patch into $\mathbf{r} \in \mathbb{R}^4$:

$$r_1 = \frac{1}{9} \sum_{i=1}^9 x_i, \quad (1)$$

$$r_2 = \frac{1}{5} \sum_{i \in \{1,3,5,7,9\}} x_i - \frac{1}{4} \sum_{i \in \{2,4,6,8\}} x_i, \quad (2)$$

$$r_3 = \frac{x_1 + x_4 + x_7}{3} - \frac{x_2 + x_5 + x_8}{3}, \quad (3)$$

$$r_4 = \frac{1}{8} \sum_{i=1}^8 |x_{i+1} - x_i|. \quad (4)$$

These descriptors capture global level, odd-even contrast, period-3 structure, and local variation.

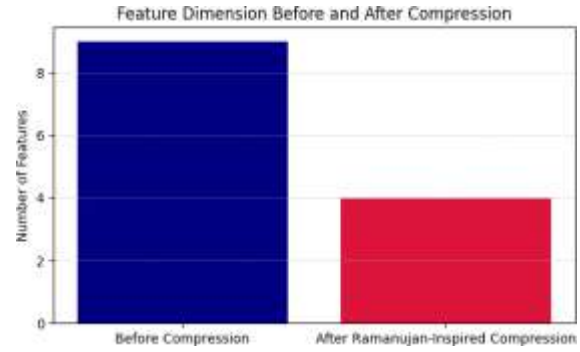


Fig. 2. Notebook-generated feature dimension before and after Ramanujan-inspired compression.

The reduced features are scaled to $[-\pi, \pi]$ and encoded through rotation gates:

$$\tilde{r}_j = -\pi + 2\pi \cdot \frac{r_j - r_j^{\min}}{r_j^{\max} - r_j^{\min}}, \quad U_{\text{enc}}(\tilde{\mathbf{r}}) = \prod_{j=1}^4 R_Y(\tilde{r}_j). \quad (5)$$

Each variational layer applies trainable rotations and entanglement:

$$U_\ell(\boldsymbol{\theta}^{(\ell)}, \boldsymbol{\phi}^{(\ell)}) = \prod_{j=1}^4 R_Y(\boldsymbol{\theta}_j^{(\ell)}) R_Z(\boldsymbol{\phi}_j^{(\ell)}) \cdot \text{CNOT}_{0,1} \text{CNOT}_{1,2} \text{CNOT}_{2,3} \quad (6)$$

The model output is

$$y^* = \langle Z_0 \rangle, \quad (7)$$

and training minimizes mean-squared error over labels in $\{-1, +1\}$:

$$L = \frac{1}{N} \sum_{n=1}^N (y_n^* - y_n)^2. \quad (8)$$

The final setup uses 4 qubits, 3 layers, Adam optimization with learning rate 0.03, batch size 25, and 25 epochs.

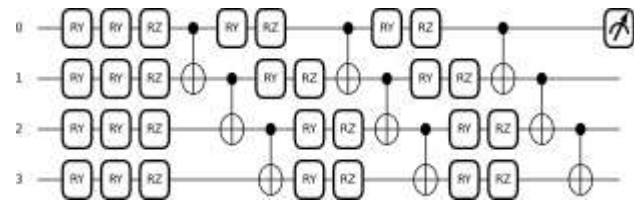


Fig. 3. Rotation-gate representation generated directly from the `quantum_circuit` definition in the uploaded notebook.

IV. ALGORITHM DESIGN

Figure 4 shows the workflow diagram of the proposed hybrid quantum-classical algorithm, and Algorithm 1 summarizes the full sequence.

Workflow diagram of the hybrid quantum-classical algorithm



Fig. 4. Workflow diagram of the proposed hybrid quantum-classical algorithm.

