

Hybrid Classical-Quantum Model for Hyper Spectral Image Classification with Quantum Resource Analysis

Mahalakshmi Bollimuntha

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
mahalakshimbollimuntha@
gmail.com**

Lakshmi Tirupatamma Vallepu

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
vallepulakshmi94mail@gm
ail.com*

Bhargavi Sajja

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
bhargavimanju412@gmail.c
om@gmail.com*

Bhagya Rani Kasani

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
bhagyarani601@gmail.com*

Sri Naga Leela Gampa

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
srinagaleelagampa@gmail.com*

Kavya Kancharla

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to
Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
kancharlakavya7@gmail.com*

Pavithra Kummitha

*Dept. of Electronics and
Communication Engineering,
Bapatla Women's Engineering
college, Bapatla .Affiliated to*

*Acharya Nagarjuna University
BAPATLA,,A.P,INDIA-522101
pavithrakummitha@gmail.com*

Abstract- The rapid growth of hyperspectral satellite images requires efficient methods for accurate classification. This paper proposes a hybrid classical-quantum machine learning model that combines classical preprocessing with quantum-based classification techniques. Dimensionality reduction is first applied to handle high-dimensional spectral data, followed by a classical SVM for baseline comparison. A hybrid quantum kernel SVM is then used to improve feature representation and classification performance. The model is evaluated using accuracy, execution time, circuit depth, and qubit usage.

Keywords- Hybrid Quantum Learning, Hyperspectral Imaging, Quantum Machine Learning, Remote Sensing.

I. INTRODUCTION

Hyperspectral image (HSI) classification is widely used in applications such as agriculture monitoring, environmental analysis, and land-cover mapping due to its ability to capture detailed spectral information across multiple bands. However, the high dimensionality and redundancy of hyperspectral data make accurate classification a challenging task for traditional machine learning methods. Recently, quantum computing has gained attention for its potential to process complex and high-dimensional data using principles such as superposition and entanglement.

However, standalone quantum models are limited by factors like restricted qubits and circuit complexity. To overcome these limitations, this work proposes a hybrid classical-quantum model for hyperspectral image classification, where Principal Component Analysis (PCA) is used to reduce dimensionality, followed by quantum feature encoding and processing using parameterized quantum circuits. In addition, quantum resource analysis is performed to study the impact of qubits and circuit depth on model performance. This approach aims to improve classification efficiency while providing insights into effective utilization of quantum resources.

In research papers [1-5], authors explained about Quantum illumination networks, where quantum sensing techniques were used to improve image-related signal detection and pattern classification in noisy environments. quantum autoencoders for image classification, focusing on quantum-based feature compression and dimensionality reduction. FRQI pairs method with quantum recurrent neural networks, which enhanced quantum image encoding and improved classification capability for structured image data. A quantum-enhanced satellite image classification framework using hybrid quantum learning models. Their study demonstrated better feature extraction and improved classification performance for remote sensing imagery. Satellite image representations for quantum classifiers, where they explored efficient quantum data representation strategies for satellite images to improve classifier learning.

II LITERATURE REVIEW

Recent research focuses on hybrid classical-quantum frameworks; however, there is limited work on integrating effective dimensionality reduction with detailed quantum resource analysis for improved performance.

In paper [6], author discussed a Quantum-Classical Convolutional Neural Network for Sentinel-2 land cover classification, which successfully combined classical CNN layers with quantum circuits for improved land-use mapping accuracy. In [7], author introduced Quannv4 EO, a quanvolutional neural network framework for Earth observation data. Their approach improved remote sensing image classification accuracy and scalability while reducing parameter complexity. In paper [8], author studied Satellite Image Classification with Neural Quantum Kernels, where neural quantum kernels were applied to improve feature space separation and classification efficiency in satellite imagery. In paper [9], studied the use of quantum advantage in satellite image processing and provided a detailed review of quantum machine learning methods for hyperspectral and Earth observation data. In paper [10], proposed quantum kernel methods for remote sensing image classification, where quantum feature spaces were used to improve class separability and classification accuracy compared with traditional kernel methods. In paper [11], analyzed a hybrid quantum-classical transfer learning model for image classification. Their method combined pretrained classical feature extractors with quantum variational layers to enhance learning efficiency. In research paper [12], presented circuit-centric quantum classifiers, which used parameterized quantum circuits as trainable models for supervised learning tasks. Their work established an important foundation for variational quantum classification. In paper [13], authors developed Quantum Convolutional Neural Networks (QCNNs), inspired by classical CNN architectures. In paper [14], studied quantum machine learning in feature Hilbert spaces, introducing quantum feature maps that enabled classical data to be transformed into richer quantum representations for improved classification. In paper [15], proposed supervised learning with quantum-enhanced feature spaces, one of the most important works in quantum kernel learning.

