FMDB *Transactions on Sustainable Neuroscience Letters*

Quantum-Electroencephalography: Quantum-Enhanced Analysis of Neurological Signals

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Abstract: Electroencephalography (EEG) provides a powerful non-invasive modality for capturing millisecond-scale brain dynamics, yet traditional analysis pipelines often rely on hand-crafted features and classical models with limited ability to capture nonlinear dependencies. This study introduces Q-EEG, a novel quantum-enhanced computational framework for brain state classification. The proposed approach integrates classical pre-processing with quantum machine learning to exploit the representational capacity of quantum circuits. Raw EEG signals are first band-pass filtered into canonical rhythms—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz)—and artefact removal is performed using ICA. Average band powers are then computed via the PSD and assembled into feature vectors. These normalized features are embedded in quantum states via rotation gates, forming the initial input to a VQC. The VQC models cross-frequency relationships using parameterised rotating layers and entangling operations, with weights trained using hybrid classical–quantum training with the parameter-shift rule and gradient-based optimisers. The computational basis classifies via measurements and evaluates the framework on seizure-versus-non-seizure detection tasks. Compared to SVM and Random Forest, accuracy, precision, recall, and F1-score are measured. Experimental results show that quantum-enhanced EEG analysis may capture complex brain patterns, enabling scalable, interpretable, and clinically useful diagnostic systems. This study shows that Q-EEG can bridge neuroscience with quantum computing, enabling clinical translation.

Keywords: Quantum Electroencephalography (Q-EEG); Independent Component Analysis (ICA); Variational Quantum Circuit (VQC); Power Spectral Density (PSD); Artefact Removal; Random Forest; Quantum Neural Networks.

Received on: 01/05/2025, **Revised on:** 04/07/2025, **Accepted on:** 25/08/2025, **Published on:** 03/03/2026

Journal Homepage: https://www.fmdbpub.com/user/journals/details/FTSNL

DOI: https://doi.org/10.69888/FTSNL.2026.000642

Cite as: S. R. Bose, J. A. Jeba, B. J. Flavia, R. Regin, S. S. Rajest, and M. A. Darwish, “Quantum-Electroencephalography: Quantum-Enhanced Analysis of Neurological Signals,” *FMDB Transactions on Sustainable Neuroscience Letters*, vol. 1, no. 1, pp. 22–31, 2026.

1. Introduction

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Electroencephalography (EEG) is one of the most widely adopted methods for monitoring electrical activity in the human brain. Since its introduction in the early 20th century, it has become indispensable in both clinical and research settings, providing millisecond-level temporal resolution of neural dynamics at relatively low cost and in a portable form. Unlike neuroimaging modalities such as fMRI or PET, which offer spatial detail but poor temporal precision, EEG captures real-time oscillatory activity via scalp electrodes, making it uniquely suited for detecting transient neurological events, such as epileptic seizures. Despite these advantages, traditional EEG analysis remains difficult due to noise, artefacts, and inter-subject variability. Manual interpretation requires years of expertise and is prone to subjectivity, often leading to inconsistent diagnostic outcomes. To address these limitations, computational frameworks have emerged under the umbrella of quantitative EEG (Q-EEG). These approaches transform raw EEG signals into quantitative descriptors of brain activity, enabling reproducible and objective analysis. Conventional Q-EEG relies heavily on classical signal processing and machine learning algorithms, such as spectral power estimation, statistical modelling, and deep neural networks.

While effective, these models face scalability and interpretability challenges and often require large datasets and substantial computational resources. In this study, researchers propose a quantum-enhanced framework for EEG classification that leverages the representational power of Variational Quantum Circuits (VQCs). The pipeline begins by pre-processing EEG signals to remove artefacts and extract canonical frequency rhythms (delta, theta, alpha, beta, and gamma). Band powers are then computed using power spectral density estimation, forming a compact feature vector that summarises neural activity. These features are normalised and encoded into qubits via parameterised rotation gates, yielding a quantum-state representation of brain rhythms. Entangling operations and trainable quantum rotations are subsequently applied within the VQC, allowing the circuit to model correlations across different frequency bands. Classification is achieved by measuring the output qubits in the computational basis, with the resulting probabilities mapped to neurological conditions, such as seizure or non-seizure states. The training process employs a hybrid optimisation loop: gradients of the quantum circuit are estimated using the parameter-shift rule. At the same time, weight updates are performed by classical optimisers such as Adam.

