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Forked hybrid architecture combining 1D-CNN and quantum convolutional networks for EEG signal classification

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Abstract

Detecting epileptic seizures from electroencephalogram (EEG) signals presents a significant challenge due to the nonlinear and non-stationary nature of brain activity. In this study, we propose a hybrid classification framework that integrates quantum-assisted and classical deep learning techniques to enhance detection accuracy and model interpretability. First, discrete wavelet transform (DWT) is applied to extract multiscale time–frequency features from raw EEG signals. Subsequently, three comparative models are developed: a conventional 1D-CNN model, an IQCNN model incorporating a parametric quantum circuit, and a novel Forked Enhanced Model that processes EEG features simultaneously through both 1D-CNN and IQCNN branches and combines them in a fully connected layer. The proposed hybrid model leverages the expressive power of quantum entanglement while preserving the robustness of classical deep learning. Evaluations using 5-fold stratified cross-validation on a real EEG dataset show that the forked architecture outperforms both classical CNNs and quantum-only based models in terms of accuracy, F1 score, precision, recall, number of incorrectly classified subjects and AUC. In this study, the best result was obtained with the Denoise IQCNNNet hybrid model. The accuracy of this model is 97.25%, precision 92.74%, recall 93.66%, F-1 score 93.15%, AUC 99.54%, number of incorrectly classified subjects are 57. This study demonstrates the feasibility and potential of hybrid quantum-classical networks in biomedical signal processing and provides a foundation for real-time clinical seizure monitoring systems.

Keywords EEG classification, Forked architecture, Hybrid deep learning, Improved quantum CNN, Biomedical signal processing

1 Introduction

Epilepsy, one of the neurological problems, has been recognised worldwide as a disease. It is also one of the main threats to human lives. Epilepsy is therefore the most common global neurological disorder. Some groups of individuals diagnosed with epilepsy have been observed to stare blankly for several seconds during a seizure, while others move their arms or legs repeatedly. In general, a diagnosis of epilepsy requires at least two seizure episodes without stimuli. The electroencephalogram (EEG) method for detecting



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brain abnormalities is one of the methods for diagnosing epileptic seizures using electrical disturbances in the human brain [1].

The normal brain activity of epilepsy patients can be categorized into pre-seizure state, seizure state, inter-seizure state and post-seizure state by analyzing EEG signals. On the other hand, an epileptic seizure is a type of seizure that causes serious consequences for the patient such as impaired consciousness and body contractions [2].

Electroencephalogram (EEG) is a type of assessment that can be used to record brain activities that can show normal and abnormal electrical activities of the human brain. Implanted devices or non-invasive devices can be used to obtain EEG signals from the human brain. Features of the disease, such as seizure and non-seizure, are analysed by trained specialists. Neurologists who perform the examination can make treatment decisions by making recommendations to patients based on the information obtained from EEG signals. The examination and analysis of EEG signals by a neurologist for the detection of the disease causes more time and cost. A very good neurologist needs several hours to analyse one day's recordings of a patient. Therefore, there is a need to develop automatic seizure detection systems [3].

When the existing approaches of automatic epileptic seizure detection were analysed, some difficulties leading to misclassification of EEG signals were identified. One of the biggest problems is the identification of distinctive features of epileptic EEG signals. The way to solve this important problem is to analyze the structure of EEG signals. Because of the dynamic nature of EEG signals, the extraction of a distinctive feature set of epileptic EEG signals is complicated by kinds in the features of seizure recordings extracted from different seizure incidents. Another challenge is to reducing the misclassification rate because of the similarity of some oscillatory and fractal properties of EEG signals in seizure and nonseizure states [4].

Machine learning (ML) is one of the most widely used methods for epileptic seizure detection. Moreover, ML methods need to realize the non-automatic design of feature extractors in order to detect epileptic seizure features that are difficult to extract different features [5]. Recently, thanks to the fast progress of ANN theory and parallel computing technology, deep learning methods have come to the forefront. Thanks to deep learning technologies, successes have been achieved in the fields of image recognition, natural language processing and emotion recognition. In addition to these areas, deep learning has also been used in medical applications. DL can automatically detect appropriate features from EEG signals. Moreover, deep learning can perform end-to-end epileptic seizure detection [6].

On the other hand, it is also known that quantum mechanics offers a new approach to solving computational problems and performs very well compared to the best classical methods. Quantum machine learning (QML) methods have been created using quantum mechanics. QML for EEG signals has been used to solve brain function and neurological problems. Methods such as Quantum SVM (QSVM), Quantum Recurrent Neural Network (QRNN), Quantum Neural Network (QNN) have been used to extract features from EEG data [7]. Some studies have also used Quantum Convolutional Neural Network (QCNN) for epilepsy class prediction [8].

In this study, three models were employed to classify EEG time-series data. The first model is a classifier based on a one-dimensional convolutional neural network (1D-CNN). The second model is a classifier utilizing an Improved Quantum Convolutional

Neural Network (IQCNN). The third model is a hybrid classifier that integrates the first two models within a bifurcated (forked) architecture. Among these approaches, the best-performing model was identified, and high accuracy in seizure detection was targeted. The dataset used in this study consists of time-series samples that represent the values of EEG signals at specific time points. To achieve optimal results, the parameters of the classifiers were tuned according to the characteristics of the dataset.

The primary objective of this study is to present a comparative analysis of traditional CNN, IQCNN, and a novel bifurcated CNN+IQCNN (IQCNNNet) architecture—which has not previously been applied to EEG classification—for the classification of epileptic EEG signals, and to highlight the contributions of quantum-layered architectures to biomedical diagnostic systems. This work represents the first study in the literature to propose a bifurcated architecture that simultaneously integrates both classical CNN and quantum-enhanced CNN (IQCNN) models for epileptic seizure detection from EEG signals. Unlike previous hybrid approaches based on sequential or parallel feature fusion, the proposed method preserves separate training pipelines for both models and combines their learned representations at the feature level, thereby maintaining the unique advantages of both paradigms. This architectural innovation introduces a new perspective to the design of quantum–classical hybrid networks in the field of biomedical signal processing.

In the first part of this study, the importance of epilepsy and the necessity of automated systems for seizure detection based on EEG signals are discussed. Current challenges and solutions are presented.

In the second section, quantum machine learning and deep learning based EEG classification approaches are reviewed and the differences between the methods in the existing literature and this work are emphasized.

In the third section, the EEG dataset used is detailed and the technical details of the applied discrete wavelet transform (DWT) and feature extraction, CNN, IQCNN and the newly proposed forked structure are explained. Model parameters, activation functions, optimization algorithms and evaluation metrics are also presented.

In the fourth section, the 5-fold cross-validation results of the developed models are presented with tables, graphs and ROC curves, and the accuracy, precision, sensitivity, F1 score and AUC performances of the models are compared.

In the fifth section, the model performances are discussed in detail and the advantages of the proposed forked structure compared to classical and quantum approaches are presented.

2 Related works

2.1 Literature research

Koike-Akino et al. applied Quantum Machine Learning (QML) methods in addition to deep learning methods for biosignal processing applications. To do this, they created a hybrid quantum-classical neural network model by integrating a variational quantum circuit for EEG, EMG, ECoG analysis with a deep neural network in a hybrid way. This model is named quEEGNet. As a result of the study, they obtained the highest test accuracy for the physiological data set created for neurological stress serial visual presentation. While the validation rate obtained using the EEGNet model is 93.73% for this dataset, this rate is 95.12% for the quEEGNet model [9].

