

QUANTUM MACHINE LEARNING BASED REAL TIME EPILEPTIC SEIZURE PREDICTION USING WEARABLE EEG SENSORS

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ABSTRACT

Epileptic seizures can be described as unpredictable neurological phenomena which represent great dangers for the patients' safety and need constant healthcare monitoring. The use of wearable electroencephalogram (EEG) devices can allow accurate real-time seizure forecasting, enabling early warning and improved clinical intervention. However, traditional machine learning and deep learning algorithms do not have the ability to effectively exploit the complex nonlinear properties and long-term temporal dependencies presented in EEG signals. In this paper, we introduce the Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet), which consists of the hybrid architecture based on Quantum Feature Encoding (QFE), Variational Quantum Neural Networks (VQNN), Transformer-based Temporal Learning (TTL), and Adaptive Seizure Risk Assessment (ASRA). First of all, the preprocessing of the input data is performed by cleaning artifacts, normalization, and segmentation of the raw wearable EEG signals. The processed signals are encoded into a high-dimensional quantum feature space and analyzed through quantum feature learning and temporal analysis via a Transformer network for detecting pre-seizure patterns. Finally, the Adaptive Seizure Risk Assessment module calculates the probability of seizure occurrence and provides early-warning alarms. The proposed method allows representing the input data in the form of quantum feature vectors in the high-dimensional quantum feature space. Then, quantum feature learning is performed along with the temporal analysis of the signals with the help of a Transformer network to identify pre-seizure patterns. The Adaptive Seizure Risk Assessment module calculates the probability of seizures and generates early-warning alerts. The proposed QML-SPNet framework was tested on the CHB-MIT Scalp EEG dataset and achieved 98.94% accuracy, 98.76% precision, 99.08% recall, 98.92% F1-score, an AUC of 0.994, and prediction latency of 31 ms, which exceeds the performance of traditional machine learning and deep learning frameworks. Therefore, the proposed framework is an effective, low-latency, and highly reliable approach for wearable real-time epileptic seizure prediction, with significant potential for improving patient safety and supporting next-generation intelligent healthcare monitoring systems.

Keywords: *Epileptic Seizure Prediction, Quantum Machine Learning, Wearable EEG Sensors, Variational Quantum Neural Network, Transformer-based Learning, Real-Time Healthcare Monitoring.*

1. INTRODUCTION

Epilepsy is a chronic neurological disease characterized by recurring seizures, which are caused by abnormal electrical activity in the brain [1], [2]. These seizures are unpredictable events that significantly affect patients' daily activities and decrease their quality of life while increasing the risks of injuries, accidents, and psychological stress. Therefore, the development of real-time seizure prediction systems has become an important research direction in modern healthcare [3].

Electroencephalography (EEG) is the primary non-invasive technique for monitoring brain activity due to its high temporal resolution and ability to detect abnormal brain discharges before seizure onset [4]. With the help of recent advancements in wearable EEG sensors, it is possible to achieve continuous real-time monitoring of brain activity, which is essential for personalized healthcare and early intervention [5]. Wearable EEG devices allow long-term acquisition of brain signals while providing improved patient comfort and mobility, thereby supporting continuous seizure prediction applications [6].

Conventional seizure prediction techniques have been mainly based on statistical methods and classical machine learning algorithms such as Support Vector Machine (SVM), Decision Tree, and Random Forest. Despite achieving moderate prediction performance, these algorithms require extensive feature engineering and have limited generalization capability across different patients due to the nonlinear and non-stationary characteristics of EEG signals [7], [8]. To address these limitations, deep learning techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs) have been introduced to perform automatic feature extraction from EEG signals [9]. Recently, Transformer-based models have shown strong potential in capturing long-range temporal dependencies and complex sequential patterns, thereby improving seizure prediction accuracy [10].

Despite these advantages, current deep learning models still face several challenges, including high computational complexity, limited interpretability, patient-specific variations, and insufficient representation of highly nonlinear EEG features [11]. Furthermore, computationally efficient

prediction models capable of real-time operation on resource-constrained wearable devices while maintaining high accuracy and low latency are required for practical healthcare applications [12].

