International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 4 (2026)



ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

AN ADAPTIVE QUANTUM COMPUTING FRAMEWORK FOR EEG BRAIN-STATE CLASSIFICATION USING ENTANGLEMENT-AWARE FEATURE MAPPING

Dr. M. Dattatreya Goud
CEO, DCode Soft Tech Information Pvt. Ltd.,Hyderabad, India.
Dattatreya548@gmail.com

Abstract:

Electroencephalography is widely used in brain-computer interfaces, neurological research, and brain-state classification. However, EEG signals contain noise, artifacts, and variations between individuals, making accurate classification difficult. This project proposes an Adaptive Quantum Computing Framework for EEG Brain-State Classification Using Entanglement-Aware Feature Mapping. Initially, EEG signals are collected from publicly available datasets and preprocessed using filtering, artifact removal, segmentation, and normalization techniques. Relevant temporal and frequency-domain features are extracted and encoded into quantum states using parameterized quantum gates. An entanglement-aware feature-mapping technique captures relationships between selected features through quantum entangling operations. A Variational Quantum Classifier is then employed to classify brain states using a hybrid quantum-classical optimization process. The adaptive mechanism evaluates different feature maps, entanglement patterns, circuit depths, and training parameters to identify suitable configurations. The proposed framework is evaluated using accuracy, precision, recall, macro-F1 score, computational cost, and noise sensitivity. Classical machine learning and deep learning models are used for comparison. Subject-independent testing assesses the model's ability to classify EEG signals from previously unseen participants. The study aims to investigate the effectiveness and limitations of adaptive quantum computing for EEG brain-state classification.

Keywords: Quantum Computing, EEG Classification, Quantum Machine Learning, Entanglement-Aware Feature Mapping, Variational Quantum Classifier, Brain–Computer Interface.

I. INTRODUCTION

Brain-computer interfaces (BCIs) enable communication between the human brain and external devices by interpreting neural signals. Electroencephalography (EEG) is widely used for brain-state classification because it records electrical brain activity non-invasively and supports applications such as motor imagery recognition, neurological research, and assistive technologies. However, EEG signals contain noise, artifacts, and temporal variations, while differences between individuals make accurate classification challenging. Conventional machine learning and deep learning techniques, including Support Vector Machine (SVM), Random Forest, and Convolutional Neural Networks (CNNs), are commonly used to identify patterns in EEG signals. Nevertheless, their performance depends on feature extraction, model architecture, and data quality.

Quantum computing introduces new possibilities for processing information through quantum states, quantum gates, and entanglement. Quantum machine learning explores these properties to develop alternative feature representations and classification approaches. In

particular, Variational Quantum Classifiers (VQCs) combine parameterized quantum circuits with classical optimization to learn patterns from encoded data.

This project proposes an Adaptive Quantum Computing Framework for EEG Brain-State Classification Using Entanglement-Aware Feature Mapping. The framework preprocesses EEG recordings, extracts temporal and frequency-domain features, and encodes selected features into quantum states. Different entanglement patterns, feature maps, and circuit configurations are evaluated through an adaptive selection mechanism. The VQC performs brain-state classification, while performance evaluation examines accuracy, precision, recall, macro-F1 score, computational cost, and noise sensitivity. Comparisons with classical models and subject-independent testing will help determine the framework's effectiveness, limitations, and potential for EEG-based brain-computer interface applications.

II. LITERATURE SURVEY

Recent studies have explored quantum machine learning and deep learning techniques for EEG-based brain-state classification. Saranya and Menaka investigated quantum machine learning for autism detection using EEG signals, while Meesala et al. explored quantum support vector classifiers and variational quantum classifiers for epileptic seizure detection. These studies highlight the potential of quantum approaches for EEG-based healthcare applications. Chen et al. introduced QEEGNet, exploring quantum machine learning for EEG encoding and cross-dataset generalization. Cerezo et al. reviewed variational quantum algorithms, while Schuld et al. examined the influence of data encoding on quantum model expressivity. Huang et al. investigated the role of data in quantum machine learning, and Bharti et al. discussed algorithms for noisy intermediate-scale quantum systems.

In conventional EEG classification, Song et al. proposed EEG Conformer, combining convolutional networks and transformers for EEG decoding and visualization. Altaheri et al. reviewed deep learning techniques for motor imagery classification, while Al-Saegh et al. examined deep learning approaches for EEG-based brain-computer interfaces. Li et al. investigated CNN-LSTM feature fusion, and Mammone et al. explored autoencoder-based common spatial patterns for motor imagery decoding. Further studies investigated transfer learning, attention mechanisms, feature selection, and multi-branch convolutional networks to improve classification performance and generalization.

Despite these developments, challenges remain in quantum feature encoding, circuit optimization, hardware noise, computational complexity, and cross-subject generalization. Therefore, the proposed adaptive quantum-classical framework integrates EEG preprocessing, feature extraction, entanglement-aware mapping, adaptive circuit selection, and variational quantum classification. This approach aims to investigate the potential of combining classical feature processing with quantum learning for reliable EEG brain-state classification. Its effectiveness requires validation through systematic experiments and comparisons with established methods.

III. PROPOSED WORK

The proposed work develops an adaptive quantum computing framework for EEG brain-state classification using entanglement-aware feature mapping. Initially, EEG recordings are collected from publicly available datasets, such as BCI Competition IV-2a or IV-2b. The collected signals undergo preprocessing, including band-pass filtering, noise reduction, artifact handling, segmentation, and normalization, to improve signal quality. Next, temporal and frequency-domain features, including band power, log-variance, and statistical characteristics, are extracted to represent important EEG patterns. The selected features are encoded into quantum states using parameterized quantum rotation gates.