Algorithm 1 Hybrid Quantum-Classical CMB Pattern Classification

Require: WMAP-derived CMB map D

Ensure: Predicted class label $\hat{y}$

- 1: Load the public CMB map and reduce its resolution
- 2: Construct overlapping length-9 local patches
- 3: Compute patch means and assign cold, neutral, and hot labels
- 4: Split the dataset into stratified train-test partitions
- 5: Standardize the 9-dimensional patch features
- 6: Train logistic regression, random forest, and SVM baselines
- 7: Compute Ramanujan-inspired compressed features $\mathbf{r} \in \mathbb{R}^4$
- 8: Select balanced cold-hot subsets for quantum evaluation
- 9: Scale the compressed features to $[-\pi, \pi]$
- 10: Encode the four features using R_Y rotations
- 11: Apply three trainable layers with R_Y , R_Z , and CNOT gates
- 12: Optimize circuit parameters with Adam for 25 epochs
- 13: Evaluate accuracy, loss, precision, recall, F1-score, and confusion matrix
- 14: Compare the quantum model with classical baseline algorithms

V. ENVIRONMENTAL SETUP

The experiments were executed in a notebook-based Python environment using `numpy`, `pandas`, `scikit-learn`, `matplotlib`, `healpy`, `astropy`, `tables`, and `PennyLane`. Quantum execution used PennyLane's `default.qubit` simulator, and the model was optimized with the Adam optimizer. This environment supports reproducible quantum simulation without requiring physical quantum hardware.

The dataset source used in the notebook is the WMAP seven-year internal linear combination map. The dataset URL is:

https://lambda.gsfc.nasa.gov/data/map/dr4/dfp/ilc/wmap_ilc_7yr_v4.fits

The processed pipeline generated a 100,000-sample tabular dataset with 9 raw patch features and one label column, and intermediate artifacts were exported to CSV and HDF5 for reproducibility.

VI. RESULT AND DISCUSSIONS

A. Model Performance

Table I reports the main performance values. On the original three-class task, logistic regression achieved 99.955% accuracy, SVM achieved 99.575%, and random forest achieved 97.250%. After compression to four features, logistic regression still achieved 99.880%, showing that most of the discriminative structure was preserved. The quantum variational model achieved 99.167% accuracy on the balanced binary subset, with macro precision 0.99, macro recall 0.99, and macro F1-score 0.99. The training loss decreased from 0.4629 in epoch 1 to 0.0894 in epoch 25, indicating stable convergence.

TABLE I
MODEL PERFORMANCE SUMMARY

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.9996	1.0000	1.0000	1.0000
Random Forest	0.9725	0.9700	0.9700	0.9700
SVM	0.9958	0.9950	0.9950	0.9950
Compressed Logistic Regression	0.9988	1.0000	1.0000	1.0000
Quantum VQC	0.9917	0.9900	0.9900	0.9900

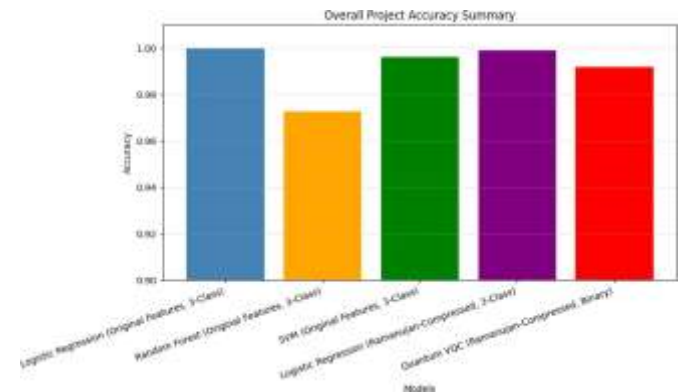


Fig. 5. Notebook-generated overall project accuracy summary across the main classical and quantum experiments.

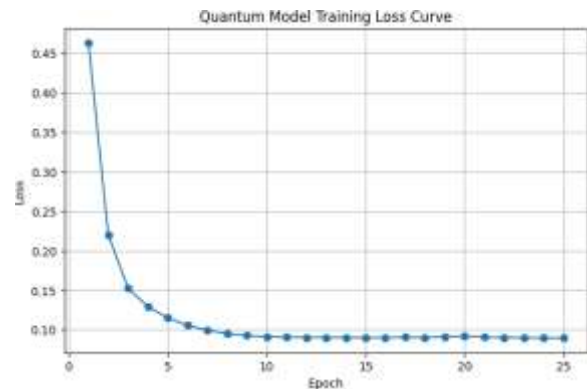


Fig. 6. Notebook-generated training loss diagram of the quantum variational model across 25 epochs.