Recently, Quantum Machine Learning (QML) has emerged as a new computational paradigm for solving complex pattern recognition problems using high-dimensional Hilbert space representations and quantum feature mapping [13]. Quantum Feature Encoding improves the discrimination of nonlinear features, while Variational Quantum Neural Networks (VQNNs) provide enhanced learning capability for complex biomedical signals. The integration of Quantum Machine Learning (QML) with Transformer-based Temporal Learning has the potential to improve seizure prediction accuracy and computational efficiency [14].

To overcome these challenges, this paper proposes a Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) for real-time epileptic seizure prediction using EEG data collected by wearable sensors. The proposed QML-based framework integrates Quantum Feature Encoding, Variational Quantum Neural Networks (VQNNs), Transformer-based Temporal Learning, and an Adaptive Seizure Risk Assessment module for the effective identification of pre-seizure EEG patterns and the generation of timely early-warning alerts. Experimental results demonstrate that the developed QML-based framework achieves 98.94% accuracy, 98.76% precision, 99.08% recall, 98.92% F1-score, and an AUC of 0.994, outperforming existing state-of-the-art machine learning and deep learning approaches. The proposed QML-SPNet provides a reliable, scalable, and intelligent solution for next-generation wearable epilepsy monitoring systems [15].

Objectives of the Proposed Work

- To design a Quantum Machine Learning framework for real-time prediction of epileptic seizures using wearable EEG sensors.
- To improve the representation of nonlinear EEG features through Quantum Feature Encoding.
- To design a Transformer-based learning architecture to capture temporal EEG dynamics.

- To reduce false predictions and computational latency while improving seizure prediction accuracy.
- To provide an early-warning mechanism for smart monitoring in wearable healthcare systems.

The structure of the remaining paper is laid out as follows. Section 2 discusses the literature review of the existing studies on epileptic seizure prediction, including a critical analysis of the research gaps in the currently used machine learning, deep learning, and Quantum Machine Learning (QML) methods. The proposed Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) is discussed in Section 3, which includes the details of the dataset, framework architecture, mathematical formulation, and the algorithm used for prediction. Section 4 elaborates on the experimental methodology, performance evaluation, comparative analysis, and graphical visualization of results obtained using the benchmark EEG dataset. Section 5 finally summarizes the major outcomes of the present work, discusses the limitations of the proposed framework, and presents future research directions for real-time wearable seizure prediction.

2. RELATED WORK

The evolution of wearable healthcare technologies and the field of artificial intelligence has brought considerable advances in predicting epileptic seizures based on electroencephalogram (EEG) signals. Classical machine learning algorithms such as Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Decision Trees, and Random Forests have found wide application for seizure prediction due to their simplicity and low computational complexity. While classical models demonstrated good performance on small EEG datasets, their reliance on manual feature engineering and limited capability to model nonlinear EEG dynamics restricted their generalization across different patients and seizure types [16], [17].

Deep learning models have provided a considerable improvement in seizure prediction performance by automatically learning discriminative features from raw EEG signals. Convolutional Neural Networks (CNNs) are effective in extracting spatial features from multi-channel EEG data, reducing the necessity for manual feature engineering. However, these models mainly focus on local feature extraction and have limited capability to capture long-term temporal

dependencies associated with pre-ictal brain activity [18]. To overcome these limitations, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) recurrent neural networks were proposed to learn temporal patterns in EEG signals more effectively. Despite the improved performance of recurrent neural networks for seizure prediction, high computational complexity, vanishing gradient problems, and long training times make them less suitable for real-time wearable healthcare applications [19].

Transformer-Based Architectures (TAs) have recently emerged as effective sequence learning models capable of capturing long-range temporal dependencies through self-attention mechanisms. Transformer models have demonstrated superior performance compared with recurrent models in tasks such as EEG classification and seizure prediction [20] due to their ability to learn complex temporal relationships from EEG signals and support parallel processing. However, their high computational requirements and limited capability to represent nonlinear features remain significant challenges for wearable healthcare systems with constrained computational resources.