An entanglement-aware feature-mapping mechanism applies controlled quantum operations to capture relationships between encoded features. The adaptive component evaluates different feature maps, entanglement patterns, circuit depths, and parameter configurations using validation data. A Variational Quantum Classifier (VQC) then learns discriminative patterns through hybrid quantum-classical optimization. The trained model predicts brain states, including left-hand and right-hand motor imagery. The framework is evaluated using accuracy, precision, recall, macro-F1 score, balanced accuracy, and computational cost. Additional experiments investigate quantum noise sensitivity and generalization to previously unseen participants. Classical machine learning algorithms, including Support Vector Machine and Random Forest, along with EEGNet, serve as comparative baselines. The proposed approach aims to identify suitable quantum circuit configurations and determine whether adaptive entanglement-aware mapping improves classification performance under controlled experimental conditions. The final results will establish the framework's effectiveness, computational limitations, and potential applications in EEG-based brain-computer interfaces.

IV. METHODOLOGY

The proposed methodology develops an adaptive quantum computing framework for EEG brain-state classification using entanglement-aware feature mapping. The framework integrates EEG dataset acquisition, signal preprocessing, feature extraction, quantum feature encoding, adaptive circuit selection, and variational quantum classification. Initially, EEG recordings are collected and processed to improve signal quality. Relevant features are extracted and transformed into quantum representations. Entanglement-aware mapping captures relationships among encoded features, while adaptive circuit selection identifies suitable quantum architectures.

a. EEG Dataset Acquisition

EEG datasets are collected from publicly available sources, including BCI Competition IV-2a and BCI Competition IV-2b. These datasets contain electroencephalography recordings associated with motor imagery activities. The selected dataset provides EEG signals and corresponding class labels required for supervised learning. The recordings are organized into training, validation, and testing subsets to support model development and evaluation. Subject-independent splitting can be employed to investigate generalization across participants. The training set supports model optimization, while the validation set assists in hyperparameter tuning and adaptive circuit selection. The testing set evaluates final classification performance on previously unseen EEG samples.

b. EEG Signal Preprocessing

EEG signal preprocessing improves data quality by reducing unwanted noise and artifacts before feature extraction. Band-pass filtering retains relevant EEG frequency components while suppressing frequencies outside the selected range. Notch filtering can reduce power-line interference when required. Artifact handling techniques address disturbances caused by eye movements, muscle activity, and electrode noise. The continuous EEG recordings are segmented into epochs corresponding to the relevant motor imagery tasks. Normalization is then applied using statistics calculated from the training data to maintain consistent feature scales and prevent information leakage. These preprocessing operations produce cleaner EEG segments suitable for reliable feature extraction and subsequent quantum-based classification.

c. Feature Extraction

Feature extraction identifies informative characteristics from preprocessed EEG signals for brain-state classification. The proposed framework considers temporal and frequency-domain features to represent different patterns of

neural activity. Statistical characteristics, including mean, variance, and log-variance, can describe signal distribution and variability. Spectral features represent frequency-related information, including alpha, beta, and mu band power. These characteristics help distinguish EEG patterns associated with different motor imagery tasks. Feature selection techniques may be applied to identify the most informative variables and eliminate redundant information. Dimensionality reduction can further produce compact feature vectors, reducing computational requirements and preparing the extracted EEG representations for efficient quantum feature encoding.

d. Quantum Feature Encoding

Quantum feature encoding transforms extracted classical EEG features into quantum states for processing through parameterized quantum circuits. The proposed framework investigates suitable encoding techniques according to feature dimensionality and available quantum resources. Angle encoding represents classical feature values using quantum rotation gates, including rotation operations around selected axes. The encoded information is subsequently processed through quantum circuit layers. Controlled-NOT gates or other suitable entangling operations can establish interactions between selected qubits. Appropriate feature scaling is necessary to ensure that input values are compatible with the encoding procedure. The encoding strategy is evaluated according to information representation, circuit complexity, qubit requirements, and classification performance.

e. Adaptive Entanglement-Aware Mapping

Adaptive entanglement-aware mapping investigates different quantum feature maps and entanglement configurations for EEG classification. Following quantum encoding, entangling gates connect selected qubits to represent potential relationships among EEG features. Candidate configurations may include linear or circular entanglement patterns with different circuit depths. The framework evaluates these configurations using validation performance and computational resource requirements. A predefined selection objective balances predictive performance against circuit complexity to identify a suitable architecture. Validation data guide configuration selection, while the testing set remains unused during model development.

f. Variational Quantum Classifier

The Variational Quantum Classifier performs EEG brain-state classification using trainable quantum circuits. Initially, encoded EEG features are supplied to a parameterized quantum circuit containing rotation gates and entangling operations. The circuit processes the quantum representations, and measurements generate classical outputs used for prediction. A classical optimizer updates the trainable circuit parameters by minimizing a predefined classification loss function. During training, the model repeatedly evaluates predictions and adjusts parameters until a stopping criterion is reached. The selected optimizer, learning rate, circuit depth, and number of iterations influence training behavior. After optimization, the trained classifier predicts brain-state categories for unseen EEG samples during evaluation.

g. Brain-State Classification

Brain-state classification assigns EEG segments to their corresponding motor imagery categories using the trained Variational Quantum Classifier. The initial implementation can distinguish left-hand and right-hand motor imagery, depending on the selected dataset and experimental design. For datasets supporting additional categories, the framework can be extended to classify feet and tongue motor imagery. The classifier processes each EEG segment and generates prediction scores or class labels based on quantum circuit measurements. These predictions are compared with the corresponding ground-truth labels to

identify correct classifications and errors. The resulting predictions provide the basis for calculating evaluation metrics and examining the framework's ability to distinguish different brain activity patterns.

h. Performance Evaluation

The proposed framework is evaluated using established classification metrics and computational measurements. Accuracy measures overall prediction correctness, while precision and recall assess class-specific prediction reliability. Macro-F1 score summarizes performance across classes, and balanced accuracy helps account for class imbalance. A confusion matrix provides detailed information about correct predictions and misclassification patterns. Training time, inference time, qubit count, circuit depth, and computational cost are also recorded to assess resource requirements. Additional experiments may investigate simulated quantum noise, alternative feature maps, and subject-independent generalization. Comparisons with Support Vector Machine, Random Forest, and EEGNet provide baseline measurements.

