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# Quantum Machine Learning for Predicting Brain Computer Interface Signals

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*Abstract*—**Brain–Computer Interface systems enable communication between the human brain and external devices by analyzing electroencephalogram signals. However, accurate prediction of brain states remains challenging due to the high dimensionality, noise, and non-linear characteristics of brain signals. Traditional machine learning approaches often face limitations in capturing complex patterns present in electroencephalogram data. This paper presents a Quantum Machine Learning based framework for predicting brain–computer interface signals using a hybrid classical and quantum approach. The proposed system processes electroencephalogram data stored in European Data Format files through signal preprocessing, feature extraction, and dimensionality reduction techniques. Classical optimization methods are combined with quantum-enhanced feature encoding and kernel-based classification to improve prediction accuracy. Experimental results demonstrate that the proposed approach achieves superior performance compared to classical machine learning models, highlighting the potential of quantum machine learning for advanced brain–computer interface applications in healthcare and cognitive monitoring**

*Index Terms*—**Brain computer interface, EEG signals, hybrid quantum-classical learning, quantum machine learning.**

## I. INTRODUCTION

Brain Computer Interface systems enable direct communication between human brain and external devices by analyzing Eeg signals. These systems are widely used in healthcare, assistive technologies, and cognitive state monitoring. However, EEG signals are noisy, non-linear, high dimensional, making accurate brain state prediction is challenging task. This paper praposes a hybrid classical-quantum framework for predicting brain computer interface signals. The praposed approach integrates classical signals processing with quantum enhanced classification techniques.

## II. METHODOLOGY

The methodology of the proposed QuantumBCI system follows a hybrid classical–quantum processing pipeline designed to efficiently analyses and classify electroencephalogram (EEG) signals. The system integrates classical signal processing techniques with quantum machine learning models to improve prediction accuracy for complex brain patterns.

A. EEG Data Acquisition: EEG data is acquired in European Data Format (EDF), which stores multi-channel brain signals along with sampling frequency and channel metadata. The uploaded EEG files are parsed using an EDF parser to extract raw time-series signals from selected scalp electrodes. The system supports both offline EEG datasets and real-time streamed EEG signals.

B. Signal Preprocessing: Raw EEG signals are inherently noisy and contain artefacts such as eye blinks, muscle movement, and power-line interference. To ensure signal quality, the following preprocessing steps are applied: Band-pass filtering to retain relevant EEG frequency bands. Notch filtering to eliminate power-line noise. Normalization to standardize signal amplitude. These steps enhance signal stability and improve feature reliability.

C. Channel Selection: Since EEG recordings consist of multiple channels, not all electrodes contribute equally to brain-state classification. Channel selection is performed to reduce redundancy and computational overhead. Channels with high signal variance and relevance to cognitive activity are selected based on statistical and domain-specific criteria.

D. Feature Extraction: Discriminative features are extracted from each EEG segment to represent neural activity efficiently.
Variance, and energy.

E. Feature Reduction and Normalization: To manage high dimensionality, dimensionality reduction techniques such as Principal Component Analysis (PCA) are applied. Feature vectors are normalized to ensure compatibility with quantum state encoding and to maintain numerical stability during training.

F. Quantum Feature Encoding: The reduced feature vectors are encoded into quantum states using amplitude and angle encoding techniques. Each feature dimension is mapped to quantum circuit parameters, allowing the quantum model to explore a high-dimensional Hilbert space. This quantum feature map enables enhanced pattern separation compared to classical representations.

G. Quantum Machine Learning Models: he proposed system employs two quantum learning models: Quantum Support Vector Machine (QSVM): Utilizes a quantum kernel computed through entangled quantum circuits for classification. Variational Quantum Classifier (VQC): Uses parameterized quantum circuits optimized through classical gradient-based methods. These models are executed on cloud-based quantum simulators using hybrid optimization.

H. Hybrid Quantum–Classical Training: Training is performed using a hybrid approach where classical optimization algorithms update quantum circuit parameters. Loss functions are minimized iteratively until convergence. This approach combines classical efficiency with quantum representational power.

I. Prediction and Decision Making: During inference, unseen EEG samples are processed through the same preprocessing and encoding pipeline. The trained quantum model predicts brain states such as cognitive load, focus, or neural activity level. The final decision is displayed on the user interface.

J. Visualization and Reporting: The system provides real-time visualization of EEG signals, predicted brain states, and model performance metrics through a web-based dashboard. Users can generate comprehensive analysis reports in PDF or CSV format for documentation and evaluation purposes.