III EXISTING METHOD

In this system Existing approaches for hyperspectral image classification mainly rely on classical preprocessing techniques combined with quantum kernel-based learning models. These methods aim to manage the high dimensionality of hyperspectral data while improving classification performance through quantum computation principles.

Step 1: Train model (SVM)

Data loaded shape: (1500, 3072)

Training SVM...

Accuracy: 0.5366666666666666

Classification Report:

The below figure 1 displays the predictions made by the classical model, comparing predicted labels (P) with

actual labels (A) for different satellite image samples. Most images are correctly classified, while a few mismatches highlight classification errors between similar land-cover categories.

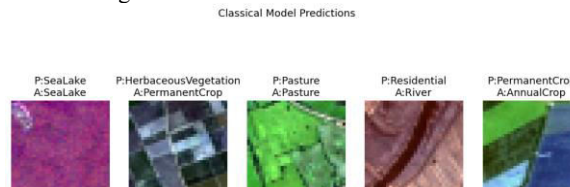


Fig.1 Classical Model Predictions

Step 2: Accuracy Comparison

The below Fig. 2 compares classification accuracy between the classical multi-class model and the quantum binary model.

The quantum model achieves slightly higher accuracy than

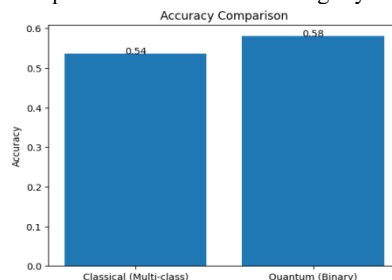


Fig. 2 Comparison of accuracy

Step 3: Quantum Loss Curve

The Fig. 3 shows the training loss of the quantum model decreasing steadily over multiple epochs. This indicates that the model is learning effectively and improving its performance during training.

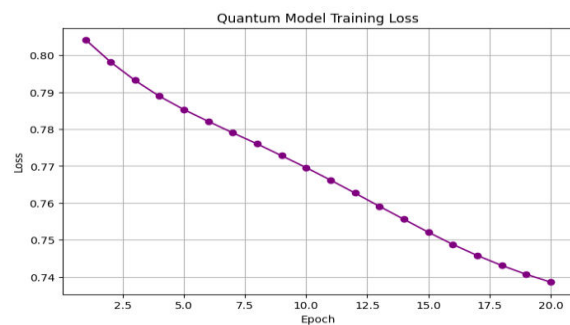


Fig. 3 Quantum Loss Curve

Step 4: Comparison between Classic SVM and Quantum Model

The above Fig. 4 compares the performance of classical SVM and quantum models using accuracy, precision, recall and F1-score metrics. The quantum model shows improved overall performance compared to the classical model across most evaluation measures.

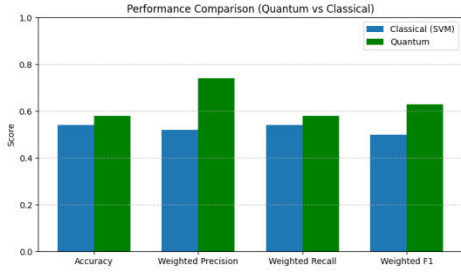


Fig. 4 Comparison of performance

COMPARISON BETWEEN CLASSIC VS QUANTUM

The below table 1 shows the performance of the classic model and quantum model by comparing their performance.