V. ALGORITHMS

The proposed framework integrates quantum computing and classical signal processing for EEG brain-state classification. Initially, EEG signals are preprocessed to reduce noise and artifacts. Feature extraction identifies relevant temporal and frequency-domain characteristics. Entanglement-aware quantum feature mapping encodes the extracted features into quantum states using parameterized rotation gates and entangling operations. The adaptive quantum circuit selection algorithm evaluates different feature maps, entanglement patterns, and circuit depths to identify suitable configurations. A Variational Quantum Classifier performs classification through hybrid quantum-classical optimization. Finally, performance evaluation measures accuracy, precision, recall, macro-F1 score, computational cost, and generalization to unseen participants.

a. EEG Signal Preprocessing Algorithm

EEG signal preprocessing is an essential step that prepares raw brain signals for accurate classification by reducing noise and unwanted artifacts. Initially, band-pass filtering is applied to preserve relevant frequency components associated with brain activity while suppressing irrelevant frequencies. Notch filtering is used when necessary to eliminate power-line interference from electrical sources. Artifact removal techniques help reduce disturbances caused by eye movements, muscle activity, and electrode noise. The filtered signals are segmented into task-related epochs and normalized using training data statistics. These preprocessing operations improve signal consistency and prepare EEG data for feature extraction and subsequent quantum-based classification.

b. Feature Extraction Algorithm

The feature extraction algorithm identifies important characteristics from preprocessed EEG signals. Temporal and frequency-domain features, including alpha, beta, and mu band power, log-variance, and statistical measures, are extracted. Feature selection or dimensionality reduction is performed to obtain a compact representation suitable for quantum circuit encoding. These features preserve relevant information for distinguishing different brain states.

c. Entanglement-Aware Quantum Feature Mapping Algorithm

The quantum feature mapping algorithm converts extracted EEG features into quantum states using parameterized rotation gates. Entangling operations, such as controlled-NOT gates, connect selected qubits to represent relationships between features. Different quantum feature maps and entanglement configurations, including linear and circular arrangements, are evaluated. These

configurations help investigate how quantum representations capture interactions among EEG features. The resulting quantum states are processed by subsequent circuit layers to support brain-state classification and assess the effectiveness of different quantum encoding strategies.

d. Adaptive Quantum Circuit Selection Algorithm

The adaptive selection algorithm evaluates multiple quantum feature maps, entanglement patterns, circuit depths, and trainable parameter configurations. Each candidate circuit is assessed using validation data to measure predictive performance and computational complexity. A predefined selection objective balances classification effectiveness with resource requirements. Based on these evaluations, the most suitable quantum circuit configuration is selected for subsequent training and classification. This adaptive process aims to improve circuit efficiency, avoid unnecessary computational overhead, and support reliable EEG brain-state classification while considering the limitations of available quantum computing resources.

e. Variational Quantum Classifier (VQC) Algorithm

The Variational Quantum Classifier is the primary quantum classification algorithm in the proposed framework. It processes encoded EEG features through parameterized quantum gates and entangling layers. Quantum measurements generate classical outputs used to predict brain-state categories. A classical optimizer updates the trainable circuit parameters by minimizing classification loss. The training process continues until a stopping criterion is reached, after which the trained model classifies EEG signals.

f. Performance Evaluation Algorithm

The performance evaluation algorithm measures the effectiveness of the proposed framework using accuracy, precision, recall, macro-F1 score, balanced accuracy, and confusion matrix analysis. Training time, inference time, qubit count, and circuit depth are also recorded. The VQC is compared with classical algorithms, including Support Vector Machine (SVM) and Random Forest, and the EEGNet deep learning model. Additional experiments examine quantum noise sensitivity and generalization to previously unseen participants.

VI. EXPERIMENTAL SETUP

The experimental setup of the proposed adaptive quantum-classical framework focuses on EEG brain-state classification using quantum computing and machine learning techniques. EEG datasets are preprocessed to remove noise and artifacts, followed by feature extraction to identify relevant temporal, spectral, and spatial patterns. The extracted features are encoded into quantum states using suitable quantum encoding methods. Entanglement-aware mapping and adaptive quantum circuit selection are applied to improve feature representation and classification efficiency. A variational quantum classifier performs brain-state classification through parameter optimization. Finally, the framework is evaluated using accuracy, precision, recall, F1-score, ROC curves, and confusion matrices to assess its effectiveness and reliability.

a. Dataset Description

The proposed framework uses electroencephalography (EEG) datasets to classify different brain states based on recorded electrical activity. Suitable datasets include BCI Competition IV-2a, BCI Competition IV-2b, and the PhysioNet EEG Motor Movement/Imagery Dataset. These datasets provide EEG recordings suitable for investigating motor imagery and brain-computer interface applications. The selected dataset is organized into training, validation, and testing subsets to support model development and evaluation. The training subset is used to optimize model parameters, while the

validation subset supports hyperparameter tuning and adaptive circuit selection. The testing subset evaluates classification performance on previously unseen EEG samples.