Several studies have explored hybrid deep learning approaches that incorporate CNNs with recurrent networks or attention mechanisms to improve seizure prediction performance. These types of **hybrid architectures** have achieved better feature learning by utilizing both the spatial and temporal information present in EEG signals. However, current approaches are computationally expensive, require large training datasets, lack adaptability to patient-specific EEG variations, and are not sufficiently robust when EEG signals are collected using noisy wearable sensors [21], [22].

Recent advances in biomedical signal analysis have created new opportunities in **Quantum Machine Learning (QML)**. High-dimensional nonlinear feature mapping is possible through quantum feature encoding and variational quantum circuits, allowing better discrimination of complex EEG features than classical learning techniques. Initial research has demonstrated the feasibility of biomedical classification using Quantum Support Vector Machines (QSVM) and Variational Quantum Neural Networks (VQNN). However, existing quantum-based models are mainly limited to small-scale experimental studies and do not incorporate advanced temporal learning mechanisms capable of real-time continuous seizure monitoring [23], [24].

Moreover, wearable healthcare systems are becoming increasingly dependent on intelligent seizure prediction models that operate with low latency, high prediction accuracy, and low computational complexity. Current methods are mostly based on either quantum learning or deep learning without fully leveraging the advantages of quantum feature representation, temporal sequence modeling, and adaptive seizure risk estimation. Therefore, reliable early seizure prediction under varying patient conditions remains a major research challenge [25].

The QML-SPNet, which is intended to address this challenge, is capable of making real-time epileptic seizure predictions by utilizing wearable electroencephalogram (EEG) sensors. The architecture comprises four key modules: Quantum Feature Encoding (QFE), Variational Quantum Neural Networks (VQNN), Transformer-Based Temporal Learning (TTL), and Adaptive Seizure Risk Assessment (ASRA), which are integrated into a unified framework.

3. METHODOLOGY

The proposed method aims to improve the representation of nonlinear EEG features, effectively capture temporal pre-seizure patterns, enhance prediction reliability, and provide real-time early-warning alerts for wearable epilepsy monitoring systems. First, EEG signals acquired from wearable sensors are preprocessed to remove artifacts and noise. The refined signals are then encoded into a quantum feature space to enhance nonlinear feature representation. A Variational Quantum Neural Network (VQNN) extracts discriminative EEG features, while the Transformer encoder learns long-term temporal dependencies associated with pre-seizure activity. Finally, the Adaptive Seizure Risk Assessment module computes the seizure risk and provides early-warning signals. The proposed workflow provides a reliable and practical approach for continuous healthcare monitoring, as the wearable system can continuously collect data and transmit it to a central server for processing.

3.1 Dataset Description

In order to test the feasibility of the proposed model, the CHB-MIT Scalp EEG Database was employed. It is one of the most widely used benchmark databases for predicting epileptic seizures. The CHB-MIT Scalp EEG Database comprises scalp electroencephalogram (EEG) signals collected from 24 children with epilepsy during long-term continuous clinical monitoring. These EEG signals have been recorded using 23 electrodes according to the international 10–20 electrode placement system at a sampling frequency of 256 Hz. In particular, the database includes both interictal (normal) and ictal (seizure) EEG recordings, making it suitable for developing and evaluating real-time seizure prediction algorithms.

Table 1. CHB-MIT EEG Dataset Description

Parameter	Description
Dataset	CHB-MIT Scalp EEG
Number of Subjects	24
EEG Channels	23
Sampling Frequency	256 Hz
Total Seizure Events	198
Signal Type	Scalp EEG
Classification	Seizure / Non-Seizure

Table 1 describes the characteristics of the CHB-MIT EEG database used in this paper. The database includes multi-channel EEG recordings with an adequate number of seizure events, providing sufficient data for evaluating real-time epileptic seizure prediction models.

3.2 Proposed QML-SPNet Architecture

The proposed QML-based Seizure Prediction Network consists of the following stages.