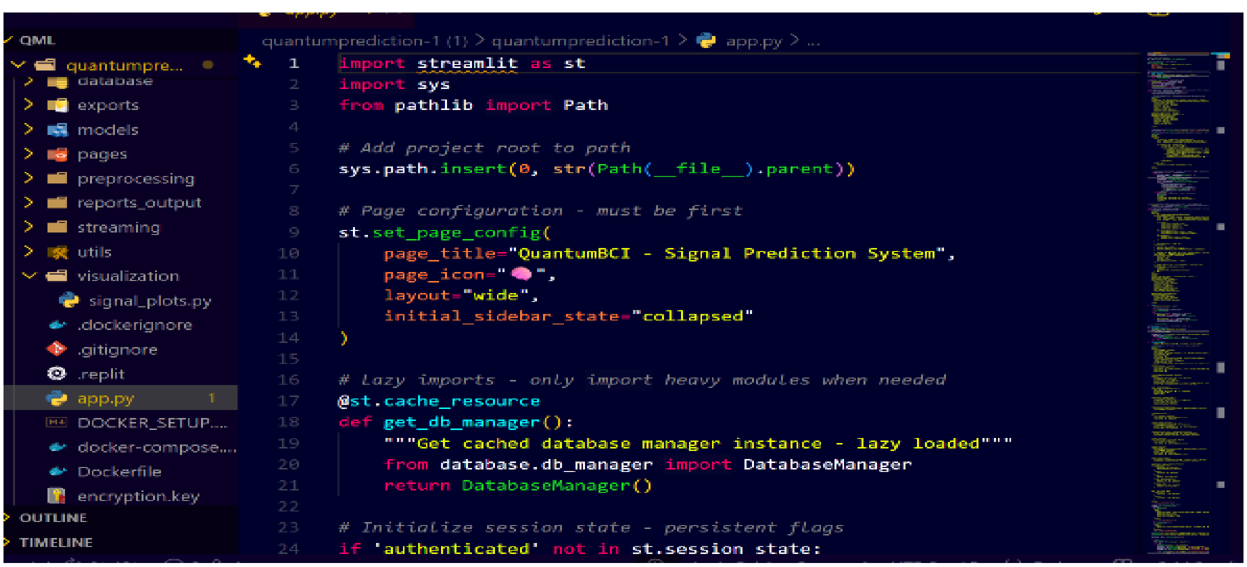


Fig 1 Website Coding

## III. PROPOSED SYSTEM

The praposed system implements a hybrid quantum machine learning framework for predicting brain computer interface signals usinf Eeg data. EEG signals stored in EDF files are used as input to the system. Initially, raw EEG data undergoes preprocessing to remove noise, power line interference, and physiologica; artefacts. Relavant channels are selected to reduce redundancy and computational complexity. Extracted time-domain and frequency-domain features are reduced using Principal Component Analysis before being encoded into quantum states. A quantum kernel-based Support Vector Machine classifier is employed to perform brain state prediction by exploiting quantum superposition and entanglement. The hybrid approach combines classical optimization with quantum-enhanced feature representation to improve classification accuracy