Cruz-Vazquez et al. proposed an emotion recognition model based on EEG signals using deep learning methods on a validated dataset. They examined various data transformation techniques, including Fourier neural networks and quantum transforms, for good separation of emotions. The CNN model combined with quantum transforms achieved 95% accuracy, especially in distinguishing the emotion of being sad [10].

Abdul-Zahra et al. performed EEG signal classification using an optimized quantum neural network. After normalizing the EEG signals, an optimized quantum neural network (QNN) was used for classification. Wavelet transform and independent component analysis were used for feature extraction. For the optimization process, they used particle swarm optimization. As a result of the study, the accuracy rate of independent component analysis is 82.4% for both feature extraction methods and 78.43% for wavelet transform [11].

Chen et al. introduced a new hybrid neural network model, QEEGNet, which integrates quantum architecture with classical EEGNet architecture to improve EEG analysis. QEEGNet uses quantum layers within the neural network. They used the BCIC-IV-2 A dataset for this study. They obtained the best result in Subject 9. They achieved 62.2% test accuracy with EEGNet and 65.3% with QEEGNet [12].

Mittal et al. propose hybrid quantum machine learning models for emotion recognition from human voice signals. The proposed quantum support vector machine (QSVM) and hybrid quantum neural network (HQNN) models use the output of Mel-Frequency Cepstral Coefficients for feature extraction from audio data. As a dataset, they used Moroccan Dialect Sentiment recognition dataset. They obtained accuracy rates of 91.5% with classical neural network, 94.5% with HQNN, 83.5% with SVM and 84.5% with QSVM [13].

Chandanwala et al. used a hybrid quantum deep learning model for emotion detection using raw EEG signal analysis. In this model, the classification process is realized by integrating the deep learning architecture and the classifier in a hybrid way by using quantum computations for feature extraction. As a result, they achieved 95% accuracy, 94% precision, 94% recall and 91% F-1 rates [14].

Sadiq et al. presented a novel automated framework that highlights the importance of multi-domain features combined with feature selection in order to enhance the performance of a learning algorithm for motor imagery EEG classification using signal decomposition methods. In their study, various combinations of signal decomposition techniques and feature selection approaches were examined and jointly employed, and a comprehensive comparison was provided among the considered methods. Among all combinations, the authors reported that variational mode decomposition, together with multi-domain features obtained via linear regression and a cascade forward neural network classifier, achieved superior classification performance compared to other state-of-the-art approaches for both subject-dependent and subject-independent BCI systems. They further stated that this method demonstrated an improvement ranging between 26.1% and 26.4% over the existing techniques in the literature [15].

Sadiq et al. proposed a multivariate empirical wavelet transform (MEWT) algorithm for the analysis of different motor imagery (MI) tasks. One of the key contributions of their study was the introduction, for the first time in MI applications, of a sub-band alignment strategy based on MEWT in order to extract common instantaneous amplitude and frequency components. Using three benchmark datasets from the BCI Competition

III, the authors conducted extensive experiments with conventional machine learning classifiers to evaluate the performance of the proposed approach. Their results showed that, by employing multilayer perceptron neural networks, logistic model tree, and least squares support vector machine (LS-SVM) classifiers for the three datasets, an average sensitivity, specificity, and classification accuracy of 98% was achieved, together with an improvement of up to 23.50% in classification accuracy compared with existing methods [16].

3 Materials and methods

3.1 Dataset used in the study

The dataset used in this study is a remodeled UCI Epileptic Seizure Recognition version of the Bonn dataset containing epileptic seizure detection. There are 100 files in this dataset and each file represents a single person. For each file, brain activity was recorded for 23.6 s. 4097 data points were sampled as a time series. Each data point is the value of the EEG recording at a different time point [17].

The UCI Epileptic Seizure Recognition dataset was divided into 23 segments, each including 4097 data points, and compared. Each partition contains 178 data points. Thus, there are 11,500 data points. Also, the last column $y \{1,2,3,4,5\}$ represents the value of the response variable. In class 1 we record seizure activity and in class 2 we record EEG values from the tumor site. Also in class 3, we identify where the tumor site is located in the brain and record EEG activity from the healthy brain region. In class 4, eyes closed indicates that the patient's eyes are closed when recording the EEG signal. In Class 5, eyes open indicates that the patient's eyes are open when recording the brain EEG signal. All topics in classes 2, 3, 4 and 5 had no epileptic seizures. Only subjects in class 1 had epileptic seizures [17].

3.2 Procedures performed in the study

In this study, as a first step, time frequency components were extracted by applying wavelet transform to the data set. Thus, feature extraction was performed. The extracted features were preprocessed in this study and thus normalization was achieved. Then, 1-D CNN, IQCNN, IQCNNNet (forked), Denoise IQCNNNet, MSPCA-IQCNNNet, RAW-CNN methods were used as classifiers. Classifiers were used with cross-validation with $k = 5$ and average evaluation metrics were obtained. Figure 1 shows the architecture of the steps implemented in this study.

The computer used in this study has 16 GB RAM, 64-Bit OS, Windows operating system. In addition, Jupyter Notebook interface of PYTHON was used. The libraries used in the software are numpy, pandas, pennylane, tensorflow, sklearn, matplotlib.

3.3 Discrete wavelet transform for feature extraction

Wavelet transform is a highly effective method for working with temporal data. It also has a general structure of the short-time Fourier transform. The short-time Fourier transform is only interested in the frequency values in all frequency ranges in the time series. The wavelet transform deals with frequency and time values in different frequency ranges and can find these values [18].

Discrete wavelet transform (DWT) is one of the most widely used feature extraction methods for EEG signals. DWT distinguishes both time and frequency characteristics