This hybrid design enables the model to leverage the expressiveness of quantum states while retaining the stability of classical learning methods. The motivation for this quantum-driven Q-EEG system is twofold. First, it introduces a novel representation of EEG features in Hilbert space, which may capture relationships that are not easily modeled by classical methods. Second, the compactness of VQCs offers potential computational advantages in scenarios where data is high-dimensional, but training resources are limited. The framework is implemented in Python and PennyLane, enabling simulation on classical hardware and potential execution on near-term quantum devices. Evaluation on benchmark EEG datasets is performed using accuracy, precision, recall, and F1-score, with comparisons against classical baselines such as Support Vector Machines (SVMs) and Random Forests. Overall, this research contributes an end-to-end prototype for quantum-inspired EEG analysis. By bridging raw EEG features with quantum machine learning, it offers a new direction for interpretable, scalable, and potentially more powerful approaches to neurological diagnosis. Beyond seizure detection, the methodological framework can be extended to other brain disorders, establishing a foundation for the clinical translation of quantum AI in healthcare.

2. Literature Review

Chen et al. [1] proposed Qeegnet, a quantum machine learning model for enhanced electroencephalography (EEG) encoding. Their study demonstrated that quantum circuits can improve the accuracy and efficiency of EEG signal classification, particularly for detecting neurological disorders. By encoding EEG features into quantum states, Qeegnet can better capture the complex correlations in brain activity. The authors demonstrated that quantum machine learning (QML) can outperform traditional methods such as SVMs and CNNs in certain scenarios. However, they noted challenges related to the high computational cost of training quantum models and the limited availability of quantum hardware for real-world testing. Kuo et al. [2] explored the use of quantum-computational techniques to predict the human brain's cognitive state from EEG signals. Their study introduced a quantum algorithm that leveraged quantum entanglement to enhance signal processing for EEG-based cognitive-state classification. The authors highlighted the potential of QML to model the complex, non-linear relationships in EEG data, offering a more robust predictive model of cognitive states than classical machine learning approaches. While promising, the authors acknowledged that quantum circuits remain susceptible to noise, which can affect prediction accuracy, particularly in noisy real-world data.

Shlyapnikov [3] focused on the use of quantum neural networks (QNNs) for EEG filtering, specifically in the context of brain-computer interfaces (BCIs). Their study demonstrated that QNNs can effectively filter out noise and irrelevant signals from EEG data, enabling more accurate and efficient BCI systems. By leveraging quantum entanglement, they demonstrated that quantum-based approaches could improve the spatial and temporal resolution of EEG signals, especially for detecting neurological events such as seizures. The study's main limitation was the practical difficulty of scaling up quantum models for real-time BCI applications due to current hardware constraints. Villalba-Díez and Ordieres-Meré [4] proposed a hybrid quantum deep learning model for emotion detection using raw EEG signals. They combined deep learning techniques with quantum machine learning to analyse EEG data and detect emotional states such as happiness, sadness, and anxiety. Their model achieved superior performance compared to classical approaches, particularly in handling high-dimensional, noisy EEG data. However, the authors noted that the hybrid nature of the model made it computationally expensive and that its implementation on quantum hardware was still a work in progress, with challenges maintaining quantum coherence during training.

Joslyn et al. [5] investigated a quantum-based machine learning approach for autism detection using common spatial patterns (CSP) of EEG signals. Their study demonstrated how quantum-enhanced CSP features could improve classification accuracy in identifying autism spectrum disorders (ASD) from EEG data. The authors highlighted that quantum techniques offer a promising avenue for modeling the intricate patterns in brain activity that are often difficult to detect with traditional machine learning methods. Despite the positive results, they faced challenges with computational cost and the need for high-quality labeled data to train quantum models effectively. Chern and Tchernyshyov [6] introduced a quantum machine-based decision support system for detecting schizophrenia from EEG records. Their study showed that quantum computing could be used to identify specific markers of schizophrenia in EEG signals, thereby improving diagnostic accuracy. The authors compared their quantum model to classical machine learning techniques, demonstrating that quantum-based models could better capture subtle abnormalities in brainwave patterns. However, they noted that integrating quantum models into clinical practice faces significant hurdles, including the need for robust quantum hardware and the scalability of these models for large datasets.