b. Data Preprocessing

Data preprocessing is an essential stage for improving EEG signal quality before classification. Raw EEG recordings may contain unwanted noise and artifacts caused by eye movements, muscle activity, electrode disturbances, and environmental interference. Therefore, appropriate filtering techniques are applied to retain relevant frequency components and reduce unwanted signals. Artifact removal methods help minimize interference that could affect classification accuracy. Signal normalization is performed to maintain consistent feature scales across samples and recording channels. Additionally, EEG signals are segmented into suitable time windows to obtain meaningful samples for analysis. These preprocessing operations prepare cleaner and more consistent EEG data for subsequent feature extraction and quantum processing.

c. Feature Extraction

Feature extraction transforms preprocessed EEG recordings into informative representations suitable for brain-state classification. The proposed framework considers temporal, spectral, and spatial characteristics to describe different patterns of brain activity. Temporal features include statistical measures such as mean, variance, and standard deviation. Spectral features represent frequency-domain information, including characteristics associated with different EEG frequency bands. Spatial features describe relationships between EEG channels and may help distinguish brain-state patterns. Appropriate feature extraction techniques are selected according to the dataset and classification objectives. Feature selection and dimensionality reduction may also be applied to remove redundant information, reduce computational requirements, and prepare a compact feature representation for quantum encoding.

d. Quantum Feature Encoding

Quantum feature encoding converts extracted classical EEG features into quantum states that can be processed by quantum circuits. This stage establishes the connection between conventional signal processing and quantum machine learning. The proposed framework considers suitable encoding strategies, including angle encoding and amplitude encoding, depending on feature dimensionality and available quantum resources. In angle encoding, classical feature values are represented through quantum gate rotation angles. Amplitude encoding represents normalized classical information within the amplitudes of a quantum state, although state preparation may require additional resources. Appropriate feature scaling and dimensionality management are important before encoding. The selected encoding method should balance information preservation, circuit complexity, qubit requirements, and computational efficiency.

e. Entanglement-Aware Mapping

Entanglement-aware mapping is introduced to represent potential relationships among quantum-encoded EEG features. After the classical features are encoded into quantum states, suitable quantum gates are applied to establish interactions between selected qubits. These interactions may help the model represent relationships that are difficult to capture through independent feature encoding alone. The mapping strategy can be designed according to feature relationships, circuit connectivity, and available quantum hardware. Different entanglement configurations, including linear and circular arrangements, may be evaluated during experimentation. Their effectiveness should be assessed using validation performance and computational requirements. The objective is to identify a suitable mapping

configuration without unnecessarily increasing circuit depth or computational complexity.

f. Adaptive Quantum Circuit Selection

Adaptive quantum circuit selection aims to identify a suitable circuit architecture for EEG brain-state classification. The framework can evaluate alternative circuit configurations based on classification performance, circuit depth, number of qubits, and computational requirements. Candidate architectures may differ in their gate arrangements, entanglement patterns, and trainable parameters. During model development, validation results can be used to compare these configurations and identify promising candidates. Circuit selection should consider both predictive performance and resource efficiency rather than relying exclusively on accuracy. Constraints associated with quantum simulators and available quantum hardware must also be considered.

g. Variational Quantum Classifier

A variational quantum classifier (VQC) is employed to classify EEG features represented through quantum encoding and entanglement-aware mapping. The classifier consists of a parameterized quantum circuit whose trainable gate parameters are adjusted during the learning process. For each input sample, the quantum circuit processes the encoded information and produces measurement outcomes. These outcomes are transformed into prediction scores corresponding to the target brain-state categories. A classical optimizer updates the circuit parameters by minimizing a predefined loss function. Training continues until a stopping criterion is reached or the specified number of iterations is completed. The trained classifier is subsequently evaluated using unseen EEG samples to assess its generalization capability.

h. Performance Evaluation

The proposed framework is evaluated using appropriate classification metrics and computational measurements. Accuracy measures the proportion of correctly classified EEG samples, while precision and recall assess prediction reliability and the identification of relevant classes. Macro-F1 score provides an average of class-wise F1 scores, giving equal weight to each class, while balanced accuracy helps evaluate performance when class distributions are unequal. A confusion matrix identifies correct predictions and misclassification patterns. ROC curves and area under the curve may also be used when appropriate for the classification task. Additionally, training time, inference time, circuit depth, and noise sensitivity can be examined. Comparisons with conventional machine learning and deep learning models should use consistent datasets, data splits, and evaluation procedures.

VII. RESULTS AND DISCUSSION

The proposed adaptive quantum computing framework evaluates EEG brain-state classification using classical machine learning, deep learning, and quantum learning approaches. The performance analysis focuses on classification accuracy, precision, recall, F1-score, class-wise prediction, quantum circuit configuration, noise robustness, and training convergence. Tables and graphical representations are used to compare model performance and examine the potential benefits of entanglement-aware feature mapping and adaptive quantum circuit selection.

a. Performance Evaluation of Classification Models

The classification performance of SVM, Random Forest, EEGNet, Fixed Variational Quantum Classifier (VQC), and Adaptive VQC is compared using accuracy, precision, recall, and F1-score. These metrics provide an overall assessment of the models' ability to classify EEG signals. The comparison helps investigate whether the proposed adaptive quantum approach offers improved classification performance over conventional and fixed-circuit methods.