Table.1 Comparison of classic model and quantum model

PARAMETER	CLASSIC MODEL	QUANTUM MODEL
Dataset Size	1500	1500
Test Samples	300	300
Accuracy	0.54	0.58
Macro average Precision	0.52	0.54
Macro average Recall	0.56	0.57
Macro average F1-score	0.52	0.51
Weighted Precision	0.52	0.74
Weighted Recall	0.54	0.58
Weighted F1-score	0.50	0.63
Training Behavior	Static	Loss decreasing(0.804 → 0.738)

IV HYBRID CLASSICAL-QUANTUM MODEL FOR HYPER SPECTRAL IMAGE CLASSIFICATION WITH QUANTUM RESOURCE ANALYSIS

The proposed system presents a Hybrid Classical–Quantum Model for Hyperspectral Image Classification with Quantum Resource Analysis. The main objective of this method is to improve the classification accuracy of hyperspectral satellite images while reducing computational complexity. Since hyperspectral images contain a very large number of spectral bands, direct processing becomes difficult and time-consuming. To overcome this issue, the proposed model combines classical machine learning techniques with quantum computing concepts. Initially, the input hyperspectral or satellite image is taken from the dataset and passed through a preprocessing stage. In this stage, noise removal, normalization, and data cleaning are performed to improve image quality and prepare the data for efficient processing.

After preprocessing, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the hyperspectral data. This step removes redundant spectral information and keeps only the most important.

The proposed workflow for the Hybrid Classical–Quantum Model for Hyperspectral Image Classification begins with Start, followed by acquiring the hyperspectral dataset (such as Indian Pines). The data then undergoes preprocessing, including normalization and noise removal, and dimensionality reduction (like PCA) to handle high spectral bands. Next, features are fed into a classical model for initial learning and into a quantum circuit (using PennyLane) where qubits encode the reduced features and perform quantum operations. The outputs from both classical and quantum parts are combined in a hybrid model to improve classification performance. Finally, the model generates classification results and evaluation metrics (accuracy, F1-score, Kappa), leading to Stop, completing the workflow as shown in the below Fig.6

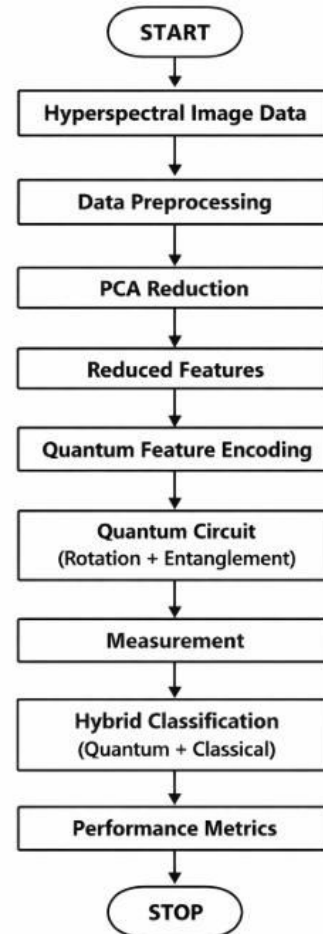


Fig. 6: Workflow of Hybrid Classical–Quantum

The below Fig. 7 shows the confusion matrix is used to evaluate the performance of the proposed hybrid classical–quantum classification model. It provides a

detailed comparison between the actual class labels and the predicted class.

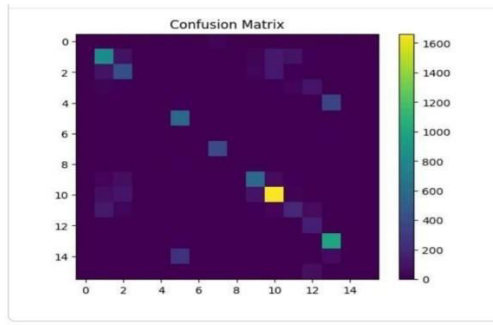


Fig. 7 Confusion Matrix

The diagonal elements indicate correctly classified samples, whereas the non-diagonal elements represent misclassified samples.