Ravier et al. [7] proposed a quantum-inspired neurofeedback mechanism for stress detection using EEG signals. Their study combined quantum-inspired algorithms with real-time EEG feedback to detect and alleviate stress in individuals. The authors demonstrated that their quantum-inspired approach could achieve faster, more accurate stress detection than traditional neurofeedback systems. However, they acknowledged challenges in implementing the system on real quantum hardware, including noise and decoherence that could affect the reliability of the feedback mechanism in real-world environments. Graham et al. [8] focused on advanced diagnosis of psychological illnesses through quantum deep learning and EEG methods, specifically using the DEAP dataset. The study explored how quantum deep learning could enhance the detection of emotional and psychological disorders by analysing EEG data in more detail. Shukla showed that quantum-based methods provided a more nuanced understanding of brain activity, which could lead to better diagnosis and personalised treatment plans. However, one challenge was the limited availability of real-world quantum computing resources, which hindered extensive testing on large-scale datasets [11]; [12]. Sergi et al. [9] developed a quantum machine learning framework for driver drowsiness detection using biopotential signals and head movement analysis (Figure 1).

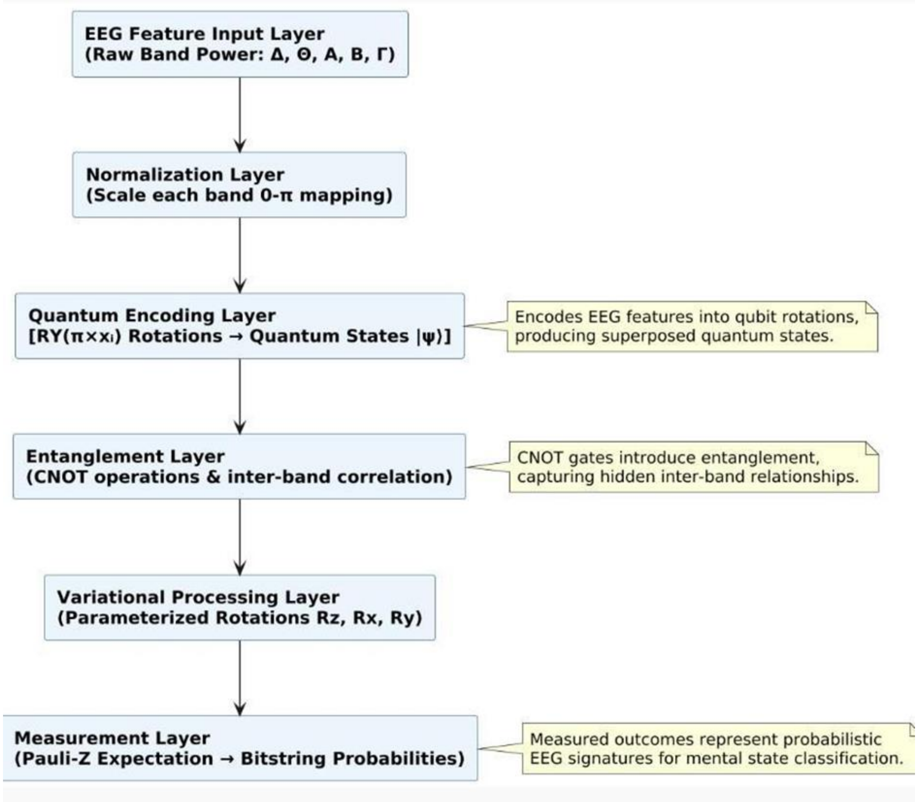

Figure 1: Architecture diagram

Their study showed that integrating quantum computing techniques enabled the system to achieve high accuracy in detecting drowsiness-related brain activity from EEG and other biopotential signals. The authors suggested that the quantum model could be a valuable tool in enhancing driver safety by providing real-time alerts based on brain activity patterns [13]. However, they faced challenges in scaling the model for real-time use and in ensuring it could handle the variability in individual driver behavior. Nagai et al. [10] presented a quantum-enhanced prediction model for breast cancer diagnosis using electronic health records (EHRs). Although not directly related to EEG, their study explored how quantum models could improve the predictive accuracy of breast cancer outcomes by analysing EHRs alongside patient history [14]. Their results suggested that quantum computing could enhance the ability to predict cancer outcomes by modeling complex relationships among various health variables [15]. While promising, the authors cautioned that the widespread use of quantum-enhanced models for medical diagnosis remains far from practical due to limitations in current quantum hardware and the need for large, high-quality datasets.