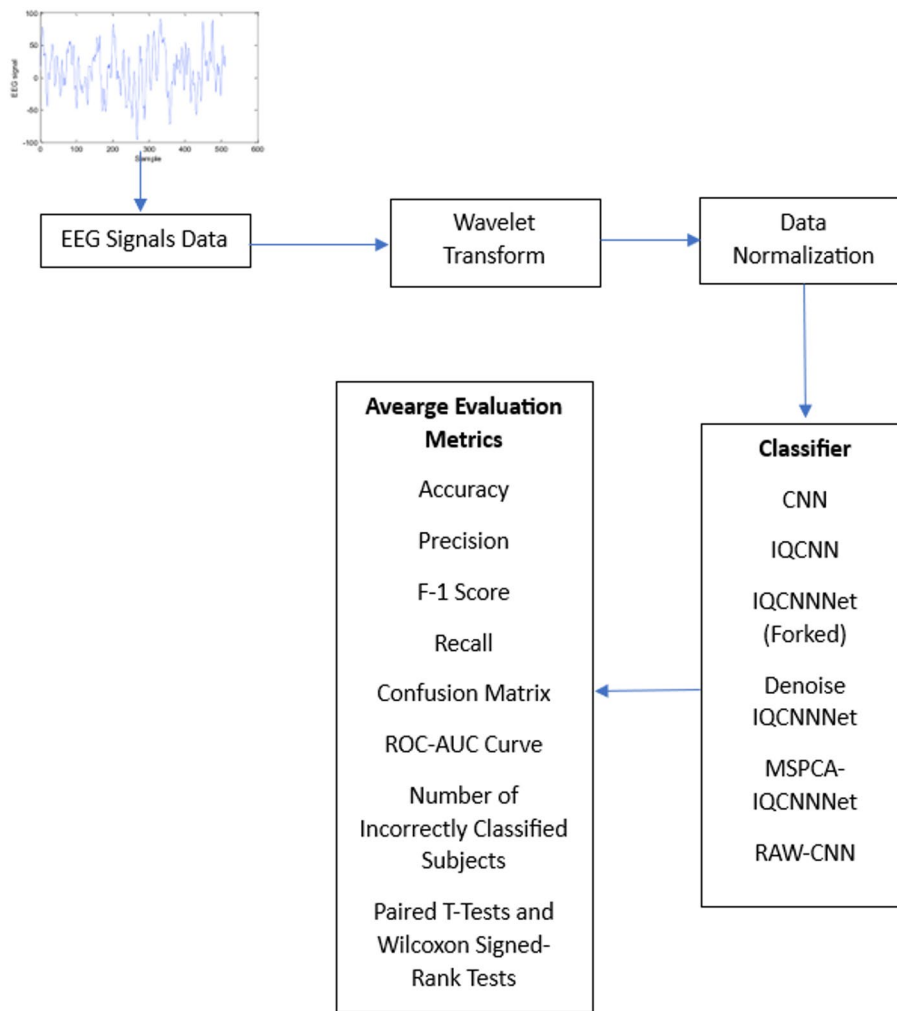


Fig. 1 Architecture of the steps applied in the study

of an input. This increases the power of classification models. It also trims unnecessary features and performs size reduction. In this way, it optimizes the classification process [19].

The input signal $\psi_{a,b}[n]$, denoted by $x[n]$, is defined as the mother wavelet function at scale a and translation b . $\psi_{a,b}[n]$ denotes the main structure used in DWT. The mother wavelet function analyzes the input signal into its frequency components. $\psi(n)$ denotes the base wavelet function. The mother wavelet function is as expressed in Eq. 1.

$$\psi_{a,b}[n] = 2^{-\frac{a}{2}} \psi(2^{-a}n - b) \quad (1)$$

DWT decomposes the input signal into wavelet coefficients. This process is as shown in Eq. 2.

$$DWT(x, a, b) = \sum_n x[n] \cdot \psi_{a,b}[n] \quad (2)$$

Equation 2 also shows how the input signal is transformed into the wavelet coefficient of scale a and the translation b [20].

Daubachies 4 main wavelets were used in this study. Decomposition level is used as 3.

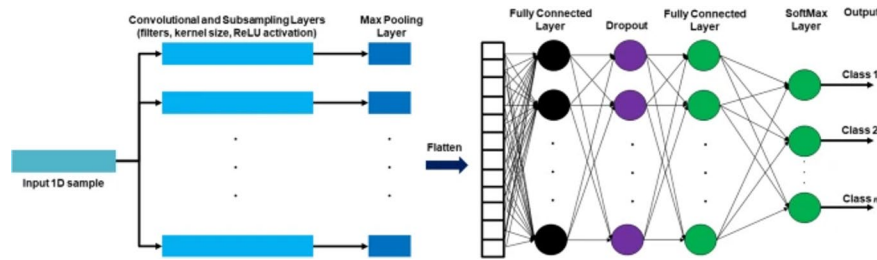


Fig. 2 1-D CNN layers for prediction of n classes

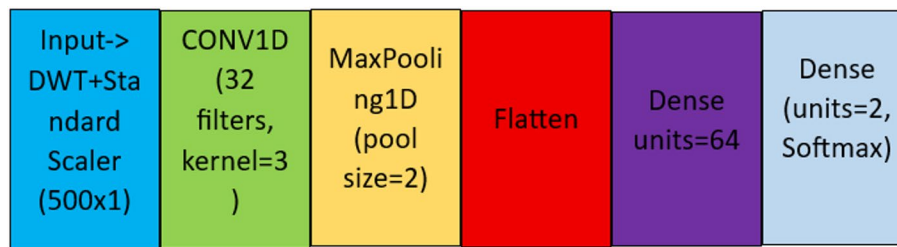


Fig. 3 Architecture of the 1-D CNN model used in the study

In this study, the features in each sample are scaled to have zero mean and unit variance using Standard Scaler. This step was followed by data normalization to speed up and stabilize the learning process during model training. In this study, after feature extraction with DWT, each EEG sample is transformed into a 500-dimensional feature vector.

3.4 One-dimensional convolutional neural network (1-D CNN)

Convolutional neural network (CNN) is a very important method for feature extraction and classification of data in medical science [21]. Convolutional neural network is a type of network that shows the closest characteristics to human performance due to its advanced architecture and optimization. In addition, CNN is also a feed-forward artificial neural network [22].

Generally, 1-D CNN architecture includes convolutional, pooling and fully connected layers. In the convolutional layer, convolutions perform feature detection of one-dimensional samples with different filtering processes. In this process, the rectifier uses the linear unit ReLU. In the maximum pooling layer, pooling is performed to select the best features from the overall feature map. The task of the smoothing layer is to adjust the multidimensional feature map to a one-dimensional array. There is also a dropout layer to prevent overfitting. The output of the classes is generated by the SoftMax function in the ram linked layer. Figure 2 shows the 1-D CNN architecture for classifying data with n classes [21].

The architecture of the 1-D CNN model used in the study is shown in Fig. 3.

In this model, a dropout value of 0.3 was used.

3.5 Improved quantum convolutional neural network (IQCNN)

QCNN is a type of quantum computational classification inspired by CNN. QCNNs share parameters within the convolutional layer of quantum circuits. They also reduce the size by following qubits in the pooling process. The main difference between

a QCNN and a CNN is that the data in a QCNN is generated in a Hilbert space that increases exponentially with the number of qubits. Whereas in classical convolution vectors are transformed into scalars, in quantum convolution more complex linear operations are performed. In QCNN, the state vector is transformed into vectors via the unitary transform. Problems defined in exponentially increasing Hilbert space are impossible to solve in a classical setting. However, QCNN uses qubits in a quantum environment to effectively solve these intractable problems [23].

In a classical model, a “0” or “1” is used for information processing. However, in a quantum structure, bits are represented by qubits. A qubit represents a small unit of information in a quantum structure. Thanks to qubits, information is processed faster than in classical computing. Qubits can be expressed individually or they can work in superposition, that is, in combination. A qubit is a state vector in Hilbert space. A qubit is represented by orthogonal vectors. These vectors are $|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $|1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ or $|\psi\rangle = \begin{pmatrix} \theta \\ \phi \end{pmatrix} = \theta|0\rangle + \phi|1\rangle$, where θ and ϕ denote the probability amplitude calculated with $|\theta|^2 + |\phi|^2 = 1$. Quantum gates use qubits as input information. It then performs rotation, translation and state change operations on a fixed qubit [24].

A quantum system with more than one qubit is a coupled quantum system. The unified quantum system is shown in Eq. 3.

$$|\psi\rangle = |\psi_1\rangle \otimes |\psi_2\rangle \otimes |\psi_3\rangle \otimes \dots \otimes |\psi_n\rangle \quad (3)$$

The state evolution of a unified quantum system is denoted by U . U is shown Eq. 4.

$$|\psi'\rangle = U |\psi\rangle \quad (4)$$

Also among the qubit gates are the Pauli X, Pauli Y, Pauli Z, Hadamard gates. The quantum circuit model of quantum state evolution is shown in Fig. 4.