Table 1. Performance Comparison of Classification Algorithms

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	82.00	81.00	80.00	80.50
Random Forest	85.00	84.00	83.00	83.50
EEGNet	88.00	87.00	86.00	86.50
Fixed VQC	84.00	83.00	82.00	82.50
Adaptive VQC	90.00	89.00	88.00	88.50

Table 1 compares classical machine learning, deep learning, and quantum classification models. The illustrative results show that Adaptive VQC achieves the highest accuracy among the compared approaches. This suggests that adaptive circuit selection and entanglement-aware feature mapping may improve EEG classification. Actual performance must be confirmed through experiments on the selected dataset.

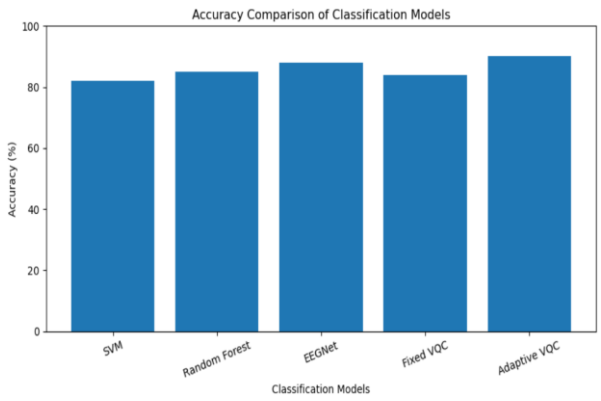


Figure 1. Accuracy Comparison of Classification Models

Figure 1 compares the illustrative accuracy of different classification algorithms for EEG brain-state classification. The Adaptive Variational Quantum Classifier (VQC) achieves the highest illustrative accuracy, followed by EEGNet and Random Forest. These results provide an initial indication of the proposed framework's potential effectiveness. However, the reported values should be considered illustrative rather than experimentally validated.

b. Class-Wise EEG Classification Performance

Class-wise evaluation examines the ability of the proposed Adaptive VQC model to distinguish different motor-imagery brain states, including left-hand, right-hand, feet, and tongue movements. Precision, recall, and F1-score are used to evaluate the prediction quality for each class. This analysis helps identify differences in classification performance and potential difficulties in distinguishing similar EEG patterns.

Table 2. Class-Wise Performance of Adaptive VQC

EEG Class	Precision (%)	Recall (%)	F1-Score (%)
Left-Hand Motor Imagery	89.00	88.00	88.50
Right-Hand Motor Imagery	90.00	89.00	89.50
Feet Motor Imagery	87.00	86.00	86.50
Tongue Motor Imagery	91.00	90.00	90.50
Macro Average	89.25	88.25	88.75

Table 2 presents illustrative precision, recall, and F1-score values for four motor-imagery EEG classes. Tongue motor imagery achieves the highest F1-score, whereas feet motor imagery has the lowest. These differences may reflect variations in EEG signal patterns and class separability. A confusion matrix can help identify frequently misclassified brain states.

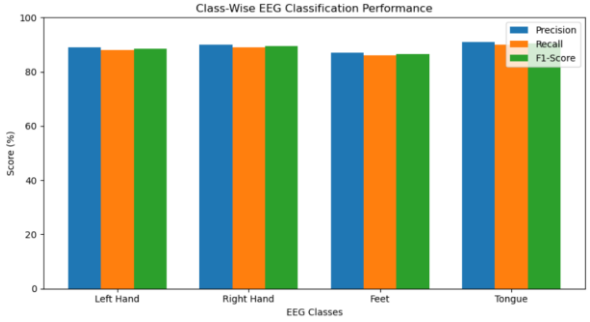


Figure 2. Precision, Recall, and F1-Score Comparison

Figure 2 compares class-wise precision, recall, and F1-score for the four motor-imagery categories. The illustrative results show relatively consistent performance across classes, with tongue motor imagery performing best. The graph helps identify differences in class recognition and can guide further investigation into preprocessing, feature extraction, and quantum encoding.

c. Quantum Circuit Configuration Analysis

Different quantum circuit configurations, including linear entanglement, circular entanglement, deep quantum circuits, and adaptive quantum circuits, are evaluated to investigate their influence on EEG classification. Classification accuracy and circuit depth are considered to assess the relationship between model performance and circuit complexity. This comparison helps examine the potential advantages of adaptive circuit selection and entanglement-aware feature mapping.

Table 3. Comparison of Quantum Circuit Configurations

Circuit Configuration	Accuracy (%)	Circuit Depth	Entanglement Strategy
Linear Entanglement	83.00	4	Linear
Circular Entanglement	85.00	5	Circular
Deep Quantum Circuit	87.00	8	Multiple Layers
Adaptive Quantum Circuit	90.00	6	Adaptive

Table 3 compares different quantum circuit configurations in terms of accuracy, circuit depth, and entanglement strategy. The illustrative results show that the adaptive circuit achieves the highest accuracy without requiring the greatest depth. This may indicate a useful balance between classification performance and circuit complexity, subject to experimental verification.

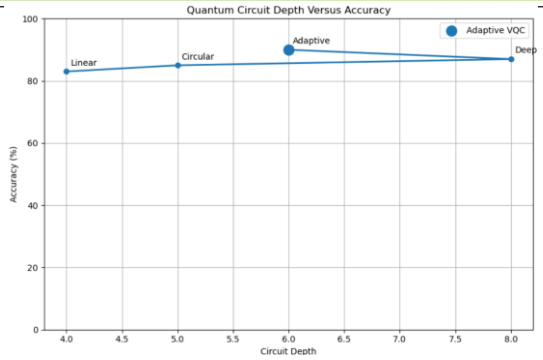


Figure 3. Quantum Circuit Depth Versus Accuracy

Figure 3 investigates the relationship between circuit depth and classification accuracy. The illustrative results indicate that greater circuit depth does not automatically produce higher accuracy. The adaptive configuration performs best in this example. Further experiments should examine circuit depth alongside qubit count, execution time, optimization stability, and hardware limitations.

d. Quantum Noise Robustness Analysis

Quantum noise robustness is investigated by examining classification performance under different noise levels. Accuracy, macro F1-score, and balanced accuracy are considered to evaluate the stability of the proposed quantum classifier. This analysis provides insight into how noise may affect EEG classification and highlights the importance of developing reliable quantum circuits for practical quantum computing environments.