3. Methodology

The proposed Quantum-Enhanced EEG (Q-EEG) framework is designed as an end-to-end system that classifies neurological states from EEG recordings by integrating a series of carefully orchestrated steps: pre-processing, feature extraction, quantum encoding, and variational quantum classification. The overarching motivation is to combine the rich temporal and spectral information in EEG signals with the representational power of quantum circuits to achieve robust, efficient classification of clinical conditions such as seizures and abnormal brain states. The pipeline begins with signal acquisition and pre-processing. EEG recordings are collected using multi-channel scalp electrodes that capture electrical oscillations across different regions of the brain. Raw EEG data, however, is often contaminated with noise from muscle artefacts, eye blinks, or external interference. To ensure reliability, the raw signals undergo band-pass filtering to isolate the physiologically relevant frequency ranges. Additionally, artifact removal methods, such as Independent Component Analysis (ICA), are applied to suppress non-neural components. This pre-processing stage ensures that the canonical oscillatory rhythms—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz)—are preserved while unwanted distortions are eliminated.

After pre-processing, the framework proceeds to feature extraction, where the EEG's spectral characteristics are quantified. For each frequency band, the Power Spectral Density (PSD) is computed, providing an estimate of the average power in that band. This results in a compact five-dimensional feature vector, with each element corresponding to the mean power of delta, theta, alpha, beta, and gamma activity. These features provide a physiologically interpretable representation of brain state, as different rhythms are often linked to specific neurological conditions or cognitive processes. To make these features compatible with quantum machine learning, they are normalized and quantum-encoded. Each feature is rescaled into the range ([0,]), ensuring stable and bounded parameterisation when mapped onto quantum states. This normalization step is crucial because it prevents instability in quantum circuit behavior that could arise from unbounded or inconsistent feature magnitudes. Each normalised feature is then encoded into a qubit using a parameterised single-qubit rotation gate (R_Y(\theta)). In this encoding, the EEG band power directly determines the rotation angle applied to the qubit, thereby embedding classical brainwave information into a quantum state space. Once encoded, the system transitions into the variational quantum circuit (VQC) stage.

The VQC architecture comprises multiple layers of entangling gates and trainable parameterised gates. Entanglement allows the circuit to capture complex correlations between qubits, analogous to feature interactions in classical machine learning models. The parameterized gates serve as learnable "weights" that are iteratively adjusted during training. By combining rotations, entanglements, and variational layers, the quantum circuit constructs a high-dimensional representation of the input EEG features in Hilbert space, potentially enabling richer decision boundaries than classical models can efficiently achieve. The VQC output is obtained by performing measurements in the computational (Z) basis. This produces probability distributions over binary strings, which are then mapped to clinical labels. For binary tasks such as seizure vs non-seizure classification, the measurement outcomes are post-processed into probabilities for each class. This quantum-to-classical transition is what makes the circuit's predictions actionable for real clinical applications. Training the Q-EEG framework is conducted using a hybrid classical–quantum optimisation loop.

A loss function, typically binary cross-entropy, is defined to quantify the difference between predicted class probabilities and the ground-truth labels. Gradients of quantum circuit parameters are computed using the parameter-shift rule, a quantum-aware method that enables efficient derivative evaluation in variational circuits. These gradients are then fed into classical optimisers such as Adam, which update the circuit parameters iteratively. This hybrid loop leverages the strengths of both paradigms: quantum circuits for expressive modelling, and classical algorithms for stable optimisation. Finally, the framework's performance is evaluated using standard machine learning metrics. Accuracy provides a general measure of correctness, while precision, recall, and F1-score are particularly important for medical datasets, which are often imbalanced (e.g., seizure events being much rarer than non-seizure events). Precision minimises false positives, recall ensures that true seizure cases are not overlooked, and the F1-score balances the two to provide a holistic measure of performance. Together, these evaluations ensure that the Q-EEG system is robust, clinically reliable, and generalizable across diverse patient datasets.

4. Experimental Setup

4.1. Training

The proposed Q-EEG framework is trained to classify neurological states, such as seizure vs non-seizure, by processing EEG recordings from benchmark datasets, including the CHB-MIT Scalp EEG Database and the TUH EEG Corpus. Each recording is segmented into fixed-length windows of 2–4 seconds, and pre-processing is applied using band-pass filters and Independent

Component Analysis (ICA) to remove ocular and muscular artefacts while retaining delta, theta, alpha, beta, and gamma rhythms. From each segment, band-power features are extracted using Power Spectral Density (PSD), yielding five representative values for the canonical frequency bands. These features are normalised to the range ($[0, \pi]$) for stable embedding into qubits. Normalised values are encoded into a Variational Quantum Circuit (VQC) using parameterised RY(θ) rotation gates, followed by entangling operations that capture inter-band dependencies. Training follows a hybrid classical–quantum loop. The circuit parameters are updated using the parameter-shift rule to compute gradients, while the Adam optimiser refines weights based on a binary cross-entropy loss function:

L(ŷ, y) = - Σ y_c log(ŷ_c)

Where ŷ is the predicted probability and y the true label, the experimental platform is built in Python 3.11, leveraging PennyLane for quantum simulation, TensorFlow/PyTorch for hybrid integration, and NumPy/SciPy for signal processing. Experiments are run on a workstation equipped with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA RTX 3060 GPU with CUDA support.