B. Confusion Matrix

The confusion behavior of the quantum model is summarized in Table II and Fig. 7. The model correctly classified 59 of 60 cold samples and all 60 hot samples. Therefore, the classifier produced one false positive and zero false negatives on the balanced test subset.

TABLE II
SUMMARY OF QUANTUM CONFUSION MATRIX INTERPRETATION

Item	Observation
True negatives	59 cold samples correctly predicted as cold
False positives	1 cold sample incorrectly predicted as hot
False negatives	0 hot samples missed by the model
True positives	60 hot samples correctly predicted as hot
Interpretation	The quantum classifier preserves full hot-class recall and makes only one mistake in the cold class.

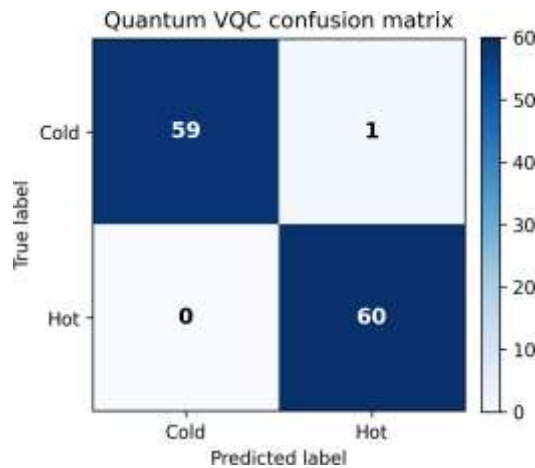


Fig. 7. Confusion matrix of the best-performing quantum model.

C. Predictions

The model predicts CMB patterns by first converting each local patch into four compressed descriptors that summarize average temperature level, parity contrast, periodic structure, and local variation. These descriptors are scaled into quantum rotation angles and passed through the four-qubit variational circuit. A positive expectation value is mapped to the hot class and a negative expectation value is mapped to the cold class. In this way, the prediction is driven by the structure of the CMB patch rather than by a single raw pixel value.

On the balanced quantum test subset, the model correctly predicted all 60 hot patches and 59 of 60 cold patches. This means the learned circuit strongly separates the two extreme temperature classes after compression. The predictions therefore show that the compressed representation preserves enough information for stable binary discrimination, even though the neutral class is excluded from the quantum phase for tractability.

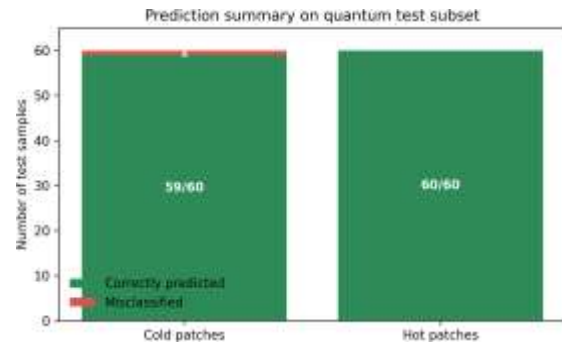


Fig. 8. Prediction summary of the quantum model on the balanced cold-hot test subset.

D. Comparative Analysis with Baseline Algorithms

The comparative behavior of all evaluated models is shown in Fig. 9. On the full three-class task, logistic regression remained the strongest model with 99.955% accuracy, followed by compressed logistic regression at 99.880%, SVM at 99.575%, and random forest at 97.250%. On the fair binary compressed subset, logistic regression and random forest both achieved 100.0% accuracy, while SVM and the quantum VQC both achieved 99.167%. This shows that the quantum branch is competitive after aggressive compression, but it does not outperform the strongest classical baselines.

