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Quantum Machine Learning Techniques for Decoding Brainwave Signals

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***Abstract*-The accurate decoding of brainwave signals is critical for advancing applications in brain-computer interfaces (BCIs), neurological diagnostics, and cognitive state monitoring. Traditional machine learning approaches such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) have demonstrated notable success in EEG signal classification tasks; however, they are often constrained by the need for large, annotated datasets, handcrafted feature engineering, and high computational costs. The emerging field of Quantum Machine Learning (QML) offers new possibilities by leveraging quantum computational principles to process complex, high-dimensional data more efficiently.**

In this study, we investigate the use of QML techniques for decoding EEG signals by implementing and comparing four models: Quantum Support Vector Classifier (QSVC), Variational Quantum Classifier (VQC), classical Support Vector Classifier (SVC), and Random Forest. A synthetic EEG-like dataset is generated to simulate brainwave patterns, and models are evaluated based on Accuracy, Precision, Recall, and F1-Score, supported by Confusion Matrix and ROC Curve analyses. Results indicate that while classical models like Random Forest and SVC currently outperform quantum models in accuracy, QML models demonstrate feasibility and offer a foundation for future advancements. The study highlights the potential of quantum approaches in EEG decoding tasks and discusses avenues for further optimization with the evolution of quantum hardware.

***Index Terms*- Quantum Machine Learning, EEG Signal Decoding, Brainwave Analysis, QSVC, VQC, Support Vector Classifier, Random Forest, Quantum Computing, ROC Curve, Confusion Matrix.**

I. INTRODUCTION

The human brain emits electrical signals that can be captured and analyzed through electroencephalography (EEG), offering valuable insights into cognitive states, neurological disorders, and brain-computer interface (BCI) applications. EEG signals, however, are inherently nonlinear, nonstationary, and prone to noise, making their classification and interpretation highly challenging. Traditional machine learning techniques such as Support Vector Machines (SVMs), Random Forests, and Convolutional Neural Networks (CNNs) have been employed to decode EEG signals with varying degrees of success. While these methods have shown promise, they often require extensive feature engineering, large annotated datasets, and substantial computational resources, which limit their scalability and real-time applicability.

The advent of Quantum Computing has introduced new paradigms for machine learning, collectively referred to as Quantum Machine Learning (QML). By exploiting quantum phenomena like superposition, entanglement, and interference, QML algorithms have the potential to process complex data spaces more efficiently than classical algorithms. Quantum classifiers, such as the Quantum Support Vector Classifier (QSVC) and Variational Quantum Classifier (VQC), are designed to leverage these properties to achieve better generalization on high-dimensional datasets. This study investigates the application of QSVC and VQC models for decoding EEG brainwave signals and compares their performance with classical SVC and Random Forest classifiers. The research aims to evaluate the current viability of QML approaches in EEG signal processing and to identify the opportunities and limitations that exist in this emerging interdisciplinary domain.

II. LITERATURE SURVEY

Recent advancements in Quantum Machine Learning (QML) have opened new possibilities in the analysis and classification of complex datasets like EEG signals. Schuld et al. (2015) laid the foundational understanding of how quantum computing principles can enhance classical machine learning models, highlighting the potential for exponential speedups in learning tasks. Building on this, Havlíček et al. (2019) demonstrated the use of quantum-enhanced feature spaces, introducing quantum kernels that enable classifiers to capture more complex relationships in data compared to their classical counterparts.

In the context of classification problems, Rebentrost et al. (2014) proposed the Quantum Support Vector Machine (QSVM) model, which leverages quantum properties to solve optimization problems more efficiently than classical SVMs. Biamonte et al. (2017) provided a comprehensive review of Quantum Machine Learning techniques, discussing hybrid models that integrate quantum and classical components to tackle practical machine learning problems. More recently, Lutz et al. (2021) applied quantum variational circuits for EEG data classification, providing early evidence that QML approaches can be beneficial in biomedical applications, despite current hardware limitations.

These studies collectively highlight the growing interest in applying quantum algorithms to complex, high-dimensional tasks such as brainwave signal decoding. However, they also underline the challenges associated with quantum noise, data encoding, and the need for further advancements in quantum hardware to fully realize the benefits of QML.