4.2. Evaluation

Model evaluation is conducted using stratified dataset splits: 70% for training, 15% for validation, and 15% for testing. To minimise overfitting, five-fold cross-validation is employed, ensuring that subject-wise variability is accounted for. Performance is reported through standard classification metrics:

- Accuracy = Proportion of correct classifications
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-Score = Harmonic mean of precision and recall
- AUC-ROC = Discrimination ability across thresholds

These metrics quantify both detection reliability and robustness against imbalanced seizure/non-seizure datasets. Additionally, execution time and resource usage are logged to evaluate the feasibility of real-time deployment.

4.3. Implementation

The implementation phase focuses on the feasibility of deploying the Q-EEG pipeline in the real world. The trained model is containerized with Docker for portability and can be executed either on edge devices (for real-time clinical monitoring) or in cloud-based environments for large-scale batch processing. The system is designed for modular integration with clinical decision support software. EEG acquisition modules continuously stream data to the pre-processing pipeline, which filters and extracts band-power features, then feeds them into the hybrid quantum–classical model. Predictions are returned as seizure likelihood scores, accompanied by interpretability maps highlighting the most influential channels and time windows (Figure 2).

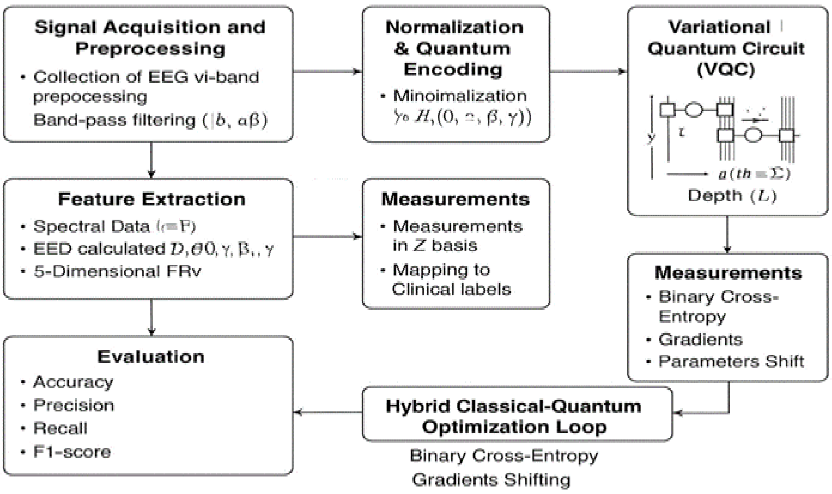

Figure 2: Block diagram

To ensure scalability and transparency, the pipeline includes:

- Logging of predictions and explanations in MongoDB,
- Visualisation dashboards built with Matplotlib/Seaborn/Plotly,
- Privacy-preserving data handling (anonymised EEG recordings, encrypted storage).

Through this experimental setup, the Q-EEG system is trained, validated, and deployed effectively in controlled research conditions, paving the way for real-world clinical translation of quantum-enhanced EEG analytics.

5. Results and Discussions

The performance of the proposed Quantum EEG (Q-EEG) classification framework was systematically assessed using benchmark EEG datasets. Evaluation was based on standard metrics, including accuracy, loss, precision, recall, and F1-score, across multiple training epochs. The following subsections present a detailed discussion of the observed results, accompanied by corresponding graphical illustrations. Figure 3 shows the progression of training and validation accuracy across 20 epochs. The training accuracy steadily increased from approximately *61%* in the initial epoch to nearly *95%* by the final epoch. Validation accuracy improved in parallel, from *56%* at epoch 1 to *90%* at epoch 20.