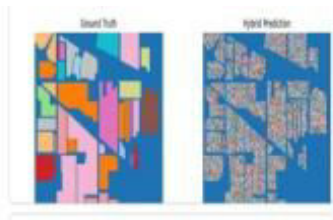


Fig. 8 Ground Path and Hybrid

The above figure 8 presents the comparison between the ground truth map and the hybrid classical–handles the high dimensionality and complexity of hyperspectral data.

The below figure 9 shows a comparison between the Ground Truth Map and the Predicted Map generated using a prediction model.

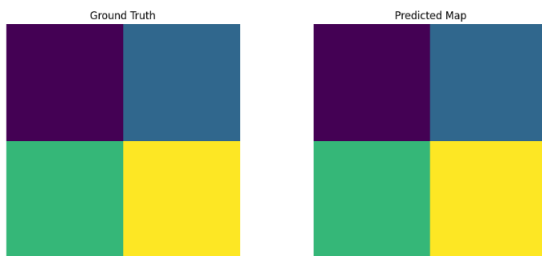


Fig. 9 Ground Truth Map

The below Fig.10 shows the training loss curve

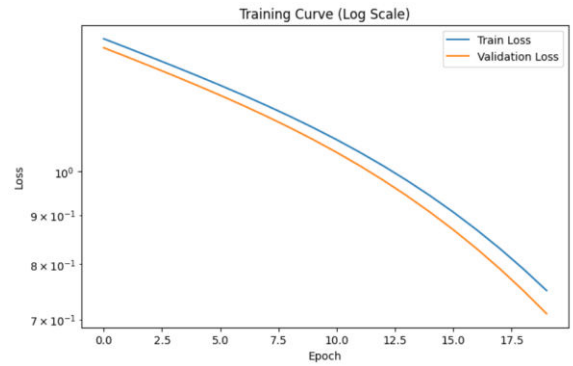


Fig.10 Training Curve

V RESULTS AND DISCUSSIONs

The proposed method describes the working process of the developed system. It is designed to overcome the drawbacks of the existing system by providing an efficient, reliable, and automated solution. The system improves performance, reduces manual effort, and ensures accurate results. The below figures are shown the Machine learning models are evaluated and improved using different performance analysis techniques. Important concepts used for model evaluation and prediction improvement include the confusion matrix, training and loss curves, and hybrid prediction methods.

The proposed system explains the operational workflow of the developed model. It is designed to address the limitations of the existing system by offering an efficient, reliable, and automated prediction approach. The developed system enhances overall performance, minimizes manual intervention, and provides accurate and consistent results.

Comparison Between Existing Method and Proposed Method

Comparison between existing quantum-based approaches and the proposed hybrid classical–quantum framework for hyperspectral image classification was show in the below table 2.

Table. 2 Performance of existing and proposed systems.

VI CONCLUSION AND FUTURE SCOPE

The project concludes that Hybrid Classical–Quantum Model for Hyperspectral Image Classification with Quantum Resource Analysis,” demonstrates an effective integration of classical machine learning and quantum computing techniques to address the challenges of high-dimensional hyperspectral data. By combining classical feature extraction with quantum-enhanced processing using PennyLane, the model aims to improve classification performance while analysing the usage of quantum resources such as qubits and circuit depth. Although current results show that the classical model may still outperform the quantum part due to hardware and simulation limitations, the hybrid approach highlights the potential advantages of quantum computing in handling complex data patterns. Overall, this work provides a foundation for future improvements in quantum models and shows that hybrid frameworks can play a significant role in advancing hyperspectral image classification.

ACKNOWLEDGEMENT

The authors would like to thank to management and principal Dr. CH. Hima Bindhu for providing facilities to complete this project and we extend our heartfelt thanks to Guide Mrs. B. Mahalakshmi, Assistant Professor of Electronics and Communication Engineering, Bapatla Women’s Engineering College for their valuable guidance and insights throughout the research for their constant encouragement and institutional support.