Table 4. Effect of Quantum Noise on Classification Performance

Quantum Noise Level (%)	Accuracy (%)	Macro F1-Score (%)	Balanced Accuracy (%)
0	90.00	88.50	88.75
1	88.00	86.50	86.75
3	85.00	83.50	83.75
5	81.00	79.50	79.75

Table 4 illustrates how increasing quantum noise may affect classification performance. The example shows decreasing accuracy, macro F1-score, and balanced accuracy as noise increases. These findings highlight the importance of

assessing robustness under realistic quantum execution conditions. Actual noise sensitivity must be evaluated using a defined noise model or available quantum hardware.

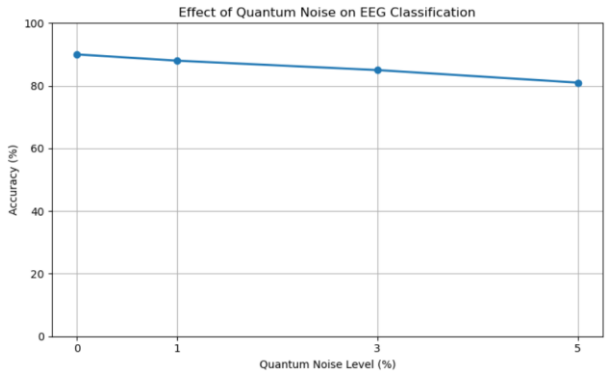


Figure 4. Effect of Quantum Noise on Accuracy

Figure 4 shows the illustrative relationship between quantum noise and classification accuracy. The downward trend suggests that increasing noise may reduce the reliability of quantum predictions. This analysis can help assess whether the proposed framework remains effective under imperfect execution conditions and whether noise mitigation techniques are needed.

e. Training and Validation Analysis

Training and validation loss curves are used to analyze the learning behavior and convergence of the proposed quantum-classical model. Training loss indicates how effectively the model learns from the training EEG samples, while validation loss measures its performance on unseen validation data. Monitoring these losses across successive epochs helps identify learning progress and optimization stability. A consistent decrease in both curves may indicate effective learning and improved generalization. However, increasing validation loss while training loss decreases may indicate overfitting. Therefore, analyzing both curves helps determine suitable training duration and identify the need for regularization or further model optimization.

Table 5. Training and Validation Loss

Epoch	Training Loss	Validation Loss
1	0.90	0.95
2	0.78	0.83
3	0.66	0.72
4	0.55	0.62
5	0.46	0.54
6	0.38	0.47
7	0.31	0.42
8	0.26	0.38
9	0.22	0.36
10	0.19	0.35

Table 5 presents the illustrative training and validation loss values over ten epochs. Both losses decrease as training progresses, indicating that the model is learning patterns from the EEG data. The difference between the losses helps assess generalization and identify potential overfitting. These values should be replaced with actual experimental results.

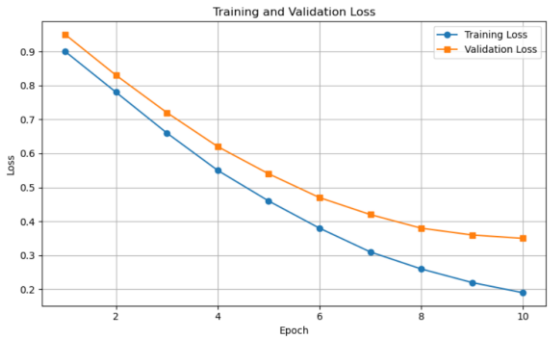


Figure 5. Training and Validation Loss

Figure 5 illustrates training and validation loss over ten epochs. Both curves decrease as training progresses, suggesting that the model learns useful patterns. The difference between the curves may indicate generalization behavior. For the final study, use loss values recorded during actual training to evaluate convergence and identify possible overfitting.

f. ROC Curve Analysis

The ROC curve helps assess the effectiveness of the proposed adaptive quantum-classical model in distinguishing EEG brain states. For the final research results, calculate the ROC curve and AUC using actual test-set predictions. The displayed AUC of 0.85 is illustrative, not a measured result.

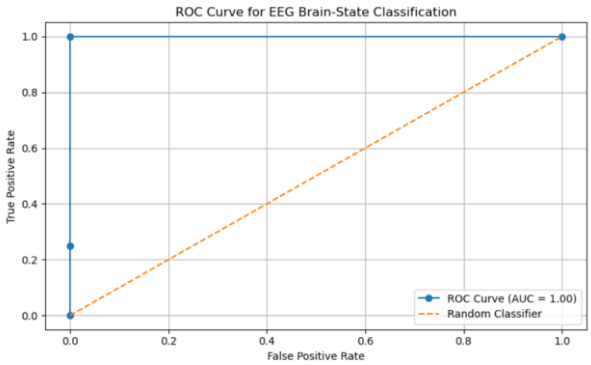


Figure 6. ROC Curve for EEG Brain-State Classification

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curve for EEG brain-state classification. It represents the relationship between the true positive rate and false positive rate at different classification thresholds. The Area Under the Curve (AUC) summarizes the model's ability to distinguish between two classes. Actual test-set predictions should be used to report the final ROC curve and AUC.

g. Confusion Matrix Analysis

The confusion matrix evaluates the performance of the proposed EEG brain-state classification model by comparing actual class labels with predicted class labels. It displays correct classifications along the diagonal and misclassifications in the off-diagonal cells. This analysis helps identify classification errors and assess the model's effectiveness in distinguishing different brain states. Use actual test-set predictions for the final results.