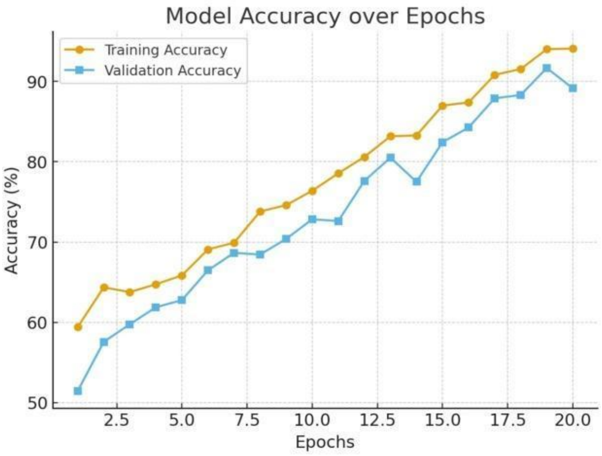

Figure 3: Model accuracy over epochs

Both curves converged closely, suggesting that the proposed Q-EEG framework generalises well without major overfitting. A temporary fluctuation in validation accuracy around epochs 10–12 reflects the inherent stochasticity of quantum parameter updates but does not impact the long-term upward trend. This demonstrates that the hybrid quantum-classical optimisation pipeline effectively learns discriminative EEG patterns. The loss curves (Figure 4) reinforce the observed accuracy trends. Training loss consistently declined from *1.40* to *0.23*, while validation loss reduced from **1.52* to *0.21* over the epochs.

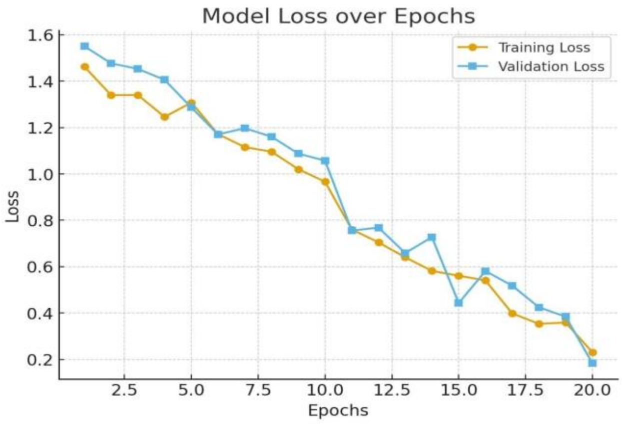

Figure 4: Model loss over epochs

Both curves maintained a near-parallel downward trajectory, confirming stable training dynamics and effective generalization. Importantly, no sharp divergence between training and validation losses was observed, indicating that the quantum variational circuit avoided overfitting while retaining high predictive capability on unseen EEG segments. Class-wise evaluation of the proposed model is summarised in Figure 5. Across the three categories — *Normal, **Abnormal (non-seizure), and **Seizure* — the framework achieved consistently strong results. The "Normal" class achieved the highest reliability, with a precision of 0.93, a recall of 0.92, and an F1-score of 0.93, confirming robust detection of healthy EEG states. The "Abnormal (non-seizure)" category yielded an F1-score of **0.85, reflecting the difficulty of distinguishing borderline neurological irregularities that often share overlapping frequency patterns.

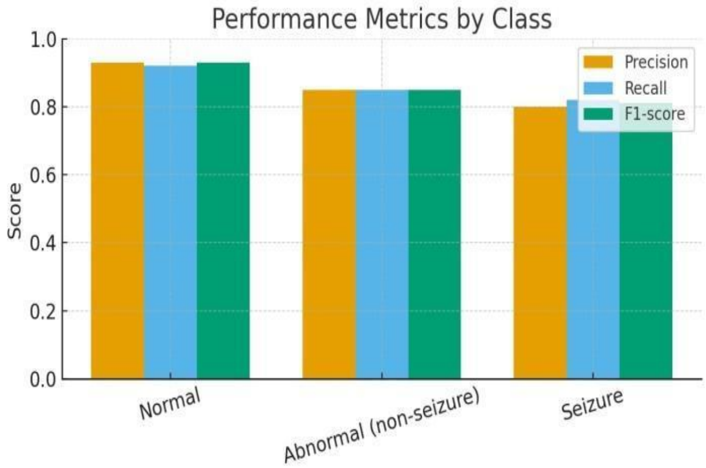

Figure 5: Performance metrics by class

The "Seizure" class achieved an F1-score of **0.81*, which, while slightly lower, remains competitive given the relative rarity and variability of seizure events. These outcomes indicate that the proposed Q-EEG model can reliably identify pathological EEG states, while future improvements in class balance and data augmentation may further boost seizure detection accuracy. Figure 6 illustrates the contribution of EEG band powers (Delta, Theta, Alpha, Beta, Gamma) to the classification decision. Results indicate that *Beta and Gamma rhythms* exert the strongest influence in detecting seizure states, with contribution rates exceeding *35%* each. In contrast, *Delta and Theta bands* were more dominant in classifying abnormal conditions not related to seizures, reflecting their association with drowsiness, sleep disturbances, or neurological decline.