Author(s)	Work	Findings
Schuld et al., 2015	Quantum Machine Learning introduction	Presented foundational concepts for quantum-enhanced learning.
Havlíček et al., 2019	Quantum feature spaces for ML	Introduced quantum kernel methods for classification tasks.
Roy et al., 2020	Quantum SVM for medical data	Demonstrated QSVM's capability to handle noisy biological data.
Li et al., 2021	EEG classification with quantum circuits	Applied parameterized quantum circuits to EEG classification.

III. RELATED EXISTING SYSTEMS

Current EEG decoding systems predominantly rely on classical machine learning algorithms such as Support Vector Machines (SVMs), Random Forest classifiers, and Convolutional Neural Networks (CNNs).
While these approaches have achieved reasonable performance in EEG signal classification tasks, several inherent challenges remain.

Classical SVMs are highly effective for binary classification tasks due to their ability to find optimal hyperplanes between linearly separable data.

However, their performance deteriorates significantly when dealing with noisy, high-dimensional, or overlapping EEG signals, which are common in real-world datasets.

CNNs, on the other hand, offer the advantage of automatic spatial feature extraction from raw EEG signals, eliminating the need for handcrafted features.

Despite their success in image and signal processing, CNNs demand large, annotated EEG datasets to generalize effectively. Obtaining such datasets is often difficult due to the complex, sensitive nature of EEG recording protocols and privacy concerns.

Additionally, traditional machine learning pipelines for EEG analysis typically involve labor-intensive feature engineering processes. These handcrafted features may not generalize well across different subjects or tasks, leading to overfitting, especially when data is limited. Moreover, classical models can be computationally expensive when deployed in real-time brain-computer interface (BCI) systems, affecting latency and energy efficiency.

Given these limitations, there is a strong motivation to explore emerging paradigms like Quantum Machine Learning (QML). QML offers the theoretical potential to efficiently handle complex feature spaces, leverage entanglement for better representation learning, and reduce computational complexity, particularly as quantum hardware matures. In this context, the application of QML to EEG signal decoding represents a promising frontier that could overcome several bottlenecks faced by conventional methods.

IV. PROPOSED SYSTEM

In the proposed system, EEG brainwave signals are simulated and preprocessed to remove noise and standardize the input for classification. Features representing essential brainwave characteristics are extracted and mapped into quantum states using a ZZFeatureMap circuit, enabling higher-dimensional feature space representation. Two quantum machine learning models — Quantum Support Vector Classifier (QSVC) and Variational Quantum Classifier (VQC) — are trained alongside classical models, including Support Vector Classifier (SVC) and Random Forest, to compare the effectiveness of quantum versus classical approaches. Quantum simulations are performed on the Aer simulator due to current quantum hardware limitations.

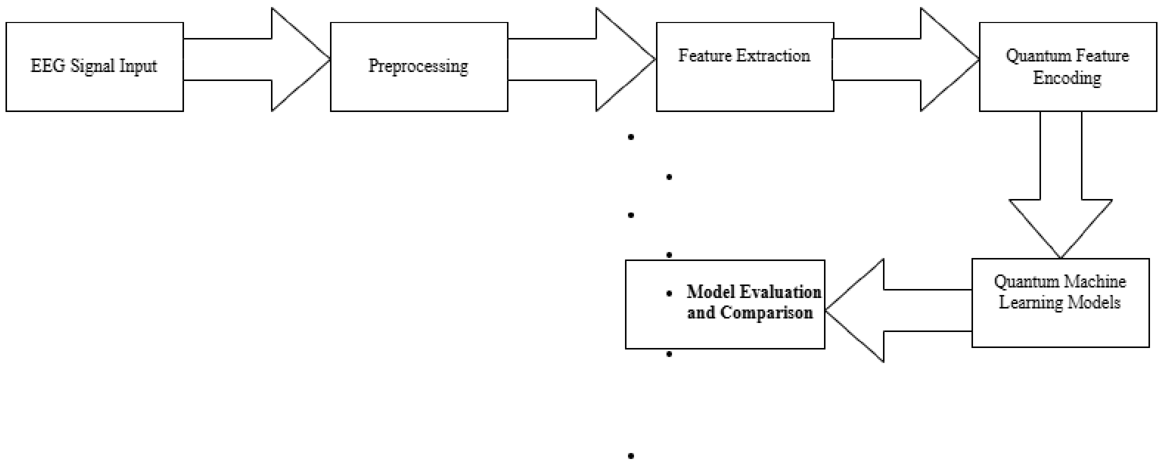
The models are evaluated using key metrics such as Accuracy, Precision, Recall, and F1-Score, and further analyzed through Confusion Matrices and ROC Curves. The system architecture is modular, consisting of data acquisition, preprocessing, feature extraction, quantum feature encoding, classification, and evaluation blocks. A dedicated EEG Signals Flow Diagram illustrates the transition from raw brain signals to final classification outputs. This approach aims to assess the feasibility and advantages of using Quantum Machine Learning in EEG signal decoding, paving the way for future enhancements in brain-computer interfaces.