For adjacent qubits, one qubit is selected for measurement. As a result of the measurement, the selected qubit has a V_i -shaped effect on the adjacent qubit [25].

On the other hand, the two-layer QCNN model is shown in Fig. 5.

The architecture of the quantum circuit created in this study is shown in Fig. 6. Figure 7 shows the architecture of the IQCNN model created in this study.

In this model, a dropout value of 0.3 was used. In this model, Angle Embedding is used to apply the data to the quantum circuit, while Strongly Entangling Layers are used to learn global properties between qubits. Additionally, the n_{qubits} value is set to 8. Additionally, the depth value is set to 8.

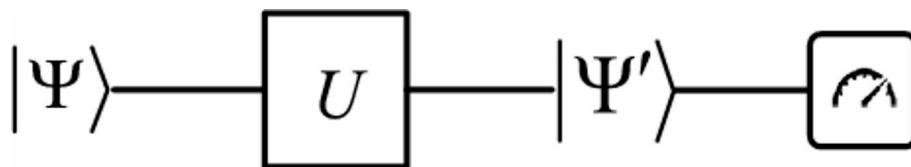


Fig. 4 The quantum circuit model of quantum state evolution

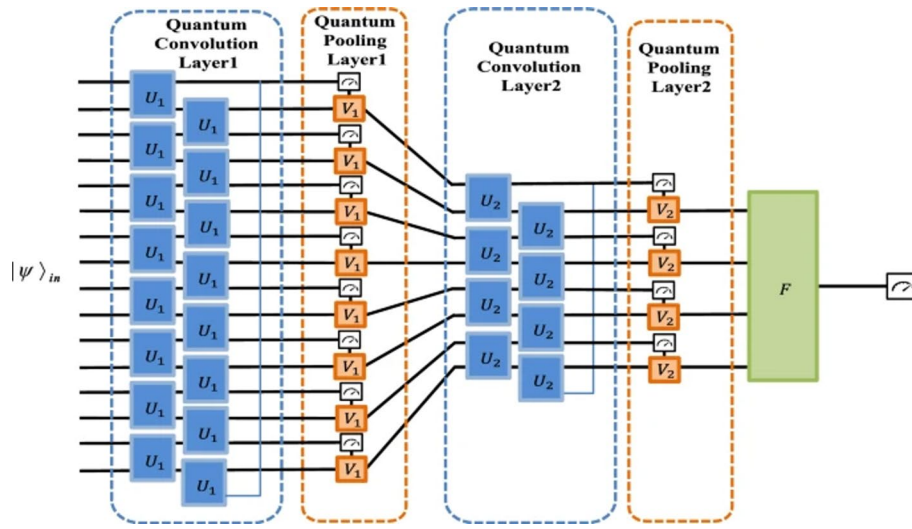


Fig. 5 The two-layer QCNN model

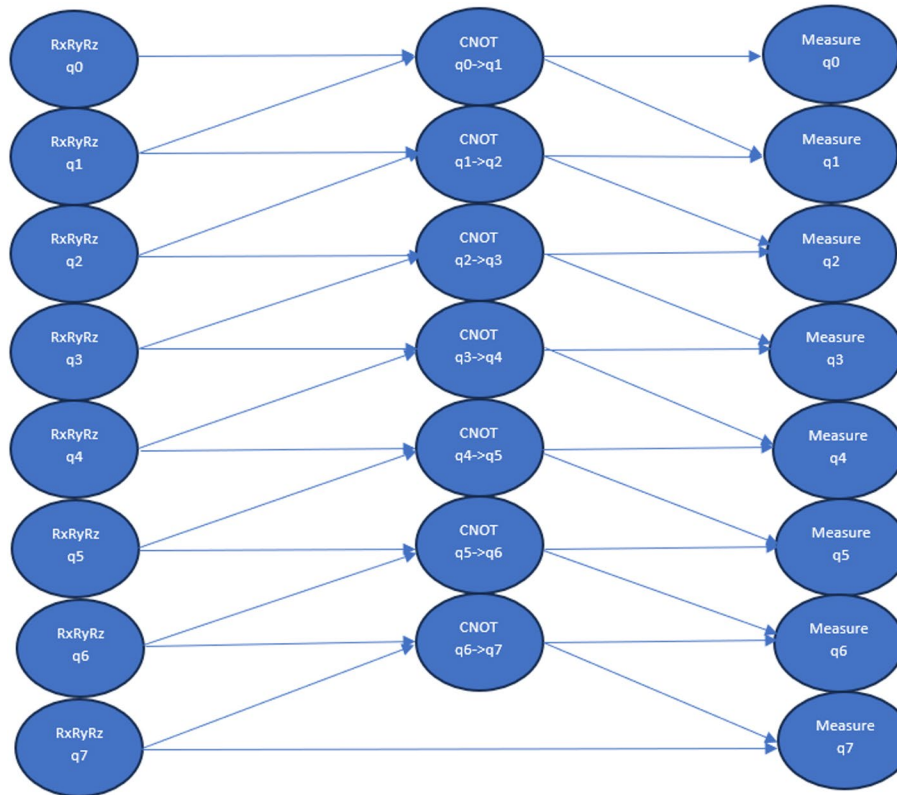


Fig. 6 Architecture of the quantum circuit created in this study

3.6 Creation of hybrid model with forked structure of 1-D CNN and IQCNN classification models (IQCNNNet (forked))

In the same way as CNN logic, convolutional layers can be stacked on top of each other to create a deep convolutional neural network. The outputs of the last convolutional layer can be applied to the input of a QNN. Classical convolutional layers can also be added to quantum convolutional layers [26].

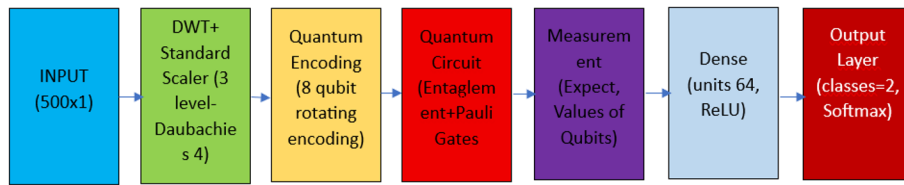


Fig. 7 Architecture of the IQCNN model created in this study

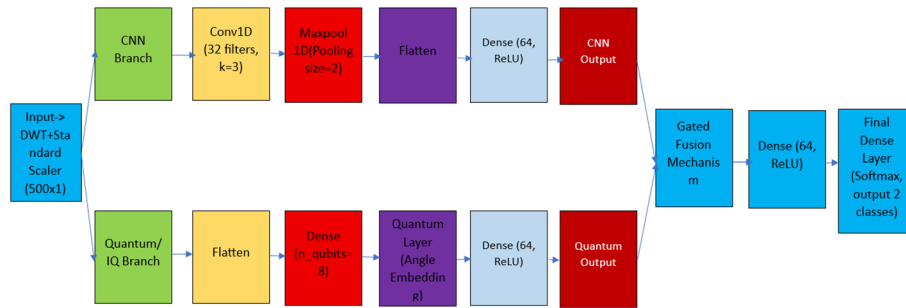


Fig. 8 Architecture of the IQCNNNet (Forked) model created in this study

On the other hand, hybrid multi-branch hybrid quantum-classical neural network models can also be created with a multi-branch strategy to overcome the difficulties in classification [26].