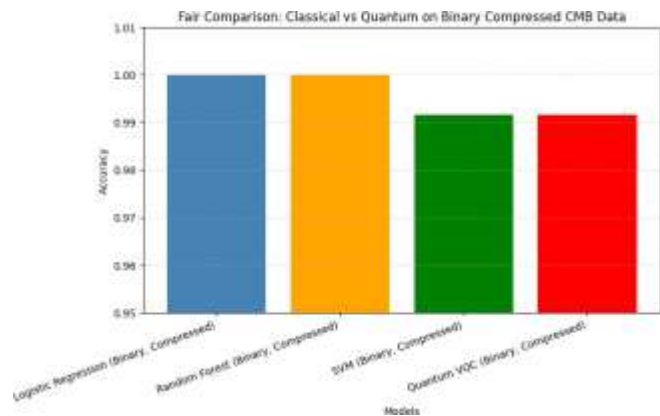


Fig. 9. Notebook-generated fair comparison of classical and quantum models on the binary compressed CMB subset.

E. Limitations and Ethical Considerations

Several limitations should be acknowledged. First, the classical models were trained and evaluated on the full three-class dataset, whereas the quantum model used a smaller balanced binary subset because variational simulation becomes expensive as dataset size grows. Second, the one-dimensional local patch representation is simpler than full spherical CMB analysis and does not capture every cosmological dependency. Third, the quantum model was evaluated only on a simulator, so hardware noise, finite shots, and calibration drift are absent.

Ethically, QML papers should avoid overstating quantum superiority when experiments use curated subsets or highly

separable data. Transparent reporting of preprocessing choices, subset sizes, and evaluation criteria is essential. Public scientific datasets should also be cited responsibly, with acknowledgement that a compressed simulation setup simplifies the complexity of full cosmological inference. The strongest claim supported here is that the proposed framework is a reproducible and meaningful hybrid QML demonstration, not evidence of general quantum advantage.

VII. CONCLUSION

This paper presented a hybrid quantum-classical framework for classifying CMB temperature-pattern patches derived from a public WMAP sky map. The workflow converted the original map into a 100,000-sample benchmark of length-9 local patches and assigned cold, neutral, and hot labels using percentile-based thresholds. Classical baselines showed that the dataset is highly separable: logistic regression achieved 99.955% accuracy, SVM achieved 99.575%, and random forest achieved 97.250%. A Ramanujan-inspired compression stage then reduced the feature space from 9 dimensions to 4 structured descriptors while still preserving 99.880% accuracy for compressed logistic regression.

The quantum branch used a 4-qubit, 3-layer variational classifier on a balanced binary subset of 400 training and 120 test samples. After angle encoding and 25 epochs of optimization, the best quantum configuration achieved 99.167% accuracy, 0.99 precision, 0.99 recall, and 0.99 F1-score, with confusion values of 59 true negatives, 1 false positive, 0 false negatives, and 60 true positives. The quantum loss also decreased from 0.4629 to 0.0894, showing stable optimization behavior. These findings demonstrate that low-qubit variational classification can remain highly competitive after structured feature compression. However, the study does not establish quantum advantage, because the strongest classical baselines remain equal or stronger on both the full three-class task and the fair binary comparison. The most appropriate interpretation is that the project demonstrates the feasibility, interpretability, and reproducibility of hybrid QML for cosmology-inspired data. Future work should investigate richer CMB representations and noisy-hardware validation. It also supports future hardware-aware quantum cosmology experiments.

REFERENCES

- [1] J.-C. Yang, S. Zhang, and C.-X. Yue, "A quantum machine learning classifier to search for new physics," *Journal of High Energy Physics*, vol. 2026, no. 23, 2026, doi: 10.1007/JHEP01(2026)023.
- [2] S. Jabeen, D. Kurdydyk, A. Palnitkar, *et al.*, "Quantum machine learning for state tomography using classical data," *Quantum Machine Intelligence*, vol. 8, art. no. 40, 2026, doi: 10.1007/s42484-026-00345-0.
- [3] F. A. Alotaibi, M. S. N. Yagmahan, K. A. Alobaid, *et al.*, "Quantum inspired feature engineering for explainable EEG signal classification," *Scientific Reports*, vol. 16, 2026, doi: 10.1038/s41598-026-41821-8.
- [4] R. K. Jha, N. Kasabov, S. Bhattacharyya, D. Coyle, and G. Prasad, "Comparative performance analysis of quantum feature maps for quantum kernel-based machine learning," *Scientific Reports*, vol. 16, art. no. 8142, 2026, doi: 10.1038/s41598-026-39392-9.
- [5] J. A. Bravo-Montes, A. Mart'ın-Toledano, C. Velasco-Gallego, *et al.*, "Design of a hybrid quantum machine learning architecture and analysis of quantum noise effects," *Scientific Reports*, 2026, doi: 10.1038/s41598-026-42216-5.