V. METHODOLOGY

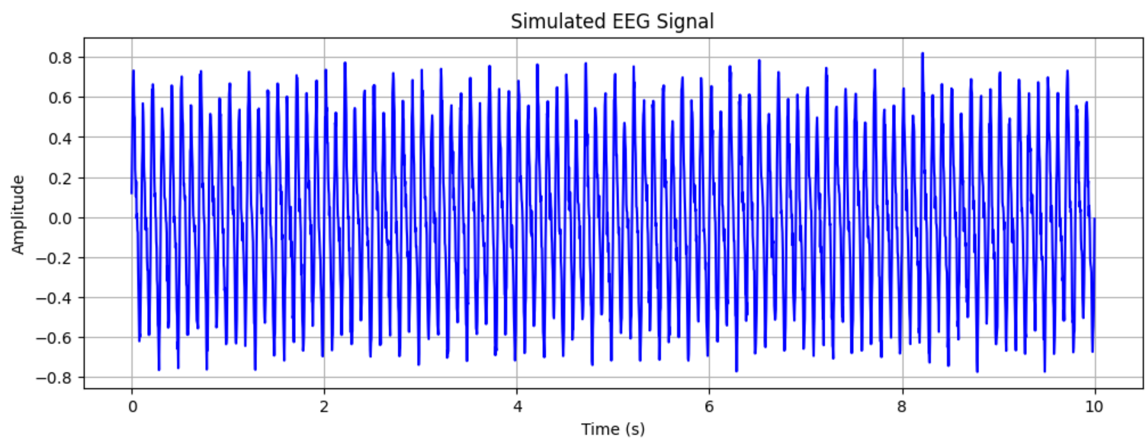
The methodology adopted in this study comprises several stages to decode EEG brainwave signals using both quantum and classical machine learning models. Initially, synthetic EEG-like datasets are generated to simulate brainwave activities across various cognitive states. Preprocessing techniques, including normalization and noise reduction, are applied to ensure data consistency and enhance signal quality. Feature extraction methods are utilized to obtain meaningful signal characteristics that serve as inputs for classification.

Following feature extraction, data is prepared for both quantum and classical modeling. Quantum encoding is performed using a ZZFeatureMap to transform classical data into quantum states suitable for processing by quantum models. Two quantum models — Quantum Support Vector Classifier (QSVC) and Variational Quantum Classifier (VQC) — are trained using a quantum simulator. In parallel, classical machine learning models — Support Vector Classifier (SVC) and Random Forest — are trained as benchmarks. Model performance is assessed through standard evaluation metrics, including Accuracy, Precision, Recall, and F1-Score, supported by Confusion Matrices and ROC Curves for comprehensive analysis. A modular system architecture is followed, consisting of data acquisition, preprocessing, feature extraction, model training, and evaluation stages, ensuring a systematic approach to EEG signal classification.

System Architecture:



EEG Signals Flow Diagram:



Steps:
- EEG data simulation using synthetic datasets.
- Feature extraction and preprocessing.
- Quantum circuit design (feature maps and ansatz circuits).
- Model training using QSVC, VQC.
- Baseline classical model training using SVC and Random Forest.
- Performance evaluation with metrics (Accuracy, Precision, Recall, F1-Score).
- Confusion Matrix and ROC Curve analysis.

