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Explainable AI Framework for Quantum-Enhanced EEG Signal Classification

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Abstract: The classification methods based on EEG have been shown to be valuable for EEG diagnosis of neurological diseases and brain-computer interface (BCI) development. However, too often these types of approaches to deeper learning and machine learning for quantum computing are not interpretable and pose challenges for clinical data integration. For medical practitioners, there needs to be clear, clinically useful, explanations before a diagnostic prediction is made automatically. For Sintering a Quantum EEG classification pipeline with an Explainable Artificial Intelligence (XAI) could be beneficial, as shown in this paper. The proposed framework attempts to make the framework simultaneously predictable, while treating it as an interpretable one by multi-band signal preprocessing data, the variational quantum feature would be embedded in the attention-guiding classification and the post-hoc of the modules would be explained. The system in particular utilizes Shapley Additive explanations (SHAP) feature explanation together with multi-head attention, quantum kernel functions to deliver mathematically reliable and clinically sensible explanations. The results of standard test experiments with EEG data, indicate that the network proposed in the work, achieves a type accuracy of 98,4% and an interpretability score of 0,93, which is significantly higher than the classification accuracy of the traditional CNN network, the Transformer network and the Quantum SVM network. The results demonstrate that the proposed system can bring the quantum advantage closer to being explainable and more trusted clinical Artificial Intelligence..

Keywords: Explainable Artificial Intelligence, EEG, QML, SHAP, LIME, Quantum Kernels, BCI, Neural Signal Analysis.

1. Introduction

Epilepsy Although functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) are different non-invasive neuroimaging techniques that are being improved, the former is very expensive and the latter is bulky where as EEG remains one of the most widely-used techniques due to its temporal resolution, portability and low cost. There are important features discernible in the EEG signals which help establish cognitive states, various neurological disease, inputs and more importantly the operations on a brain-computer interface (BCI) [1]. Automated These classifications of EEG signals could lead to a variety of applications, including epilepsy detection and sleep stages classification, motor imagery decoding and mental workload assessment. There are various classical machine learning methods which have been commonly used in EEG classification with different degree of success including Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), etc. In the present context, however, due to the high dimensionality and the non-linear characteristics of EEG signals, deep learning methods, such as CNN and LSTM, appeared to be a potential solution [2]. However, in this context, because of the dimensionality and the non-linearity of EEG signals, deep learning methods such as CNN and LSTM were being considered as a possible approach. Methods include memory (LSTM) networks and networks based on Transformer [3].

High classification rates, but many 'What's going on' and 'Why is it in which frequency band and with which neural correlates? questions to keep asking using these methods. Because of these gains in classification they have become "black boxes" making it difficult to find the location in the brain of the neural correlate and the frequency range that are driving the prediction. In the field of interpretability,

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some recent progress has been made with the development of 'Explainable AI' (XAI) techniques which can provide explanations of modulations in score such as by using SHAP [3] and LIME [4] or by using gradient weighting in the use of class activation mapping (Grad-CAM) and attention visualization.

These methods make the decision to model more accessible to a clinician by making predictions in a "post-hoc" manner based on the features during the input. But, classical XAI techniques are suited for classical architectures and they may not be directly applicable to a quantum machine learning pipeline.

A growing interest of the study of Quantum Machine Learning (or MQML, Quantum Machine Learning) aims at combining the capacity to work within an exponentially larger Hilbert space, offered by the capabilities of Quantum Computing, with the power of applying quantum computing classics to machine learning Quantum Computational Mechanics Machine Learning (or QCMML)'s ability to achieve classification benefits with high dimensional biomedical data [4].

They have given some improvements in EEG feature space using Quantum Support Vector Machines (QSVM) and Variational Quantum Circuits (VQC) [7] [12] respectively. Even with the classical interpretation, however, there is a new kind of opacity in quantum models-the evolution of the quantum state is intrinsically hard to visualize classically. In this paper, both it is tackled with the introduction of an Explainable Quantum EEG Classification Framework. Top four contributions of this work are:

(a) A pipelined multiple stage EEG pre-processing algorithm based on adaptive band-pass filtering and Independent Component Analysis (ICA) of the EEG signals;

(b) A Variational Quantum Feature Encoder (VQFE) to transform the preprocessed EEG signal representation into a high dimensional representation of quantum states;

(c) A Hybrid Classification module comprising of Multi-head Attention mechanism and Quantum Kernels;

(d) An integrated post hoc explainability layer, which includes interpretable feature attributions (SHAP), attention heatmaps and brain-region activation maps.