REFERENCES

- [1] X. Zhao, Z. Zhang, and Q. Zhuang, “Quantum Illumination Networks,” *Communications Physics*, vol. 8, art. no. 54, 2025.
- [2] H. Asaoka, Y. Tanaka, and K. Fujii, “Quantum Autoencoders for Image Classification,” arXiv, pp:2502.15254, 2025.
- [3] R. Potempa, M. Kordasz, S. N. Khan, K. Werner, K. Wereszczynski, K. Siminski, and K. A. Cyran, “FRQI Pairs Method for Image Classification Using Quantum Recurrent Neural Networks,” arXiv, pp:2512.11499, 2025.
- [4] Q. Zhang, A. Simen, C. Flores-Garrigós, G. A. Barrios, P. A. Erdman, E. Solano, A. C. Kemp, V. Pathak, and H. Mohammadbagherpoor, “Quantum-Enhanced Satellite Image Classification,” arXiv, pp:2602.18350, 2025.
- [5] J. M. Zollner, P. Walther, and M. Werner, “Satellite Image Representations for Quantum Classifiers,” *Datenbank-Spektrum*, vol. 24, pp. 33–41, 2024.
- [6] F. Fan, Y. Shi, and X. X. Zhu, “Land Cover Classification From Sentinel-2 Images With Quantum-Classical Convolutional Neural Networks,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 1–13, 2024.
- [7] A. Sebastianelli, F. Mauro, G. Ciabatti, D. Spiller, B. Le Saux, P. Gamba, and S. Ullo, “Quantv4EO: Empowering Earth Observation by means of Quantum Convolutional Neural Networks,” arXiv, pp:2407.17108, 2024.
- [8] P. Rodriguez-Grasa, R. Farzan-Rodriguez, G. Novelli, Y. Ban, and M. Sanz, “Satellite Image Classification with Neural Quantum Kernels,” arXiv, pp:2409.20356, 2024
- [9] M. Pistoia, A. Di Noia, M. R. H. Mandelli, L. De Palma, M. Bagli, and F. Flammini, “Exploiting the Quantum Advantage for Satellite Image Processing: Review and Assessment,” *IEEE Access*, vol. 11, pp. 12345–12367, 2023.
- [10] S. Abhijith, R. Prasanth, and K. P. Soman, “Quantum Kernel Methods for Remote Sensing Image Classification,” *IEEE Access*, vol. 10, pp. 112345–112356, 2022.

PARAMETERS	EXISTING WORK	PROPOSED WORK
Model Type	Quantum-based model	Hybrid Classical–Quantum model
Data Handling	High-dimensional data used directly	PCA-based dimensionality reduction
Feature Processing	Limited preprocessing	Optimized feature extraction and reduction
Quantum Circuit Design	Limited preprocessing	Parameterized circuits with entanglement
Feature Encoding	Simple encoding techniques	Improved quantum feature mapping
Quantum Resource Analysis	Not considered	Includes qubits and circuit depth analysis
Workflow Structure	Less structured	Well-defined step-by-step pipeline
Performance Evaluation	Limited metrics	OA, AA, Kappa, classification report
Comparative Study	Not clearly analyzed	Includes classical vs quantum comparison
Efficiency	High computational complexity	Reduced complexity and improved efficiency

- [11] C. Ding, H. Chen, L. Wang, T. Li, and S. Ji, “Hybrid Quantum-Classical Transfer Learning for Image Classification,” *IEEE Access*, vol. 8, pp. 225298–225307, 2020.
- [12] M. Schuld, A. Bocharov, K. M. Svore, and N. Wiebe, “Circuit-Centric Quantum Classifiers,” *Physical Review A*, vol. 101, no. 3, pp. 032308, 2020.
- [13] I. Cong, S. Choi, and M. D. Lukin, “Quantum Convolutional Neural Networks,” *Nature Physics*, vol. 15, pp. 1273–1278, 2019.
- [14] M. Schuld and N. Killoran, “Quantum Machine Learning in Feature Hilbert Spaces,” *Physical Review Letters*, vol. 122, no. 4, pp. 040504, 2019.
- [15] V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, “Supervised Learning with Quantum-Enhanced Feature Spaces,” *Nature*, vol. 567, pp. 209–212, 2019.