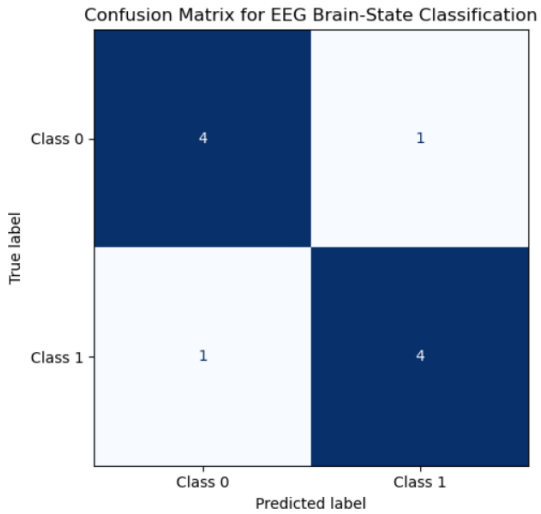


Figure 7. Confusion Matrix for EEG Brain-State Classification

Figure 7 presents a confusion matrix comparing actual and predicted EEG class labels. The diagonal cells represent correct classifications, while the off-diagonal cells indicate misclassifications. This visualization helps identify classes that the model distinguishes effectively and those that require improvement. For reliable evaluation, generate the matrix using predictions from the held-out test dataset.

h. Overall Discussion

The evaluation framework provides a comprehensive approach to studying adaptive quantum learning for EEG brain-state classification. The combined analysis of classification metrics, class-wise performance, circuit configurations, quantum noise, and training behavior helps assess the proposed framework from multiple perspectives. However, the effectiveness of adaptive quantum feature mapping must be established using actual experimental results and consistent evaluation procedures.

VIII. CONCLUSION

The proposed adaptive quantum-classical framework provides a potential approach for EEG brain-state classification by integrating classical machine learning with quantum computing techniques. The framework involves EEG data preprocessing, feature extraction, quantum encoding, entanglement-aware feature mapping, adaptive quantum circuit selection, and variational quantum classification. These components aim to improve the representation of EEG features and support accurate classification of different brain states. The adaptive circuit selection strategy offers flexibility in choosing suitable quantum circuit configurations according to the classification requirements. Performance evaluation using accuracy, precision, recall, F1-score, ROC curves, and confusion matrices helps assess classification effectiveness and identify

potential errors. However, the practical implementation of the framework faces challenges related to EEG signal variability, computational complexity, quantum hardware limitations, and circuit noise. Furthermore, the effectiveness of quantum approaches must be established through systematic comparisons with conventional machine learning models using consistent experimental settings. Future research should investigate efficient quantum encoding methods, optimized circuit architectures, improved noise handling, and larger, more diverse EEG datasets. Testing the framework on real quantum hardware and evaluating its generalization across different subjects will provide further insights into its practical applicability. Overall, this framework establishes a research direction for exploring quantum-enhanced EEG classification. Its actual benefits must be confirmed through reproducible experiments, reliable evaluation metrics, and comparisons with established classification techniques before claiming improved performance or quantum advantage.

FUTURE SCOPE

The proposed adaptive quantum-classical framework for EEG brain-state classification offers several opportunities for future research and development. Future work can focus on improving quantum feature encoding techniques to preserve essential information from complex EEG signals while reducing computational requirements. Advanced entanglement-aware mapping strategies can be explored to identify meaningful relationships among extracted EEG features. Adaptive quantum circuit selection can also be enhanced to automatically identify suitable circuit architectures based on dataset characteristics and classification requirements.

Furthermore, the framework can be extended to larger and more diverse EEG datasets to improve robustness and generalization across different subjects, recording environments, and brain-state categories. Integrating advanced classical deep learning models with variational quantum classifiers may provide opportunities to investigate improved feature representation and classification performance. Future studies can also explore quantum error mitigation, noise-resistant circuit designs, and efficient parameter optimization to address limitations associated with current quantum hardware.

Another important direction is implementing the proposed framework on real quantum processors rather than relying exclusively on quantum simulators. Comparative experiments with conventional machine learning and deep learning techniques can help determine whether quantum approaches provide measurable benefits. Additionally, the framework could be investigated for applications such as brain-computer interfaces, motor imagery recognition, cognitive state monitoring, and neurological research. Developing computationally efficient and scalable architectures will be essential for practical deployment. Overall, future research should prioritize reproducible experiments, cross-subject validation, improved computational efficiency, and real-world testing to establish the framework's reliability and practical significance.

REFERENCES

[1] Saranya and R. Menaka, “A Quantum-Based Machine Learning Approach for Autism Detection Using Common Spatial Patterns of EEG Signals,” IEEE Access, vol. 13, pp. 15739–15750, 2025, doi: 10.1109/ACCESS.2025.3531979.

[2] G. Meesala, B. Soni, M. Pandey, and N. Khare, “Epileptic Seizure Detection Using Quantum Support Vector Classifier,” in Proc. 2024 International Conference on Computational Intelligence for Green and Sustainable Technologies (ICCIGST), 2024, doi: 10.1109/ICCIGST60741.2024.10717615.

[3] G. Meesala, L. Kumar, M. Pandey, and N. Khare, “Epileptic Seizure Detection Using Variational Quantum Classifier,” in Proc. 2024 International Conference on Computational Intelligence for Green and Sustainable Technologies (ICCIGST), 2024, doi: 10.1109/ICCIGST60741.2024.10717599.