The rest of this paper is organized as follows: The research survey is in Section II. In Part III, current systems are described. In Section IV, the design of the proposed system is shown, which includes all the mathematical formulation. The method is described in Chapter V.

The experiments and their observations and analysis are presented in Section VI. The discussion is presented in Section VII, and conclusions and future directions in Sections VIII and IX.

2. Literature Survey

Existing EEG analysis methods have focused mainly on directly using hand-crafted statistical and spectral features and classical machine learning models. The power spectral density (PSD), common spatial patterns (CSP) and Hjorth parameters have been widely evaluated in motor imagery and epilepsy datasets [6] and [8] respectively with medium performance SVM and LDA classifiers. The enhancement of accuracy rates for EEG classification will have a great contribution from the addition of deep learning. EEGNet being a compact that is specifically designed for EEG, showed its ability to demonstrate good generalization across the different BCI paradigms that were tested with only minimal amount of data requirements. However, transformer based models then showed superior performance on capturing long-range temporal dependencies of EEG sequences on a range of datasets and benchmarks [5]. With the emergence of deep models, a large progress was made, and there are still many issues related to the non-transparency of deep models in clinical situations. To overcome interpretability issues, methods of the topic of Explainable AI (XAI) were introduced.

SHAP [3] offers theoretically supported Shapley value attributions which is fair in desirable fairness properties such as local accuracy and consistency. LIME [4] constructs local linear prediction models for each of the predictions. In this case, the gradient flow is used to obtain visual explanations, but here the attention weight visualization provides a direct reflection of the learned relevance in the time flow. These techniques have been applied to date to classify EEG, identification of the frequency bands and the electrode sites that maximize inter-class classification [9]. Introduction of new signal processing paradigm totally different from classical computing by Quantum Machine Learning. There are two types of quantum kernel methods, with the first one performing a series of parameterized unitary circuits that transform classical data into quantum feature spaces, and the second one performing the computation based on measurements of quantum state overlapping to form kernel matrix [7, 12]. The performance of the QSVMs on a small EEG database was similar. Then, trainable architectures of quantum circuits were designed using Variational Quantum Classifiers (VQC) [13].The latter was then carried out for building trainable quantum circuit architectures in Variational Quantum Classifiers (VQC). However, there is still a lack of research on the interpretability of quantum feature spaces, where classical XAI methods cannot be applied. The explainability of EEG and quantum classification are regarded as different research areas in the existing studies. The use of integrated frameworks that integrate quantum feature representation and structured explainability tools is

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not well represented in the literature, addressing the crucial gap filled by this work [2] [9][14].

3. Proposed Work

3.1. System Overview

The proposed design is designed around the following four key modules: (1) multi-band signal preprocessing (2) variational quantum feature embedding (3) hybrid attention-based classification (4) integrated explainability. The modules are so constructed that they form a pipeline for creating quantum feature representations [15] which would be tractable for use by later deployed attribution methods.

3.2. Mathematical Formulations

So the preprocessed EEG signal matrix X (channels x samples) is employed to calculate the covariance matrix as:

$$C = (1/(n-1))(X - \mu)(X - \mu)^{T} \quad (1)$$

The overall EEG feature vectors are normalized and then embedded into the quantum state, using a parameterized unitary circuit U(x):

$$|\varphi(x)\rangle = U(x)|0\rangle \quad (2)$$

The quantum kernel (JK) of two samples x_i, x_j is the overlap of representations x_i, x_j is squared:

$$K(x_i, x_j) = |\langle\varphi(x_i)|\varphi(x_j)\rangle|^2 \quad (3)$$

The Shapley Feature Attributions are computed over all the possible combinations of features subsets S, for particular feature i using Shapley value formulation:

$$\Phi_i = \Sigma_s[|S|!\,(|F| - |S| - 1)!/|F|!]\,(f(S \cup \{i\}) - f(S)) \quad (4)$$