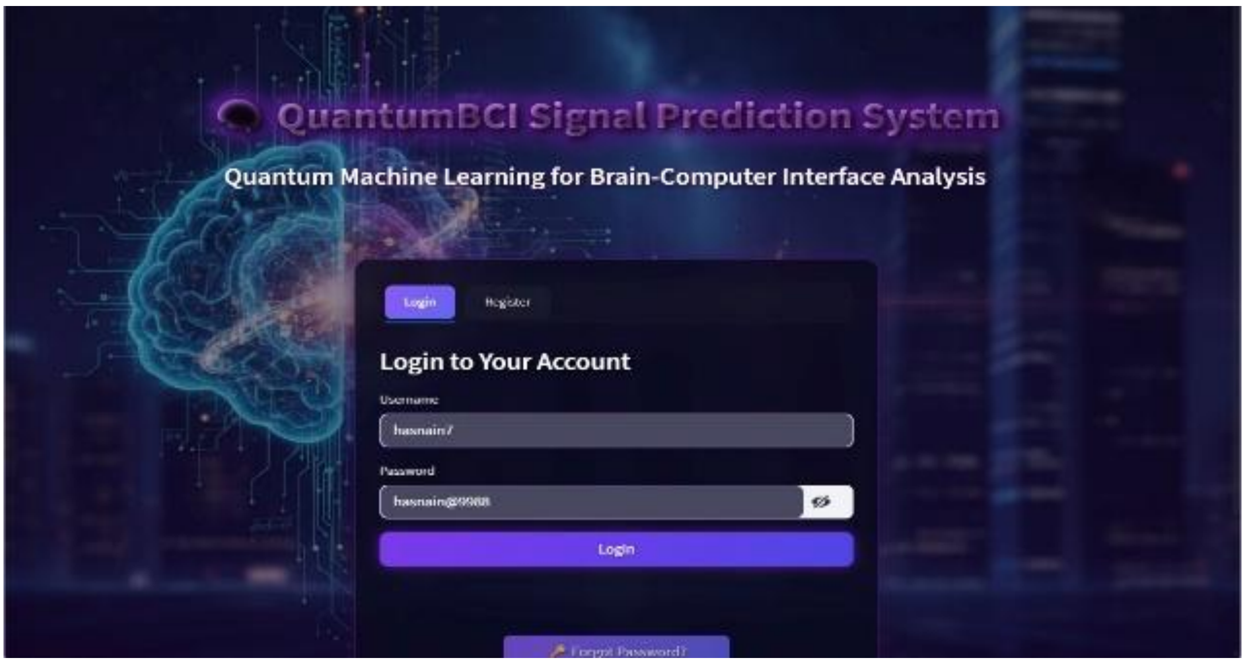


Fig 2 Website dashboard

## IV. PREPROCESSING

Preprocessing is a critical stage in the proposed QuantumBCI system, as raw electroencephalogram signals are highly susceptible to noise, artefacts, and inter-subject variability. EEG recordings often contain unwanted components such as power-line interference, baseline drift, eye-blink artefacts, and muscle activity, which can significantly degrade classification performance if not handled properly. Initially, bandpass filtering is applied to the raw EEG signals to retain only the relevant frequency components associated with brain activity. A typical passband of 0.5–50 Hz is selected to remove low-frequency drift and high-frequency noise. In addition, a notch filter is used to suppress power-line interference at 50 Hz. These filtering operations improve the signal-to-noise ratio while preserving meaningful neural information. After filtering, signal normalization is performed using z-score normalization to standardize amplitude variations across EEG channels and recording sessions. This step ensures that all channels contribute equally during feature extraction and learning. To further improve signal quality, artefact reduction techniques are employed to minimize the influence of eye movements and muscle contractions. Channel selection is then carried out to retain only the most informative electrodes, reducing computational complexity. Finally, the preprocessed signals are segmented into fixed-length windows to enable consistent feature extraction. This structured and cleaned EEG data serves as a reliable input for feature extraction and subsequent quantum machine learning stages.

## V. TRAINING THE MODEL

The training process involves both classical and qml. Extracted features are normalized and reduced using PCA to match the number of available qubits. The reduced features are encoded into quantum states using angle encoding techniques. A Quantum kernal is computed using parameterized quantum circuits, and a support vector machine is trained using the quantum kernal matrix. This hybrid training approach enhances learning capacity and improves generalization on limited EEG datasets.

## VI. QUANTUM MODEL ARCHITECTURE

The quantum machine learning component uses a parameterized quantum circuit for feature encoding and classification. Classical features are mapped into quantum states using angle encoding techniques. The circuit consists of rotation gates followed by entangling layers to capture complex feature relationships. A Quantum Support Vector Machine (QSVM) is implemented using a quantum kernel that measures the similarity between encoded EEG samples. Additionally, a Variational Quantum Classifier (VQC) is employed to optimize trainable parameters using a classical optimizer in a hybrid learning loop.

## VII. COMPUTATIONAL COMPLEXITY COST

The classical preprocessing and feature extraction stages have polynomial time complexity, while the quantum kernel computation scales with the number of qubits and circuit depth. Although quantum simulation introduces overhead, the hybrid framework reduces classical computation for high-dimensional feature spaces. This analysis highlights the potential scalability advantage of quantum models when deployed on real quantum hardware in the future.

## VIII. SYSTEM IMPLEMENTATON AND USER INTERFACE

This section describes the implementation of the proposed Quantum Machine Learning–based Brain–Computer Interface system and its interactive web-based user interface. The system is designed to support real-time EEG signal visualization, quantum model execution, and result analysis through an intuitive dashboard.