In this study, the 1D-CNN model and the IQCNN model were used separately. However, to achieve better performance by employing these models in a hybrid manner within a forked structure, a merging process was carried out. To accomplish this, it is crucial that both models are used independently without altering any of their parameters. In this third model, the features extracted from the input data by 1D-CNN and IQCNN in two separate branches were subsequently combined to produce the output of a new classifier. The architecture of this third model is presented in Fig. 8.

The novelty of this forked design lies in its structural independence: each branch (1D-CNN and IQCNN) is trained on the same input features but learns its representations independently before fusion. This approach enables the model to preserve both the expressive power of quantum entanglement and the robustness of classical convolutional learning. Moreover, such forked hybridization has not previously been applied or reported for EEG signal classification, making this study an original contribution to quantum-aware deep learning research.

The input EEG signal for the mathematical model of the study is as in Eq. 5.

$$X \in \mathbb{R}^n \quad (5)$$

This signal is transformed using Daubechies-4, Level-3 DWT in Eq. 6:

$$\tilde{x} = DWT_{db4,,L3}(x) \in \mathbb{R}^m \quad (6)$$

Here $DWT_{db4,,L3}$ shows the wavelet transform operator, $\tilde{x}$ represents the 1D feature vector obtained after DWT (e.g., 500 dimensions).

Let the CNN branch be denoted by $C(\cdot)$. In this case, the feature vector is obtained as shown in Eq. 7.

$$h_{cnn} = C(\tilde{x}) \in \mathbb{R}^d \quad (7)$$

If the quantum-inspired branch is expressed as $Q(\cdot)$, the output of the quantum branch's characteristic vector is shown as in Eq. 8. Both the CNN and quantum branch outputs are represented as vectors of the same size d .

$$h_{quantum} = Q(\tilde{x}) \in \mathbb{R}^d \quad (8)$$

Subsequently, a scalar “importance score” (gate) is calculated for each branch as shown in Eq. 9.

$$s_1 = W_1^T h_{cnn} + b_1, s_2 = W_2^T h_{quantum} + b_2 \quad (9)$$

These scores are normalized using the Softmax function as shown in Eq. 10.

$$a_1, a_2 = \text{Softmax}(s_1, s_2) \quad (10)$$

Subsequently, as shown in Eq. 11, the two branches are merged using gated fusion.

$$z = a_1 \cdot h_{cnn} + a_2 \cdot h_{quantum} \in \mathbb{R}^d \quad (11)$$

The gated feature vector z is expressed as a vector and is fed into the fully connected layer and softmax output as shown in Eq. 12. $\varnothing$ represents the ReLU function, while W_c , b_c represents the classifier hidden layer weights.

$$u = \varnothing(W_c z + b_c) \quad (12)$$

The final result is shown in Eq. 13.

$$\hat{y} = \text{Softmax}(W_0 u + b_0) \in \mathbb{R}^2 \quad (13)$$

The complete expression of this model from input to output is as shown in Eq. 14.

$$\hat{y} = \text{Softmax}(W_0 \varnothing(W_c [a_1 C(DWT(x)) + a_2 Q(DWT(x))] + b_c) + b_0) \quad (14)$$

In this model, a dropout value of 0.3 was used. In this model, Angle Embedding is used to apply the data to the quantum circuit, while Strongly Entangling Layers are used to learn global properties between qubits. Additionally, the n_qubits value is set to 8. Additionally, the depth value is set to 8.

To ensure balanced feature representation during fusion, both CNN-derived and quantum-derived feature vectors were normalized using standard feature scaling techniques before concatenation. This step prevents scale dominance and improves training stability.

3.7 Creation of a noise-suppressed IQCNNNet (denoise IQCNNNet) architecture

The objective of this model developed in the study is to create an IQCNNNet (Forked) structure with noise suppression in a forked architecture. The proposed architecture first subjects the raw signals to a Daubechies-4-based three-level DWT (db4, L3) transformation, separating them into multi-scale frequency components. This choice of DWT is based on its ability to strongly represent the microscopic morphological differences between cancerous and non-cancerous tissues in the frequency domain.

Following this stage, the model applies a wavelet threshold-based denoise process to suppress high-frequency noise in the signals. This process ensures that the biological signal is preserved, resulting in a clean and information-rich representation. This allows the model to have a higher signal-to-noise ratio in the subsequent learning layer while preserving tissue-specific spectral features without distortion. In this model, the section shown in Fig. 8 has been added before sending data to the input of the IQCNNNet (Forked) structure. The working diagram of the created Denoise-IQCNNNet model is shown in Fig. 9.

3.8 The IQCNNNet (forked) model with noise suppression via MSPCA

This model was developed to further strengthen the wavelet-based approach used in the study by incorporating a multi-scale statistical analysis preprocessing method. The core idea of the model is that the multi-band signals obtained through DWT should not only be processed by frequency decomposition, but also through PCA-based dimensionality reduction and noise suppression. In this way, dominant variance structures in the signal are preserved, while redundant, low-importance, or noise-driven components are removed.

In this model, the raw input signal is first decomposed into multiple frequency sub-bands using a three-level Daubechies-4 (db4) DWT. PCA is then applied separately to each sub-band, and the first $k=3$ components with the highest variance are retained. Thus, noise reduction and feature compaction are achieved simultaneously. This procedure is known in the literature as MSPCA (Multi-Scale PCA) and is recognized as an effective method particularly in biomedical signal processing. In this model, PCA was used in place of the wavelet-based denoising method previously employed in the DWT-Denoise IQCNNNet architecture. For this reason, we refer to this configuration as MSPCA-IQCNNNet.

3.9 Classification of RAW EEG signals using CNN

In this study, EEG data used without any preprocessing must be classified using the CNN employed in this study to create a model. This is because the effect of preprocessing will be observed in this way. For this purpose, raw EEG data was fed into the classifier, which we refer to as the RAW CNN model. This model proved that the increase in performance was not due to the CNN, but also due to the preprocessing steps performed.

3.10 Activation function, optimizer, loss function

In this study, ReLU activation function is used as the activation function. The mathematical expression of the ReLU activation function is given in Eq. 15 [27].

$$ReLU(y) = \max(0, y) \quad (15)$$

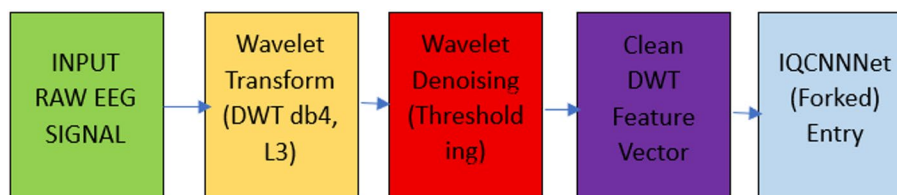


Fig. 9 Architecture of the Denoise-IQCNNNet model created in this study

Adam optimization method is used as the optimization method. The Adam optimization method is used as the optimization method. Equation 16 shows the mathematical expression of the Adam optimizer. M is the moving medium, G is the slope in the current batch, T is the number of iterations, B_1 is the hyperparameter of the algorithm [28].