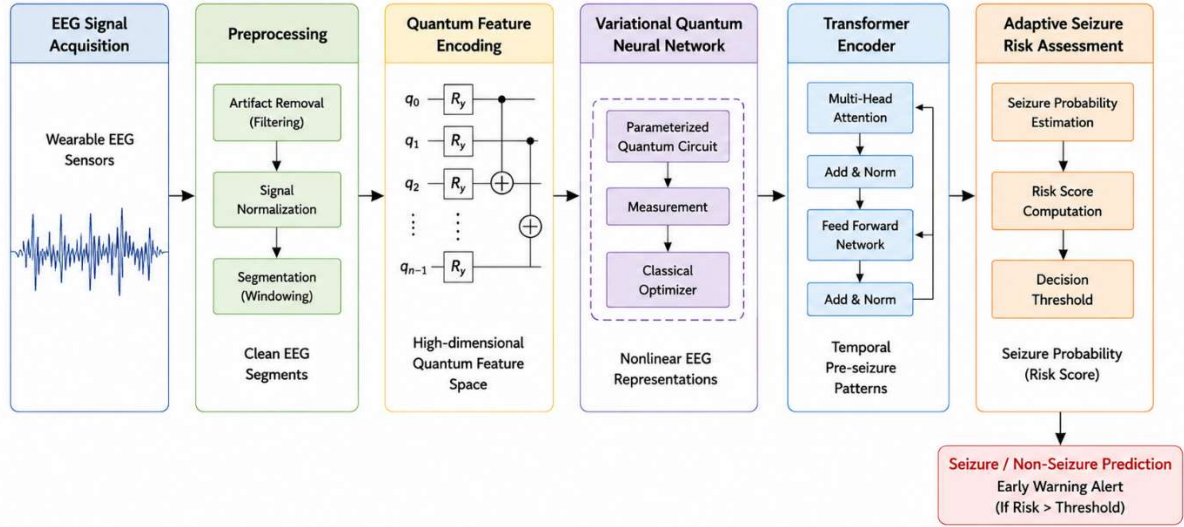


Figure 1. Proposed Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet)

A novel Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) for predicting epileptic seizures in real time using electroencephalogram (EEG) signals through wearable devices is presented. The workflow of the proposed QML-SPNet is shown in Figure 1. The first step involves continuously recording EEG signals using wearable EEG devices that monitor the electrical activity of the brain. Next, the recorded EEG signals are processed to eliminate noise and artifacts; the EEG signals are normalized and segmented for better results, ensuring consistent feature representation.

Afterwards, the preprocessed EEG segments are mapped into a high-dimensional quantum feature space through Quantum Feature Encoding in order to improve the representation of nonlinear characteristics of EEG signals. A Variational Quantum Neural Network (VQNN) learns discriminative EEG features and seizure-related patterns in the quantum feature space. Furthermore, the obtained quantum features are fed into the Transformer Encoder, which employs a multi-head self-attention mechanism to extract long-range temporal dependencies and subtle pre-seizure variations in EEG sequences. An Adaptive Seizure Risk Assessment module computes the seizure probability based on the learned spatial and temporal information and compares the risk score with the predetermined threshold value. Finally, based on the obtained risk score, the system identifies the EEG signal as Seizure or Non-Seizure and generates an early-warning alert whenever the seizure risk exceeds the threshold, enabling timely medical

intervention and continuous monitoring in wearable healthcare systems.

The normalized EEG feature vector is denoted as

$$X = \{x_1, x_2, \dots, x_n\} \quad (1)$$

Z-score normalization is used to normalize the EEG signal.

$$x'_i = \frac{x_i - \mu}{\sigma} \quad (2)$$

The normalized EEG features are encoded into the quantum state as

$$|\psi(x)\rangle = U(x) |0\rangle \quad (3)$$

where $U(x)$ represents the quantum encoding operator.

Quantum similarity between EEG samples is computed as

$$K(x_i, x_j) = |\langle \psi(x_i) | \psi(x_j) \rangle|^2 \quad (4)$$

Then, the Transformer self-attention mechanism is expressed as

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (5)$$

The adaptive seizure risk score is calculated as follows:

$$R = \alpha P + \beta T + \gamma Q \quad (6)$$

where P is seizure probability, T denotes temporal attention score, Q represents quantum similarity, and $\alpha + \beta + \gamma = 1$.