A. EEG Data Upload and Processing Module

The EEG data upload module allows users to upload electroencephalogram recordings in European Data Format (EDF). Once uploaded, the system automatically parses the EDF file and initiates preprocessing, including filtering, normalization, and segmentation. This module ensures seamless integration between raw EEG acquisition and subsequent quantum machine learning analysis

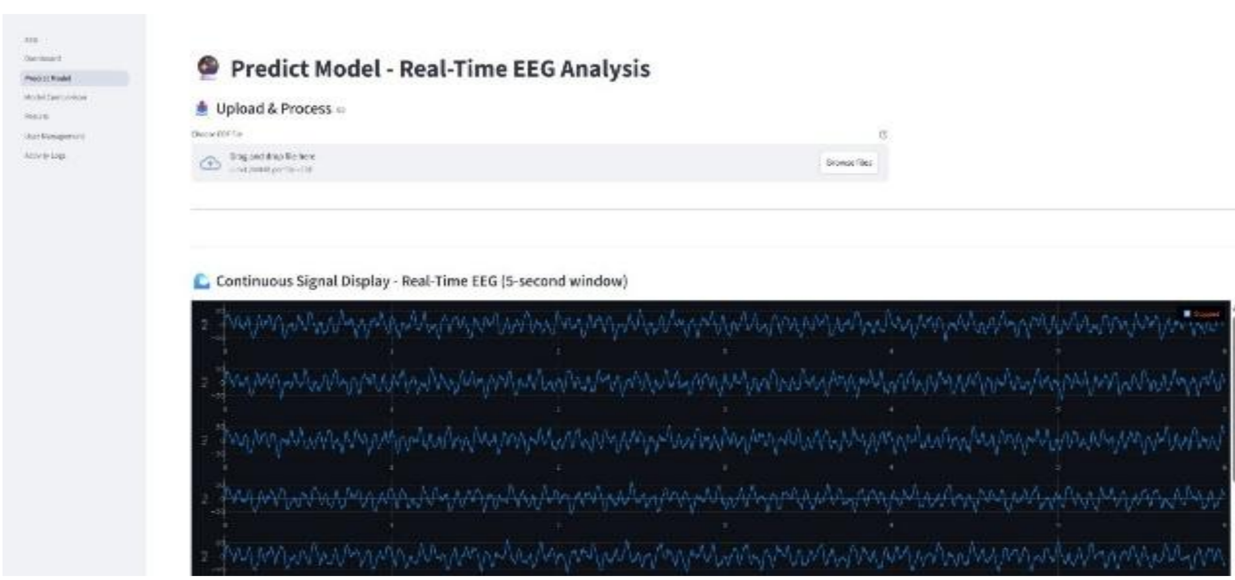


Fig. 3 illustrates the EDF upload interface used for initiating real-time EEG processing.

B. Real-Time EEG Signal Visualization

The system provides continuous visualization of EEG signals using a sliding window mechanism. Multi-channel EEG waveforms are displayed in real time with a fixed five-second window, allowing users to observe temporal variations in neural activity across different electrodes.

This real-time display aids in validating signal quality and identifying abnormal patterns before classification


Fig. 4 shows the real-time EEG signal display with multi-channel waveforms.

C. Quantum Machine Learning Prediction Module

The prediction module integrates Quantum Support Vector Machine (QSVM) and Variational Quantum Classifier (VQC) models. Preprocessed EEG features are encoded into quantum states using parameterized quantum circuits.

The trained quantum models then perform classification to predict cognitive and neural states such as low neural activity, focus, or sleep stages.

The system executes quantum circuits using a cloud-based quantum simulator and displays prediction results along with execution time and model accuracy.

D. Advanced Quantum ML Analysis and Performance Metrics

The advanced analysis module provides detailed performance metrics of the quantum models. It displays QSVM training accuracy, testing accuracy, quantum kernel configuration, processing time, and predicted brain state.

A comparison between classical machine learning output and quantum prediction is also included to highlight the performance improvement achieved through quantum learning.