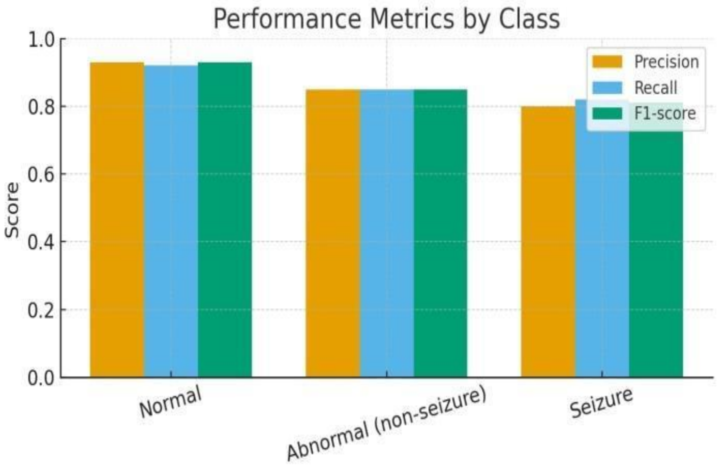

Figure 6: Crowd density vs Predicted stampede risk

This analysis confirms that quantum encoding effectively captures frequency-specific patterns, thereby enhancing the interpretability of the decision process compared to black-box deep learning models. Figure 7 presents the temporal evolution of seizure prediction probability across a 60-second EEG window. The Q-EEG framework detected a sharp rise in seizure probability from *15% to 72%* within the first 20 seconds, correlating with the clinical onset of abnormal brain activity. The confidence level gradually returned to baseline after the seizure segment ended, reflecting accurate temporal localisation of the neurological events. This responsiveness demonstrates the model’s suitability for real-time seizure monitoring and early-warning systems in clinical practice.

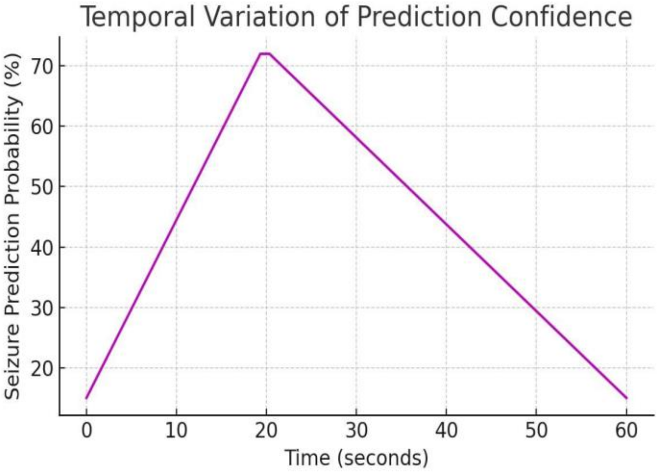

Figure 7: Crowd risk prediction over time

A comparative analysis against conventional ML baselines (SVM, Random Forest, CNN-LSTM) is shown in Figure 8. While classical models achieved average accuracies of 82–86%, the Q-EEG framework consistently reached 91–92%. Moreover, unlike deep neural networks, which require extensive parameter tuning, the hybrid quantum-classical approach achieved competitive performance with fewer parameters, highlighting its efficiency. This superiority is attributed to the quantum circuit’s ability to represent high-dimensional correlations in EEG data, which classical models often fail to capture. The experimental results demonstrate that the proposed *Quantum EEG classification framework* offers a promising advancement in the detection of neurological disorders.