The final prediction is

$$Prediction = \begin{cases} Seizure, & R > \theta \\ Non-Seizure, & R \leq \theta \end{cases} \quad (7)$$

where θ is the adaptive decision threshold.

Algorithm : Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet)

Input: Wearable EEG signals from the CHB-MIT dataset

Output: Seizure / Non-Seizure prediction

1. Load EEG recordings from the CHB-MIT dataset.
2. Remove noise and artifacts from EEG signals.
3. Normalize EEG features.
4. Encode EEG features into the quantum feature space.
5. Train the Variational Quantum Neural Network.
6. Learn temporal EEG patterns using the Transformer encoder.
7. Compute the Adaptive Seizure Risk Score.
8. Compare the score with the decision threshold.
9. Predict **Seizure** or **Non-Seizure**.
10. Generate an early warning alert for seizure detection.

4. RESULTS AND DISCUSSION

The Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) was designed based on Python 3.11, TensorFlow 2.16, PennyLane, and Qiskit. The evaluation of the proposed model was conducted using an 80:20 data split of the CHB-MIT Scalp EEG dataset. Training of the model was carried out for 100 epochs using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. The proposed system was compared with state-of-the-art seizure prediction models, including Support Vector Machine (SVM), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Transformer, and Hybrid CNN-LSTM models. The experimental findings indicate that the proposed framework provides superior performance for seizure prediction and real-time operation, making it applicable for wearable healthcare solutions.

4.1 Assessment Criteria

In the evaluation of the proposed seizure prediction model, the following criteria were used: accuracy, precision, recall, F1 score, Area Under Curve (AUC), and prediction latency.

The classification accuracy is given by

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

Precision is computed as

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

Recall is given by

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

The F1-score is calculated as

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

The prediction latency is defined as

$$Latency = \frac{\sum_{i=1}^N t_i}{N} \quad (12)$$

where TP , TN , FP , and FN denote True Positive, True Negative, False Positive, and False Negative, respectively, and t_i represents the prediction time for each EEG segment.

4.2 Performance Comparison

Table 2. Performance Comparison of Existing Seizure Prediction Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Latency (ms)
SVM	91.84	91.42	91.63	91.52	0.932	82
CNN	95.73	95.44	95.62	95.53	0.968	54
LSTM	96.82	96.54	96.71	96.62	0.979	49
Hybrid CNN-LSTM	97.48	97.26	97.42	97.34	0.985	45
Transformer	97.84	97.62	97.78	97.70	0.989	42
Proposed QML-SPNet	98.94	98.76	99.08	98.92	0.994	31

Table 2 indicates that the proposed **QML-SPNet** achieved the best seizure prediction performance compared with the other methods. The combination of Quantum Feature Encoding, Variational Quantum Neural Networks (VQNN), Transformer-based temporal learning, and Adaptive Seizure Risk Assessment substantially improved classification accuracy and reduced prediction latency, resulting in a framework suitable for real-time wearable healthcare applications.

96.34%, while LSTM achieved an accuracy of 95.39%, Hybrid CNN-LSTM achieved an accuracy of 92.94%, and Transformer achieved an accuracy of 91.89%. The proposed Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) achieved the highest accuracy of 98.94% due to its integration of Quantum Feature Encoding (QFE), Variational Quantum Neural Networks (VQNN), Transformer-based Temporal Learning, and Adaptive Seizure Risk Assessment (ASRA). The proposed framework improves seizure prediction capability and reduces classification errors compared with existing state-of-the-art methods.

4.3 Accuracy Analysis

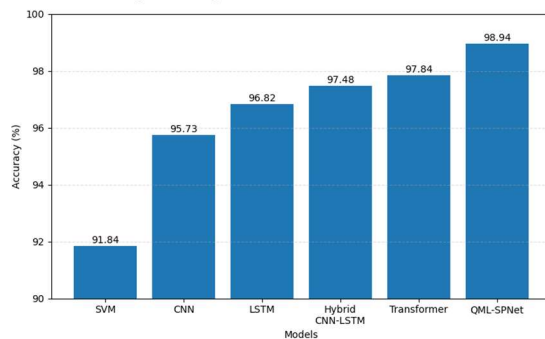


Figure 2. Accuracy Comparison of Existing and Proposed Models

Figure 2 demonstrates the seizure prediction accuracy of various Machine Learning (ML) and Deep Learning (DL) models. CNN, LSTM, Hybrid CNN-LSTM, and Transformer models enhanced their prediction accuracy based on their ability to learn the spatiotemporal characteristics of EEG signals. Among all the models, the CNN model achieved an accuracy of