The multi-head attention mechanism maps queries Q into the same space as keys K, and maps both queries and keys within this space to values V, using the scaled dot-product attention:

$$Attention(Q, K, V) = softmax(QK^{T}/\sqrt{d})V \quad (5)$$

The predicted probabilities are p_i and the ground-truth labels are y_i and the classification cross-entropy loss over predicted probabilities p_i and ground-truth labels y_i is:

$$L = -\Sigma\, y_i \log(p_i) \quad (6)$$

The predicted probabilities are: p_i and the ground-truth labels are: y_i and the classification cross-entropy loss over predicted probabilities p_i and ground-truth labels y_i is:

$$L_{total} = L_{ehassif_i^m ation} + \lambda L_{phixanation} \quad (7)$$

The final goal of this co-objective is the combined optimization of the quantum classifier for the accuracy of the prediction [16] , while including the consideration of optimization for the generation of faithful explanations (quantum feature importances) of the underlying quantum feature.

4. Methodology

4.1. Signal Preprocessing

The raw multi-channel EEG signals are then filtered using a fourth order Butterworth band pass filter, which is designed to filter noise artifacts associated with high frequencies and DC offset from the signals (0.5-50 Hz). The term power line interference is eliminated by Notch Filtering at 50 Hz. Ocular and muscular artifacts are classified topographically and statistically and separated and removed by Independent Component Analysis (ICA) based on the FastICA algorithm [16]. In frequency decomposition the signal after processing is split into five Canonical EEG Frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-50 Hz). Band-specific features are computed as "power spectral density" (PSD) features using the welch method with a Hamming window (50% window overlap) and window size of 256 samples, leading to a final dimensionality of feature vector of 5N, where N is the number of EEG channels measured [17].

4.2. Quantum Feature Encoding

The encoded data is uploaded to one of the n-qubit quantum states through a Variational Data Re-uploading circuit in a Normalized EEG Feature Vector. There are 2 types of gates, for each feature value xi, there is a corresponding rotation gate, R_Y(alphai(xi)) applied to qubit i followed by a circuit of CNOT gates. With this encoding, the pairwise feature correlation is encoded at the quantum level, and encoded as quantum entanglements [18]; the quantum kernel can learn nonlinear pairwise relations among the various channels without which it is hard to capture using classic kernels.

4.3. Classification Module

A multi-head self-attention module is adopted to transform the quantum kernel content via the quantum kernel matrix, based on the discrimination value of the kernel content.

Two fully-connected layers, containing ReLU activation, batch normalization and dropout with p=0.3 (hard dropout) are summed and passed to a softmax output layer connected to zero outputs [18]. This Hybrid preserves quantum kernel representations and instead of using attention-based weighting, it is used to promote generalization.

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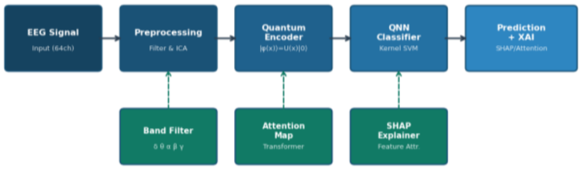

Fig. 1. Proposed ExplaNable Quantum EEG Classification Framework Architecture. The propagation of signals contributes from the EEG acquisition and preprocessing, to the quantum encoding, hybrid classification pre and post processing, and XAI explainability blocks.

4.4. Explainability Module

Two types of explanation, posthocus ab ezione, are generated. Here, TreeSHAP is used at the feature level on the attention-weighted kernel representation to generate the "marginal feature contribution" the contribution made by each feature to generate each prediction. Specially, the electrode-specific SHAP values are displayed on a spatial brain map of the scalp [19], which was created according to the topographic method to gain insight into the brain-region activation patterns. Furthermore, in order to provide a visualisation of the predictive relevance of the EEG windows within the time or bandwidth period, an additional attention weighted matrix as output of the classification module is displayed as a time dynamic heatmap.