- [6] N. Dowling, M. T. West, A. Southwell, *et al.*, "Adversarial robustness guarantees for quantum classifiers," *npj Quantum Information*, vol. 12, art. no. 16, 2026, doi: 10.1038/s41534-025-01129-3.
- [7] I. Montalbán, E. F. Combarro, and J. Raniella, "A framework to study the relationship between classical data and quantum characteristics in quantum machine learning," *The Journal of Supercomputing*, vol. 82, art. no. 234, 2026, doi: 10.1007/s11227-026-08396-7.
- [8] G. Singh, H. Jin, and K. M. Merz Jr., "Benchmarking MedMNIST dataset on real quantum hardware," *Scientific Reports*, vol. 16, art. no. 9017, 2026, doi: 10.1038/s41598-026-35605-3.
- [9] V. Lopatkin, A. Sagingalieva, L. Lusnig, *et al.*, "Quantum hybrid feature selector," *EPJ Quantum Technology*, 2026, doi: 10.1140/epjqt/s40507-026-00491-1.
- [10] G. S. Franco, F. Mahlow, P. M. Prado, *et al.*, "Quantum phases classification using quantum machine learning with SHAP-driven feature selection," *Quantum Information Processing*, vol. 25, art. no. 106, 2026, doi: 10.1007/s11128-026-05132-1.
- [11] C. Daka and S. Bhattacharyya, "A novel quantum convolutional neural network framework for quantum-enhanced classification of pixelated colour images," *Scientific Reports*, 2026, doi: 10.1038/s41598-026-45140-w.
- [12] G. Sergioli, C. Cuccu, C. S. Rieger, *et al.*, "A quantum-inspired classification for random mixed states," *Scientific Reports*, vol. 16, art. no. 10668, 2026, doi: 10.1038/s41598-026-44068-5.
- [13] S. Mourya, H. Leipold, and B. Adhikari, "Contextual quantum neural networks for stock price prediction," *Scientific Reports*, vol. 16, art. no. 4454, 2026, doi: 10.1038/s41598-025-34413-5.
- [14] A. Tanji, H. Yano, and N. Yamamoto, "Quantum phase classification via partial tomography-based quantum hypothesis testing," *Scientific Reports*, vol. 16, art. no. 4555, 2026, doi: 10.1038/s41598-025-34610-2.
- [15] J. F. Hoorn and J. K. W. Ho, "Observer effect modulates classification in a quantum epistemic framework," *Scientific Reports*, 2026, doi: 10.1038/s41598-026-46604-9.
- [16] R. Palanivel and P. Muthulakshmi, "Error mitigation using quantum neural Q network in secure qutrit distribution on Cleve's protocol on quantum computing," *Quantum Information Processing*, vol. 23, art. no. 147, 2024, doi: 10.1007/s11128-024-04342-9.
- [17] R. Palanivel and P. Muthulakshmi, "Design and analysis of quantum transfer fractal priority replay and Mirdad priority loss algorithms for quantum reinforcement learning," in *Data Management, Analytics and Innovation, ICDMAI 2024, Lecture Notes in Networks and Systems*, vol. 997. Singapore: Springer, 2024, doi: 10.1007/978-981-97-3242-5_27.
- [18] R. Palanivel and P. Muthulakshmi, "Design and analysis of parallel quantum transfer fractal priority replay with dynamic memory algorithm in quantum reinforcement learning for robotics," *IET Quantum Communication*, 2024, doi: 10.1049/qt2.12111.
- [19] R. Palanivel and P. Muthulakshmi, "Quantum prioritized experience replay with MaDi-based priority and quantum circuit mechanisms for optimizing reinforcement learning," *International Journal of Advanced Technology and Engineering Exploration*, vol. 11, no. 121, pp. 1664–1680, 2024, doi: 10.19101/IJATEE.2024.111100094.