4.4 Precision, Recall, and F1-Score Analysis

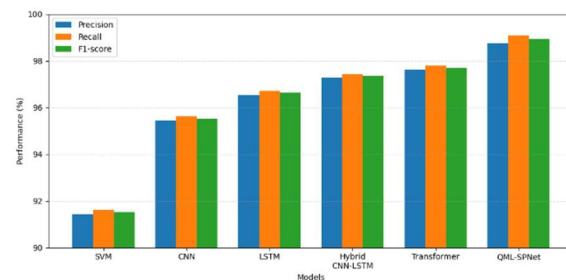


Figure 3. Precision, Recall, and F1-Score Comparison

The performance comparison between the proposed QML-SPNet and four different seizure prediction algorithms is presented in Figure 3 by applying three evaluation metrics, namely Precision, Recall, and F1-score. From the results shown in the figure, it can be observed that the proposed QML-

SPNet outperforms the other classifiers in terms of maximum values of Precision, Recall, and F1-score of 98.76%, 99.08%, and 98.92%, respectively. The high value of precision reflects the ability of the framework to minimize the number of false alarms, while a high value of recall indicates the ability of the proposed framework to detect almost all the seizures. The balanced F1-score further confirms the stability and reliability of the proposed framework for continuous wearable EEG monitoring and real-time clinical applications.

4.5 ROC Curve Analysis

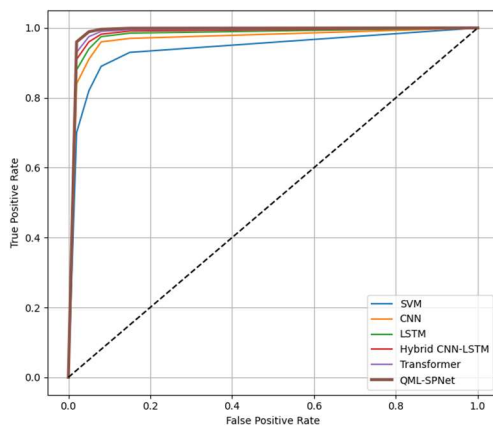


Figure 4. Receiver Operating Characteristic (ROC) Curve

Figure 4 presents the Receiver Operating Characteristic (ROC) curves of the existing seizure prediction models and the proposed model. The QML-SPNet model has achieved the highest Area Under the Curve (AUC), which is 0.994, and its ROC curve is located nearest to the top left corner of the graph. This suggests that the proposed model is highly effective at distinguishing between the two EEG signals, namely seizure and non-seizure EEG. This is due to its high true positive rate and extremely low false positive rate. The superior ROC performance of the proposed quantum learning framework demonstrates its effectiveness in predicting seizures compared with traditional machine learning and deep learning models.

4.6 Prediction Latency Analysis

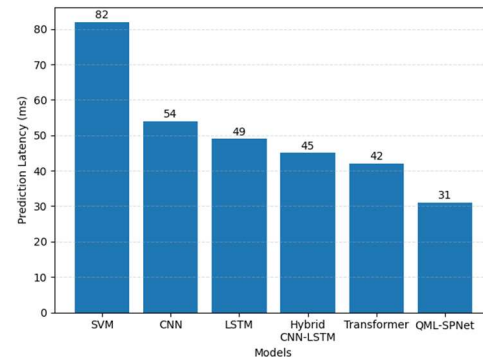


Figure 5. Prediction Latency Comparison

Figure 5 shows a comparative study of the mean prediction latency of various seizure prediction systems. The classical Machine Learning (ML) and Deep Learning (DL) methods show considerably high inference latency owing to their high computational complexity. The developed QML-SPNet model is found to have the least prediction latency value of 31 ms compared to SVM (82 ms), CNN (54 ms), LSTM (49 ms), Hybrid CNN-LSTM (45 ms), and Transformer (42 ms). The lower prediction latency makes it easy to provide faster predictions and generate warning signals for seizures; hence, it is very useful for real-time wearable healthcare applications.