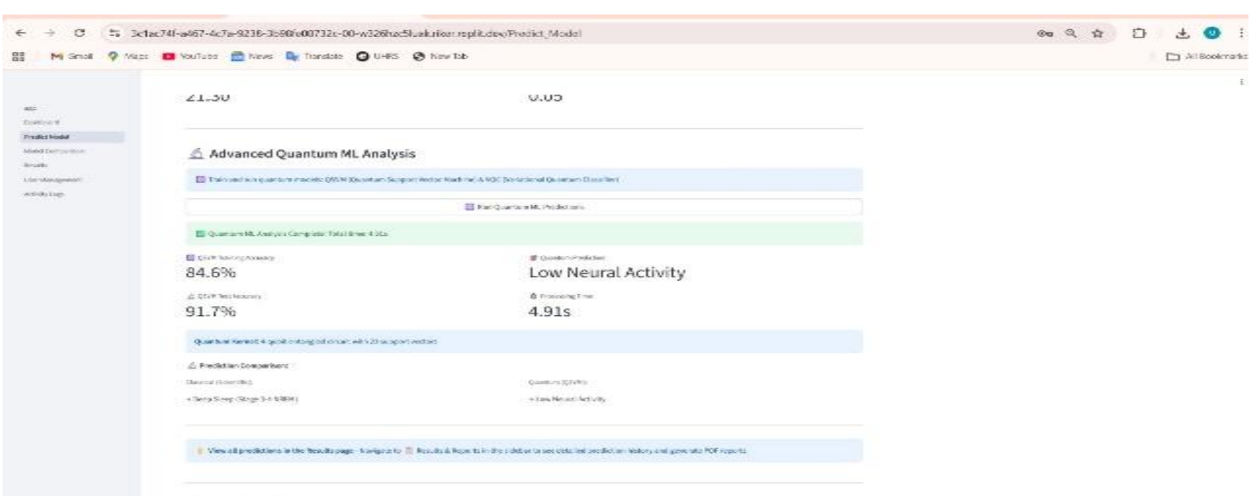

Fig. 5 illustrates the advanced quantum machine learning analysis dashboard.

The overall performance evaluation of the AI-enabled IoT-based smart Air Quality Monitoring System demonstrates that the system reliably monitors environmental parameters in real time while maintaining high accuracy and responsiveness. The ESP8266 microcontroller successfully integrates multiple sensors (MQ135, MQ6, DHT11, and GPS), and transmits data to the cloud server with an average communication latency of less than one second.

## IX. SYSTEM WORKFLOW DESCRIPTION

The overall workflow of the proposed QuantumBCI system follows a modular and sequential pipeline. Initially, EEG data is uploaded through the user interface and parsed using an EDF reader. The signals are then preprocessed to remove noise and artefacts. Relevant EEG channels are selected, and discriminative features are extracted and reduced using dimensionality reduction techniques.

The processed features are encoded into quantum states and passed to the quantum machine learning models for classification. The predicted brain states are visualized in real time and stored for report generation and future analysis.

## X. HOW TO USE THE PROPOSED SYSTEM

The proposed QuantumBCI system is designed for ease of use and real-time operation. The workflow for operating the system is described below:

### A. EEG Data Input

- Upload electroencephalogram data in European Data Format (EDF) files through the web-based interface.

### B. Signal Processing

- The system automatically performs preprocessing, including filtering, normalization, channel selection, and feature extraction.

### C. Quantum Prediction

- The processed features are encoded into quantum states, and the quantum machine learning model (QSVM/VQC) is executed to predict brain states.

### D. Visualization

- Predicted brain states, EEG waveforms, and performance metrics are visualized in real time on the dashboard.

### E. Report Generation

- The system supports exporting
- prediction results and analysis reports in PDF or CSV format for further study and documentation.

## XI. ADVANTAGES OF THE PROPOSED SYSTEM

The key adavantages of praposed syatem:

- improved classification accuracy.
- Better handling of non-linear EEG patterns
- Hybrid quantum–classical efficiency
- Real-time visualization
- Scalable and modular design

## XII. RESULT

The Quantum Machine Learning–based Brain–Computer Interface signal prediction system was successfully implemented and evaluated. Experimental results demonstrate that the proposed system achieves improved classification accuracy compared to conventional classical machine learning approaches. The hybrid quantum–classical framework effectively handles high-dimensional EEG data and captures complex neural signal patterns.The findings confirm the feasibility, robustness, and effectiveness of quantum machine learning for advanced brain–computer interface applications, particularly in cognitive monitoring and healthcare-oriented decision support systems.

## XIII. FUTURE SCOPE

Future enhancements include deployment on real quantum hardware platforms such as IBM Quantum and IonQ. The system can be extended to support multi-class brain state classification and real-time EEG streaming using WebSocket-based pipelines. Integration with deep quantum neural networks and edge-based EEG devices can further improve real-time performance and scalability.

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