$$M_T = B_1 M_{t-1} + (1 - B_1) G_T \quad (16)$$

The mathematical expression of the Softmax function used in this study is shown in Eq. 17 [29].

$$f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}} \quad (17)$$

The loss function used in this study is cross-entropy. Its mathematical expression is shown in Eq. 18 [29].

$$L_i = -\log \left(\frac{e^{f_{y_i}}}{\sum_j e^{f_i}} \right) \quad (18)$$

3.11 Evaluation metrics

In this study, precision, accuracy, recall, F1-Score, confusion matrix (CM), AUC, ROC-AUC curve metrics were used as performance metrics. Accuracy is shown in Eq. 19, precision in Eq. 20, recall in Eq. 21, and F-1 Score in Eq. 22 [30].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (19)$$

$$Precision = \frac{TP}{TP + FP} \quad (20)$$

$$Recall = \frac{TP}{TP + FN} \quad (21)$$

$$F-1Score = 2 * \frac{recall * precision}{recall + precision} \quad (22)$$

In statistical classification, the table used to evaluate model performance after data classification is called a confusion matrix. The confusion matrix (CM) is a widely used evaluation tool in data science for both binary and multi-class classification problems. Figure 10 shows an example of a confusion matrix [31].

The Receiver Operating Characteristic (ROC-AUC) curve is a visual tool for comparing classification models. It is widely used in statistical analysis, data mining, and machine learning applications. The ROC-AUC curve illustrates model performance on a two-dimensional graph by plotting the true positive rate against the false positive rate. Additionally, the area under the ROC curve (AUC) provides a quantitative measure of the model's overall performance [32]. Figure 11 illustrates an example of a ROC-AUC curve.

Since cross validation is performed for $k=5$ in this study, the results of all performance metrics are averaged for 5 values. For this reason, when writing the results, the performance metrics are written as average performance metrics.

		Actual Value (as confirmed by experiment)	
		positives	negatives
Predicted Value (predicted by the test)	positives	TP True Positive	FP False Positive
	negatives	FN False Negative	TN True Negative

Fig. 10 CM example

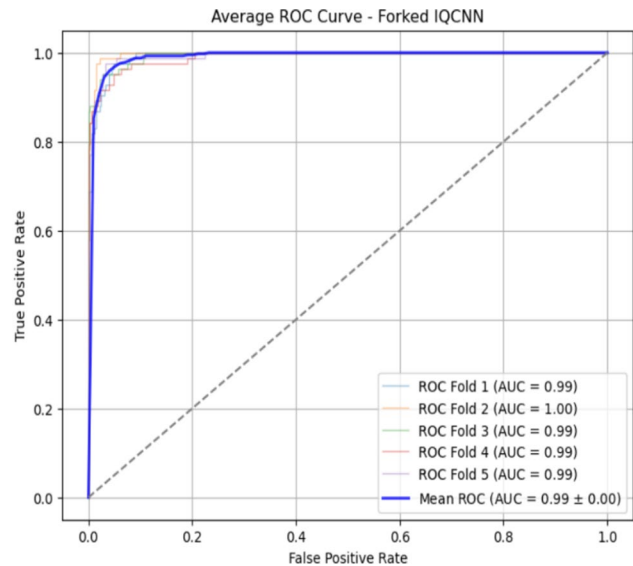


Fig. 11 The ROC-AUC curve example

This study also calculated the number of incorrectly classified subjects. While conventional classification metrics such as ACC, F1, and AUC provide an overall assessment of model performance, they operate at the sample level and do not reflect patient-level reliability, which is crucial in clinical applications. Therefore, in this study, we additionally report the number of incorrectly classified subjects which represents the count of unique patients for whom the model produced at least one misclassification. This metric is particularly important in medical contexts, as even a single incorrect prediction for a given patient may lead to a wrong diagnosis. From this perspective, the proposed method demonstrates not only high sample-level performance but also improved patient-level robustness and diagnostic reliability.

In this study, both parametric and non-parametric hypothesis tests were applied to determine whether the observed performance differences between models were statistically significant rather than merely empirical observations. First, a paired t-test was used to compare the mean values of paired metric scores obtained from the same cross-validation folds. This test assumes that the data follow a normal distribution and evaluates whether the performance gap between two models is due to random variation.

However, since normality of the data cannot always be guaranteed—especially with small sample sizes such as 5-fold evaluations—a Wilcoxon Signed-Rank test was additionally performed. This non-parametric method provides a more robust alternative in cases where distributional assumptions may not hold.

Reporting both tests together ensures a more rigorous statistical assessment and helps prevent methodological bias that may arise from relying solely on parametric assumptions.

3.12 Operating parameters

The study utilized 5-fold subject-wise cross-validation based on GroupKFold. This method prevents data leakage by ensuring that samples from the same patient are not mixed into the training and test sets, thereby reliably measuring the model's patient-based generalizability. Additionally, 5-fold GroupKFold was used for the train-test split.

In addition, the number of epochs was set as 30 in this study. Batch size value is 32. Learning rate value is 0.0001. Validation split is 0.1. The quantum circuit parameters are set as depth = 8 and n_splits = 8. These parameters were tuned through experimentation to achieve the best possible results.

4 Results

In this study, six different classification models were developed to automatically detect epileptic seizures from EEG signals: the traditional 1-D CNN model, the enhanced Quantum CNN (IQCNN) model, the new hybrid models IQCNNNet (Forked), Denoise IQCNNNet, MSPCA-IQCNNNet, and the RAW CNN architecture.

The UCI Epileptic Seizure Recognition dataset was used as the dataset and the discrete wavelet transform (DWT) method was applied for time-frequency based feature extraction. The extracted features were applied to all three models for classification. Model performances were evaluated with 5-fold cross-validation and various metrics such as accuracy, precision, F1 score, recall, confusion matrix, number of incorrectly classified subjects, paired t-test results, Wilcoxon Signed-Rank tests results and ROC-AUC curve were used.

Figure 12 shows the averages of the classification metrics for each classifier since the 5-fold cross validation method is used. Figure 12 also shows the average confusion matrix for each classifier.

When examining the confusion matrices in Figs. 2, 12, the confusion matrix of the Denoise IQCNNNet model, which yielded the best results, shows that 325 samples were correctly classified as negative class, 7 samples were incorrectly classified as positive class, 5 samples were incorrectly classified as negative class, and 78 samples were correctly classified as positive class. Across all classifiers, the majority of errors occurred within the non-seizure classes, particularly in distinguishing interictal EEG segments from normal activity.