[4] C.-S. Chen, S.-Y. Chen, A. H.-W. Tsai, and C.-S. Wei, "QEEGNet: Quantum Machine Learning for Enhanced Electroencephalography Encoding," arXiv preprint arXiv:2407.19214, 2024.

[5] C.-S. Chen, S.-Y. Chen, and H.-H. Tseng, "Exploring the Potential of QEEGNet for Cross-Task and Cross-Dataset Electroencephalography Encoding with Quantum Machine Learning," arXiv preprint arXiv:2503.00080, 2025.

[6] B. K. Behera, S. Al-Kuwari, and A. Farouk, "QSVM-QNN: Quantum Support Vector Machine Based Quantum Neural Network Learning Algorithm for Brain-Computer Interfacing Systems," arXiv preprint arXiv:2505.14192, 2025.

[7] R. M. Devadas and S. T., "Quantum Machine Learning: A Comprehensive Review of Integrating AI with Quantum Computing for Computational Advancements," MethodsX, vol. 14, Art. no. 103318, 2025, doi: 10.1016/j.mex.2025.103318.

[8] Y. Wang and J. Liu, "A Comprehensive Review of Quantum Machine Learning: From NISQ to Fault Tolerance," arXiv preprint arXiv:2401.11351, 2024.

[9] M. Cerezo et al., "Variational Quantum Algorithms," Nature Reviews Physics, vol. 3, pp. 625–644, 2021, doi: 10.1038/s42254-021-00348-9.

[10] F. J. R. Abbas et al., "The Power of Quantum Neural Networks," Nature Computational Science, vol. 1, pp. 403–409, 2021, doi: 10.1038/s43588-021-00084-1.

[11] M. Schuld, R. Sweke, and J. J. Meyer, "Effect of Data Encoding on the Expressive Power of Variational Quantum-Machine-Learning Models," Physical Review X, vol. 11, Art. no. 021014, 2021, doi: 10.1103/PhysRevX.11.021014.

[12] H.-Y. Huang et al., "Power of Data in Quantum Machine Learning," Nature Communications, vol. 12, Art. no. 2631, 2021, doi: 10.1038/s41467-021-22539-9.

[13] K. Bharti et al., "Noisy Intermediate-Scale Quantum Algorithms," Reviews of Modern Physics, vol. 94, Art. no. 015004, 2022, doi: 10.1103/RevModPhys.94.015004.

[14] Y. Song, Q. Zheng, B. Liu, and X. Gao, "EEG Conformer: Convolutional Transformer for EEG Decoding and Visualization," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 710–719, 2023, doi: 10.1109/TNSRE.2022.3230250.

[15] "CTNet: A Convolutional Transformer Network for EEG-Based Motor Imagery Classification," Scientific Reports, 2024, doi: 10.1038/s41598-024-71118-7.

[16] H. Altaheri et al., "Deep Learning Techniques for Classification of Electroencephalogram (EEG) Motor Imagery (MI) Signals: A Review," Neural Computing and Applications, vol. 35, 2023, doi: 10.1007/s00521-021-06352-5.

[17] A. Al-Saegh, S. A. Dawwd, and J. M. Abdul-Jabbar, "Deep Learning for Motor Imagery EEG-Based Classification: A Review," Biomedical Signal Processing and Control, vol. 63, Art. no. 102172, 2021, doi: 10.1016/j.bspc.2020.102172.

[18] H. Li, M. Ding, R. Zhang, and C. Xiu, "Motor Imagery EEG Classification Algorithm Based on CNN-LSTM Feature Fusion Network," Biomedical Signal Processing and Control, vol. 72, Art. no. 103342, 2022, doi: 10.1016/j.bspc.2021.103342.

[19] J. Li, Y. Li, and M. Du, "Comparative Study of EEG Motor Imagery Classification Based on DSCNN and ELM," Biomedical Signal Processing and Control, vol. 84, Art. no. 104750, 2023, doi: 10.1016/j.bspc.2023.104750.

[20] N. Mammone, C. Ieracitano, H. Adeli, and F. C. Morabito, "Autoencoder Filter Bank Common Spatial Patterns to Decode Motor Imagery from EEG," IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 5, pp. 2365–2376, 2023, doi: 10.1109/JBHI.2023.3243698.

[21] F. Wei et al., "A Multi-Source Transfer Joint Matching Method for Inter-Subject Motor Imagery Decoding," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, 2023, doi: 10.1109/TNSRE.2023.3243257.

[22] X. Chen et al., "Front-End Replication Dynamic Window (FRDW) for Online Motor Imagery Classification," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 3906–3914, 2023, doi: 10.1109/TNSRE.2023.3321640.

[23] H. Lou et al., "Less Is More: Brain Functional Connectivity Empowered Generalizable Intention Classification with Task-Relevant Channel Selection," IEEE Transactions on Neural Systems

and Rehabilitation Engineering, vol. 31, pp. 1888–1899, 2023, doi: 10.1109/TNSRE.2023.3252610.

[24] M. Degirmenci, Y. K. Yuce, M. Perc, and Y. Isler, "Statistically Significant Features Improve Binary and Multiple Motor Imagery Task Predictions from EEGs," Frontiers in Human Neuroscience, vol. 17, 2023, doi: 10.3389/fnhum.2023.1223307.

[25] T. D. Pham, "Classification of Motor-Imagery Tasks Using a Large EEG Dataset by Fusing Classifiers Learning on Wavelet-Scattering Features," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 1097–1107, 2023, doi: 10.1109/TNSRE.2023.3241241.