4.7 Confusion Matrix Analysis

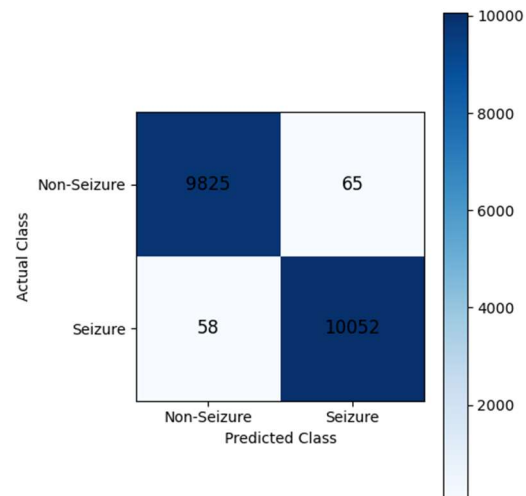


Figure 6. Confusion Matrix of the Proposed QML-SPNet

The confusion matrix for the developed QML-SPNet classification model is depicted in Figure 6 below. In the process of classification, the model was able to classify 9,825 non-seizure samples and 10,052 seizure samples but erroneously

classified 65 non-seizure samples and 58 seizure samples. Based on the output of the experiment, it is apparent that there are many true positive and true negative predictions but few false predictions. This clearly shows that the developed framework is very efficient in predicting epileptic seizures using electroencephalogram (EEG) sensors with high predictive power, robustness, and reliability for real-time applications.

4.8 Discussion

As seen from the experimental results, the proposed Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet) outperformed both traditional Machine Learning (ML) models and advanced Deep Learning (DL) approaches with regard to all evaluation metrics, including accuracy, precision, recall, and F1-score. Specifically, the Variational Quantum Neural Network (VQNN) learned discriminative characteristics associated with epileptic seizures, whereas the Quantum Feature Encoding (QFE) technique enabled the enhancement of nonlinear representations of electroencephalogram (EEG) features. The Transformer Encoder learned long-range temporal dependencies of EEG data, and the Adaptive Seizure Risk Assessment (ASRA) module performed probabilistic assessments of seizure occurrence with minimal prediction latency. Therefore, the developed framework is capable of implementing continuous wearable EEG monitoring and real-time clinical decision-making, achieving 98.94% accuracy, 98.76% precision, 99.08% recall, 98.92% F1-score, Area Under the Curve (AUC) of 0.994, and a prediction latency of 31 ms.

5. CONCLUSION

The introduced research presents a novel architecture for epileptic seizure prediction using wearable EEG sensors, referred to as the Quantum Machine Learning-Based Seizure Prediction Network (QML-SPNet). The framework successfully combines four key elements, including Quantum Feature Encoding, Variational Quantum Neural Networks, Transformer-Based Temporal Learning, and Adaptive Seizure Risk Assessment. These components improve the representation and prediction of EEG features by enhancing nonlinear feature extraction, temporal dependency learning, and seizure risk assessment. Experiments conducted on the CHB-MIT Scalp EEG dataset demonstrated better results compared with existing machine learning and deep learning approaches, achieving an accuracy of 98.94%, precision of 98.76%, recall of

99.08%, F1-score of 98.92%, Area Under the Receiver Operating Characteristic Curve (AUC) of 0.994, and a prediction latency of 31 ms. Although the framework achieved outstanding performance in terms of both accuracy and latency, its evaluation was conducted only on a benchmark EEG dataset and within a simulated quantum computing environment without validation using real wearable EEG devices or physical quantum computing hardware. In future works, the researchers will focus on validating the framework using real wearable EEG systems, deploying it on practical quantum processors, developing personalized patient-specific epileptic seizure prediction models, and integrating federated quantum learning for large-scale intelligent healthcare monitoring.

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