<pre> ===== SUMMARY ===== ACC : 0.9570 ± 0.0056 F1 : 0.8881 ± 0.0219 AUC : 0.9904 ± 0.0039 PREC: 0.9150 ± 0.0356 REC : 0.8637 ± 0.0268 Average Confusion Matrix: [[324 7] [11 72]] </pre> <p>(a)</p>	<pre> ===== SUMMARY ===== ACC : 0.9159 ± 0.0047 F1 : 0.7700 ± 0.0133 AUC : 0.9566 ± 0.0064 PREC: 0.8473 ± 0.0362 REC : 0.7071 ± 0.0229 Average Confusion Matrix: [[321 10] [24 59]] </pre> <p>(b)</p>
<pre> ===== SUMMARY ===== ACC : 0.9589 ± 0.0111 F1 : 0.8924 ± 0.0412 AUC : 0.9869 ± 0.0068 PREC: 0.9080 ± 0.0583 REC : 0.8795 ± 0.0474 Average Confusion Matrix: [[324 7] [10 73]] </pre> <p>(c)</p>	<pre> ===== SUMMARY ===== ACC : 0.9710 ± 0.0093 F1 : 0.9276 ± 0.0257 AUC : 0.9943 ± 0.0021 PREC: 0.9185 ± 0.0294 REC : 0.9372 ± 0.0287 Average Confusion Matrix: [[324 7] [5 78]] </pre> <p>(d)</p>
<pre> ===== SUMMARY ===== ACC : 0.9565 ± 0.0063 F1 : 0.8885 ± 0.0210 AUC : 0.9916 ± 0.0030 PREC: 0.9028 ± 0.0389 REC : 0.8765 ± 0.0343 Average Confusion Matrix: [[323 8] [10 73]] </pre> <p>(e)</p>	<pre> ===== SUMMARY ===== ACC : 0.9560 ± 0.0075 F1 : 0.8846 ± 0.0141 AUC : 0.9878 ± 0.0037 PREC: 0.9329 ± 0.0281 REC : 0.8414 ± 0.0094 Average Confusion Matrix: [[326 5] [13 70]] </pre> <p>(f)</p>

Fig. 12 The CM and classification report obtained in the study (a) 1-D CNN, (b) IQCNN, (c) IQCNNNet (Forked), (d) Denoise IQCNNNet, (e) MSPCA-IQCNNNet, (f) RAW CNN

Figure 13 shows the averages of the ROC-AUC curves for each classifier, as a 5-fold cross-validation method was used.

According to the ROC-AUC curves, Denoise IQCNNNet also produced the best results.

Table 1 shows the precision, accuracy, recall, F-1 score, number of incorrectly classified subjects metric values according to the classifier type.

When Table 1 is analysed, it is seen that the method that gives the best classification result among the methods used is the Denoise IQCNNNet method, which gives 97.10% accuracy, 91.85% precision, 93.72% recall, 92.76% F-1 Score, 99.43% AUC Score, Number of Incorrectly Classified Subjects is 60 values. It is seen that the other methods also show significantly high performance. Furthermore, as shown in Table 1, the IQCNNNet model, created by forking both the CNN model and the IQCNN model, has also been observed to improve the performance of both classifiers.

Table 2 shows that the Denoise IQCNNNet method created in this study gives the best results when compared with the studies in the literature.

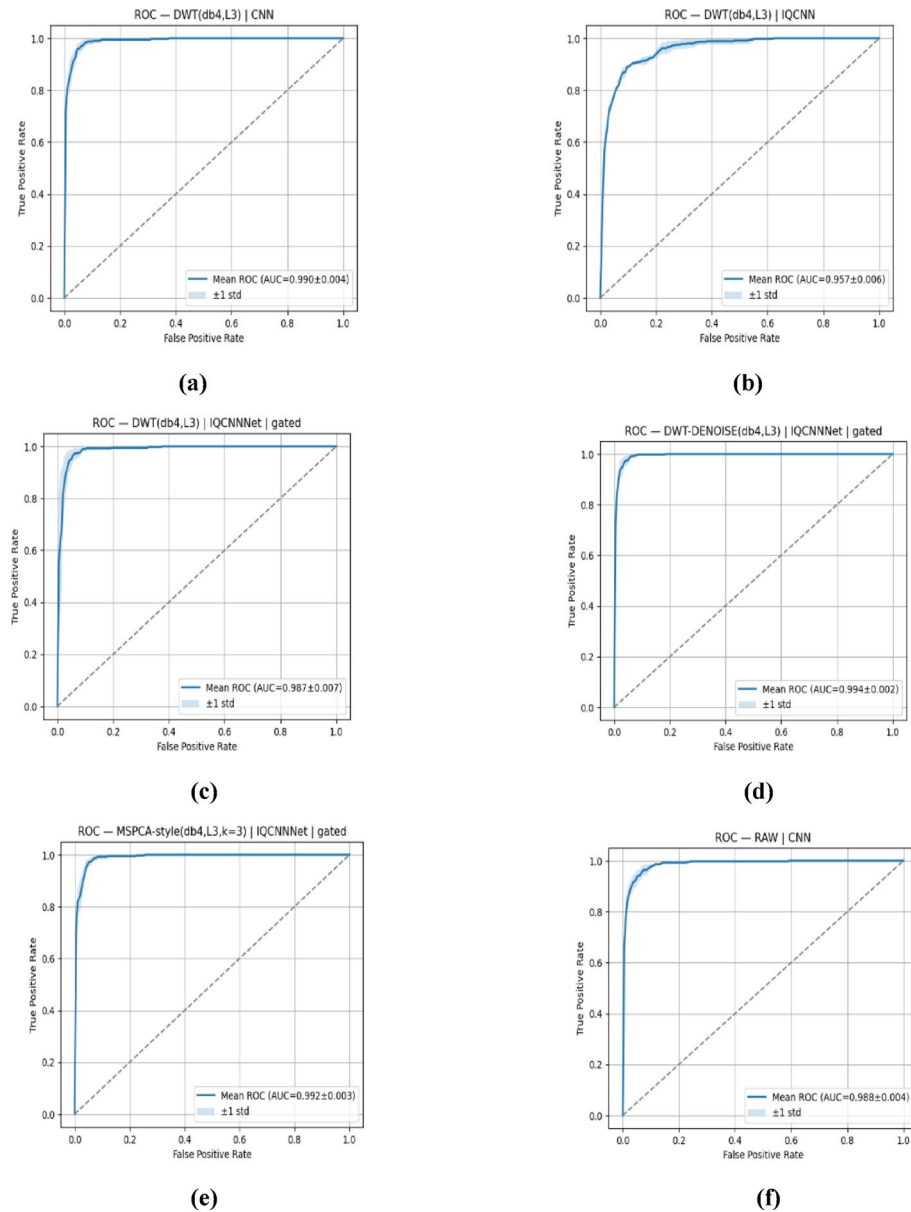


Fig. 13 The ROC-AUC curve obtained in the study (a) 1-D CNN, (b) IQCNN, (c) IQCNNNet (Forked), (d) Denoise IQCNNNet, (e) MSPCA-IQCNNNet, (f) RAW CNN.