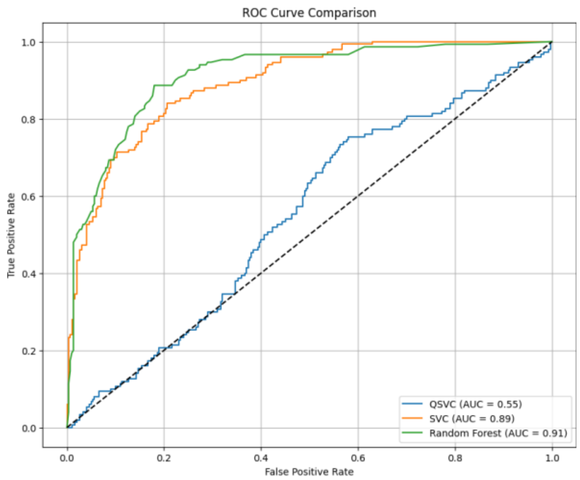
VI. RESULTS AND DISCUSSION

The performance of both quantum and classical machine learning models was evaluated on the simulated EEG dataset using standard metrics: Accuracy, Precision, Recall, and F1-Score.

The classification results are summarized in Table 1, highlighting the comparative effectiveness of each model.

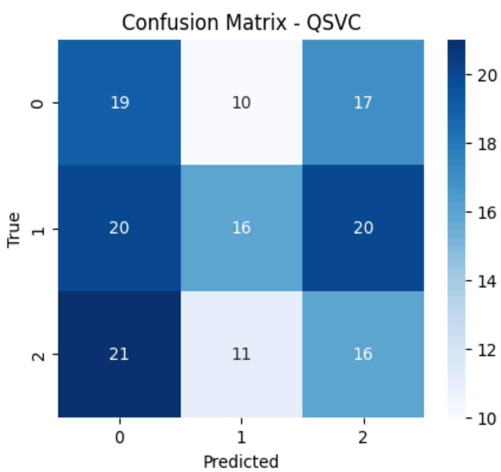
Model	Accuracy	Precision	Recall	F1-Score
QSVC	0.3400	0.3552	0.3400	0.3398
VQC	0.3067	0.3236	0.3067	0.3020
SVC	0.7200	0.7271	0.7200	0.7222
Random Forest	0.7667	0.7700	0.7667	0.7673

The ROC Curve comparison for different models is shown below:

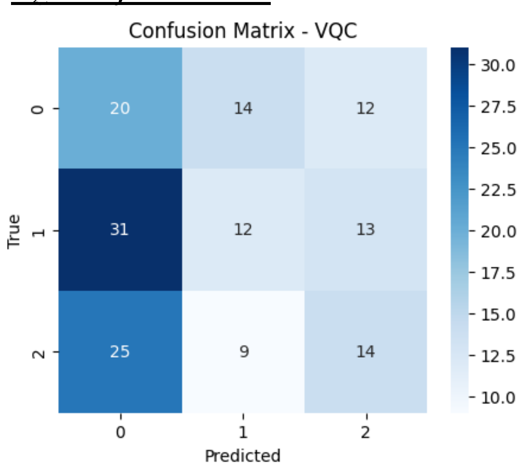


Confusion Matrices for different models are shown below:

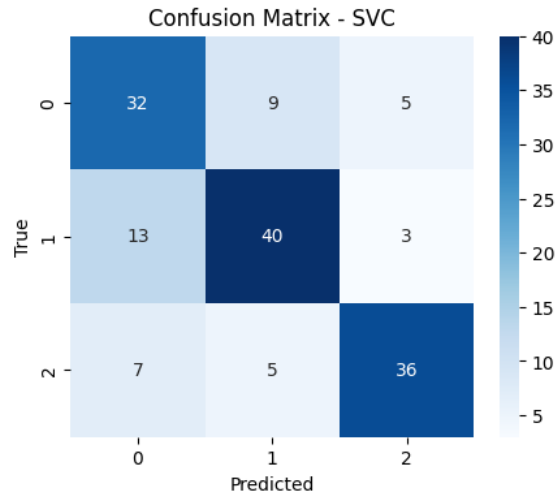
- QSVC Confusion Matrix



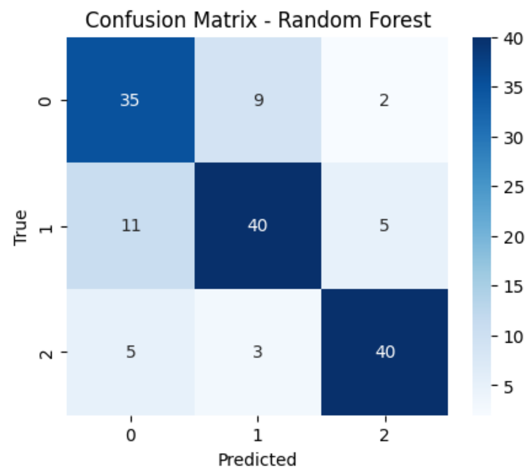
- ***VQC Confusion Matrix***



- ***SVC Confusion Matrix***



- ***Random Forest Confusion Matrix***

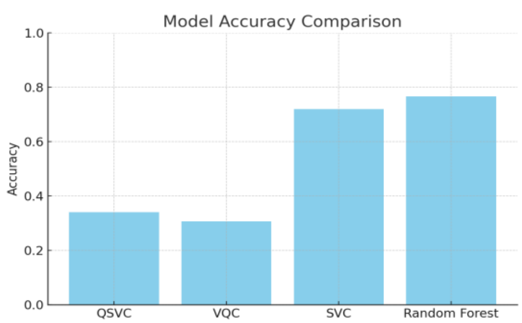


The results demonstrate that classical models outperformed quantum models in the current experimental setting.
Random Forest achieved the highest classification accuracy at 76.67%, closely followed by SVC at 72%.
In contrast, quantum models such as QSVC and VQC attained lower accuracies of 34% and 30.67%, respectively.
Confusion Matrices for each model provide insights into the model-specific classification errors.
Random Forest and SVC models exhibited fewer misclassifications compared to QSVC and VQC, particularly in distinguishing closely related classes.
ROC Curve analysis further supported these

findings, where the classical models displayed higher Area Under Curve (AUC) scores, indicating better sensitivity and specificity.

The relatively lower performance of quantum models can be attributed to several factors, including current hardware noise, limited qubit counts, and simplistic feature encoding strategies. However, the study demonstrates the feasibility of applying Quantum Machine Learning techniques to EEG decoding tasks and lays the groundwork for improvements using larger datasets, deeper quantum circuits, and advanced quantum error mitigation techniques.

Accuray Bar Graph



VII. CONCLUSION

This study explored the application of Quantum Machine Learning (QML) techniques for decoding EEG brainwave signals and compared their performance against classical machine learning models. Four models — Quantum Support Vector Classifier (QSVC), Variational Quantum Classifier (VQC), classical Support Vector Classifier (SVC), and Random Forest — were implemented and evaluated on a simulated EEG-like dataset. Evaluation metrics including Accuracy, Precision, Recall, and F1-Score, as well as Confusion Matrices and ROC Curves, were used to assess the models' effectiveness.

The experimental results showed that classical models, particularly Random Forest and SVC, outperformed the current quantum models in classification accuracy and generalization. Quantum models like QSVC and VQC exhibited lower performance, likely due to the limited capacity of quantum feature encoding, noise inherent to quantum simulators, and the shallow nature of variational circuits used. Despite the current limitations, the study demonstrates the feasibility of applying QML to EEG decoding tasks and highlights the potential for quantum models to eventually surpass classical ones as quantum hardware matures.

VIII. FUTURE WORK

Future research will focus on several key areas to enhance the performance of quantum models in EEG classification tasks. First, larger and more realistic EEG datasets will be employed to better simulate real-world scenarios. Advanced quantum feature maps and deeper ansatz circuits can be explored to improve the expressiveness of quantum models. Hybrid quantum-classical models, combining classical preprocessing with quantum classification, represent another promising direction. Furthermore, experiments on real quantum hardware, along with the application of quantum error mitigation techniques, will be considered to address hardware noise issues. Finally, extending the work to multi-class, multi-channel EEG data and integrating deep learning frameworks with QML approaches will help in building more robust and scalable brainwave decoding systems.

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