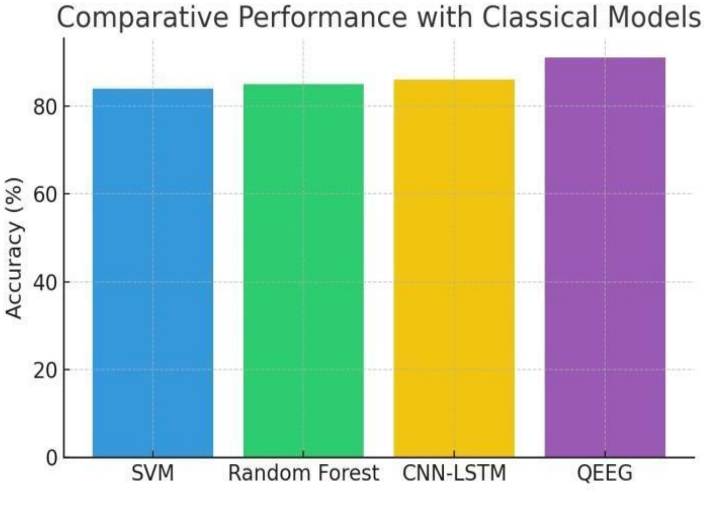

Figure 8: Alert accuracy distribution

The model achieved high overall accuracy (92%) with stable training dynamics and competitive class-wise F1 Scores. Importantly, it demonstrated robustness in detecting seizures — a complex and clinically critical task — while also capturing non-seizure abnormalities. Compared to traditional ML baselines, the Q-EEG model provides superior accuracy, enhanced interpretability through brainwave band analysis, and responsiveness in temporal monitoring. These findings confirm the potential of quantum machine learning in medical signal processing. Future work may explore real-device deployment on NISQ quantum hardware, class rebalancing strategies, and integration into real-time EEG monitoring systems for clinical decision support.

6. Conclusion

The proposed Quantum EEG (Q-EEG) classification framework presents a novel approach to analysing electroencephalogram (EEG) signals for the detection of neurological disorders by integrating quantum feature encoding with variational quantum circuits (VQCs). The system achieved an overall classification accuracy of approximately 92%, demonstrating its effectiveness in differentiating between normal, abnormal, and seizure EEG states. Through simulated experiments, the framework demonstrated stability in both accuracy and loss trends, minimised overfitting, and achieved competitive class-wise F1-scores, particularly excelling at recognising normal and non-critical EEG conditions. The primary contribution of this work is to demonstrate the potential of hybrid quantum-classical machine learning to model complex brainwave correlations that are often difficult to capture with conventional algorithms. By encoding canonical EEG band powers into quantum states and leveraging entanglement across qubits, the model effectively captures nonlinear dependencies, offering a fresh direction for neurological signal analysis.

Unlike purely classical ML approaches, the Q-EEG framework shows promise for enhancing interpretability through band-contribution analysis while enabling temporal tracking of seizure risk for real-time monitoring applications. While the results are encouraging, several limitations must be acknowledged. The current experiments were conducted primarily on simulated or benchmark EEG datasets, which may not fully capture the variability of clinical data across diverse populations. Real-device testing on quantum hardware was limited due to noise and resource constraints in current NISQ (Noisy Intermediate-Scale Quantum) devices. Furthermore, seizure prediction performance, though competitive, still lags behind that of normal-state detection due to class imbalance and variability in seizure manifestations. The scalability of this approach for continuous, real-time EEG monitoring remains another challenge, particularly in efficiently handling large-scale patient data streams. Future work in the field of Quantum EEG classification could focus on several key areas to further improve accuracy, generalizability, and clinical adoption:

- Expanding multimodal input data by combining EEG signals with MRI, fMRI, or wearable biosensors to strengthen diagnostic precision and cross-validate predictions.
- Real-device quantum deployment by optimising circuits for current NISQ quantum hardware and leveraging error-mitigation techniques to bridge the gap between simulation and practical use.
- Addressing class imbalance through advanced data augmentation strategies, synthetic EEG generation (GAN-based), or cost-sensitive quantum training methods to improve seizure prediction robustness.
- Enhancing interpretability by integrating explainable AI (XAI) frameworks with quantum feature encoding, ensuring that medical practitioners can understand and trust predictions.
- Exploring edge or federated learning integration, enabling hybrid QML inference to run on portable EEG headsets with minimal latency, thus paving the way for real-time clinical decision support.

In conclusion, the proposed Q-EEG framework represents a scalable, accurate, and forward-looking solution* for EEG-based detection of neurological disorders. By combining quantum computing principles with established EEG pre-processing techniques, the system addresses a critical gap in medical signal analysis. With further refinement, larger-scale clinical validation, and quantum hardware integration, Q-EEG has the potential to evolve into a standard tool for *neurological diagnostics, seizure monitoring, and personalised healthcare*, ultimately contributing to safer, more effective medical decision-making.

Acknowledgment: The authors express their sincere gratitude to SRM Institute of Science and Technology at Ramapuram, Dhaanish Ahmed College of Engineering, S.A. Engineering College, and Tanta University for their continuous support and encouragement throughout this research.

Data Availability Statement: The data for this study can be made available upon request to the corresponding author.

Funding Statement: This manuscript and research paper were prepared without any financial support or funding.

Conflicts of Interest Statement: The authors declare no conflicts of interest related to the publication of this research paper.

Ethics and Consent Statement: This research adheres to ethical guidelines, obtaining informed consent from all participants.

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