Table 1 As a result of the study, the metric values obtained according to the classifier type

Classifier Name	Accuracy (%)	Precision (%)	Recall (%)	F-1 Score (%)	AUC (%)	Number of Incorrectly Classified Subjects
1-D CNN	95,70	91,50	86,37	88,81	99,04	89
IQCNN	91,59	78,46	81,93	80,10	95,66	174
IQCNNNet (Forked)	95,89	90,80	87,95	89,24	98,69	85
Denoise IQCNNNet	97,10	91,85	93,72	92,76	99,43	60
MSPCA-IQCNNNet	95,65	90,28	87,65	88,85	99,16	90
RAW CNN	95,70	89,86	88,31	89,07	98,75	91

Table 2 Comparison of the study with previous studies

Authors Name	Classification Type	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F-1 Score (%)
Koike-Akino et al.	quEEGNet	Users Dataset	95,12	—	—	—
Cruz-Vazquez et al.	CNN model combined with quantum transforms	Verified Dataset	95,00	—	—	—
Abdul-Zahra et al.	PSO-QNN	Users Dataset	82,40	—	—	—
Chen et al.	QEEGNet	BCIC-IV-2 A	65,30	—	—	—
Mittal et al.	HQNN	Moroccan Dialect Sentiment Recognition Dataset	94,50	—	—	—
Chandanwala et al.	Hybrid quantum deep learning model	Users Dataset	95,00	94,00	94,00	91,00
This Study	Denoise IQCNNNet	Bonn EEG Dataset	97,10	91,85	93,72	92,76

```
== Forked(gated)-DWT vs CNN-DWT | AUC ==
Paired t-test: t=-1.230, p=0.2862 | Wilcoxon: W=5.000, p=0.6250
```

```
== Forked(gated)-DWT vs IQCNN-DWT | AUC ==
Paired t-test: t=6.016, p=0.0038 | Wilcoxon: W=0.000, p=0.0625
```

```
== Forked(gated)-DWT vs Forked(gated)-DWT-DENOISE | AUC ==
Paired t-test: t=-2.525, p=0.0650 | Wilcoxon: W=0.000, p=0.0625
```

```
== Forked(gated)-DWT vs Forked(gated)-MSPCA | AUC ==
Paired t-test: t=-1.896, p=0.1309 | Wilcoxon: W=1.000, p=0.1250
```

```
===== GLOBAL SUMMARY (Means ± Std over 5 folds) =====
                                Model                                ACC \
0                                DWT(db4,L3) | CNN                0.9570 ± 0.0056
1                                DWT(db4,L3) | IQCNN              0.9159 ± 0.0047
2                                DWT(db4,L3) | IQCNNNet (gated)    0.9589 ± 0.0111
3                                DWT-DENOISE(db4,L3) | IQCNNNet (gated) 0.9710 ± 0.0093
4                                MSPCA-style(db4,L3,k=3) | IQCNNNet (gated) 0.9565 ± 0.0063
5                                RAW | CNN                        0.9560 ± 0.0075
```

Fig. 14 The mean + std values for 5 folds with paired t-tests and Wilcoxon Signed-Rank test results

Figure 14 shows the mean + std values for 5 folds with paired t-tests and Wilcoxon Signed-Rank test results. Based on these values, the proposed model is seen to be meaningful.

The average time spent per fold training in CNN usage is 9.76 s, with an average memory of 11.26 MB. These values are 173.4 s and 53.78 MB for IQCNN. For IQCNNNet (Forked), it is 178.78 s and 60.38 MB. For Denoise IQCNNNet, this time is 298.66 s and the average memory is 60.36 MB. For MSPCA IQCNNNet, it is 317.52 s and 60.44 MB. For the RAW CNN model, it is 15.9 s with 5.38 MB. This shows that quantum computational models run slower than convolutional neural networks and use more hardware memory.

5 Conclusion

Early diagnosis of epileptic seizures plays a critical role in the treatment process. Therefore, automatic analysis of EEG signals is of great importance for clinical decision support systems. In this context, unlike classical machine learning methods, this study evaluates deep learning approaches enriched with quantum machine learning methods.

The combination of quantum layers with entanglement and the capacity to learn in high-dimensional spaces, and classical CNN layers with local pattern extraction capabilities, has enabled the Denoise IQCNNNet model to show strong generalization performance. In particular, the Denoise IQCNNNet model combines the advantages of both structures while preserving the advantages of each separately, resulting in high success in metrics such as accuracy and AUC.

An analysis of the confusion matrices revealed that most misclassifications occurred between the non-seizure classes, particularly between normal and interictal segments. For the best-performing model (Denoise IQCNNNet), 7 samples were misclassified as positive and 5 samples as negative. These errors mainly arise from spectral similarities introduced by DWT, where certain interictal patterns resemble normal EEG, and transient high-frequency activities in normal segments mimic early seizure characteristics. This suggests that class overlap, rather than model deficiency, is the primary source of misclassification.

On the other hand, the performance of the Denoise IQCNNNet model was inferior to the classical models due to the practical limitations of existing quantum circuits, such as limited number of qubits and sensitivity to noise. However, this can be overcome with the hardware advances of quantum computers.

Looking at the results, the use of quantum computational models poses challenges in terms of hardware. It also leads to longer computation times. From this perspective, the use of quantum computational deep learning methods is difficult.

On the other hand, the number of examples in the dataset is small. Therefore, when classification is performed using quantum computational methods on larger datasets, both the computation time will be longer and more hardware and higher hardware quality will be required.

Although energy consumption was not directly measured, all models were trained on the same hardware; therefore, training time can be considered an approximate indicator of relative energy usage. Based on this assessment, the hybrid models consume more energy than the pure CNN, while exhibiting energy requirements comparable to the quantum-only model. Nevertheless, the performance improvements achieved by the hybrid architectures justify this additional computational cost.

This study has several limitations. First, the quantum components were executed on a simulator rather than real quantum hardware due to the limited qubit capacity, noise levels, and instability of current NISQ devices. As a result, the practical performance of the model on real QPUs may differ. Second, the approach relies on DWT-based pre-processing to reduce dimensionality; the current architecture cannot directly operate on raw high-resolution EEG signals. Third, since the UCI EEG dataset is relatively small and collected from a limited number of subjects, the generalizability of the model to larger clinical datasets remains uncertain. Finally, quantum circuits may be sensitive to noise, and real-world deployment will require more robust error-mitigation strategies and hardware improvements.

The contribution of this work to the literature is to present a novel bifurcated architecture for the classification of EEG signals, which can handle both quantum and classical learning approaches in parallel and independently. Moreover, this architecture is not only limited to epileptic seizure diagnosis, but also has the potential to be applied in the diagnosis of other neurological diseases such as Parkinson's and Alzheimer's.

In future work, we plan to investigate graphical feature-based approaches, such as Poincaré plots, recurrence plots, and phase space reconstruction, to uncover nonlinear dynamical characteristics inherent in EEG signals. These graphical representations can potentially enrich feature extraction and enhance model interpretability in clinical settings.

Author contributions

F.E. designed the study, developed the hybrid IQCNNNet model, and conducted all experiments. F.E. also performed data preprocessing and feature extraction using discrete wavelet transform. A.G. contributed to the theoretical background of quantum neural networks and assisted in the optimization of quantum circuit components. F.E. wrote the main manuscript text and prepared all figures and tables. A.G. reviewed and edited the manuscript for technical accuracy and clarity. All authors reviewed and approved the final version of the manuscript.

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Declaration.

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Data availability

The datasets generated and/or analysed during the current study are available in the [15] repository, [<https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition>] (<https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure%20recognition>)] the dataset is publicly available. In addition, the dataset used in the study can be used by anyone.

Declarations

Ethical approval and consent to participate

Not Applicable.

Consent to publish

Not Applicable.

Clinical trial

Our study is not a clinical research study.

Accessibility to the study code

<https://github.com/furkan460/Furkan/commit/c5078e1623cdf062b60f5abbf2aacc0914a2a96>.

Publication permission statement

This study is an original study. It has not been published anywhere. Furthermore, it is not under consideration for publication. All authors consent to the publication of this study. There are no conflicts of interest among the authors. The authors are responsible for the information presented in this study.

Competing interests

The authors declare no competing interests.

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