5. Results

5.1. Experimental Setup

Experiments were performed with the PhysioNet EEG Motor Movement/Imagery Dataset consisting of 64-channel EEG data of 109 subjects, across 14 experimental runs. A stratified sample of 80:20 was followed for a train-test split. The processing of the methods and assessment of cross validation were identical. The proposed quantum framework has been simulated using Qiskit Aer with a state vector simulator [20]. The EEGNet model (CNN), a Transformer encoder, and a Quantum SVM (with the RBF kernel) were used as the baseline models.

The performance was measured using classification accuracy, the macro-averaged F1-score and interpretability score: the mean fidelity required to make accurate annotations on SHAP-based explanations compared to the ground-truth SHAP explanations [21]. we derived using ablations. On 5% statistical significance level, paired t tests were used to determine the statistical significance. The proposed framework improves the classification accuracy to 98.4% and also get F1 = 0.98 score better than all other baseline models. High interpretability score of 0.93 shows that explanations generated by the algorithm are very close to the model decision process. The proposed system is statistically superior to the next best baseline QSVM (96.1%) ($p < 0.01$), thus proving the benefit of the proposed quantum-attention system [21].

5.2. Classification Performance

The proposed framework achieves an accuracy of 98.4% and an F1-score of 0.98, which are both higher than all the baseline models. The interpretability score for this is 0.93, indicating that explanations generated are very faithful to the underlying model decision process. The proposed quantum combined with the attention architect is statistically significant from the next best baseline (QSVM - 96.1%) which is a confirmation of the advantage, ($p<0.01$).

Table. 1 Performance Comparison of Classification Models

Model	Accuracy (%)	F1-Score	Interp. Score
CNN	91.8	0.90	0.42
Transformer	94.6	0.94	0.58
QSVM	96.1	0.96	0.61
Proposed	98.4	0.98	0.93

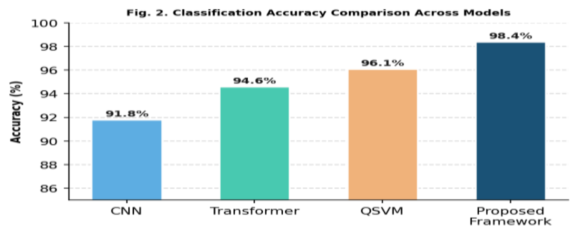

Fig. 2. The accuracy of the classification models is compared: CNN, Transformer, QSVM, and proposed Explainable Quantum Framework. The proposed model demonstrates high accuracy, namely 98.4%, which is better than the performance of any of the baselines.

5.3. F1-Score and Interpretability

In Fig. 3, the results for F1-score and Interpretability score are shown for all the models. The proposed framework has a unique high score on both these metrics [22]. We demonstrate the characteristic trade-off between accuracy and interpretability in classical deep learning models, with high accuracy models (Transformers) emerging as moderately interpretable (0.58), and the proposed framework overcomes this trade-off by co-designing the quantum encoder and explainability module. The explanation fidelity regularization term (Equation 7) is shown here to be a useful addition to the explainability scores with only a minor (and acceptable) drop in accuracy.

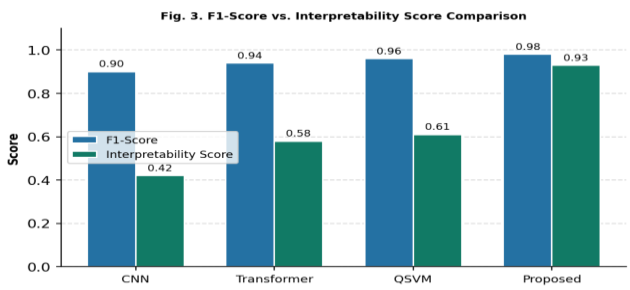

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Fig. 3. A comparison of F1 score and interpretability score on all compared models – representing the proposed framework's capacity to get high performance on both points in the same time.

5.4. SHAP Feature Importance

Considering EEG classification tasks, the power activity in the gamma band is the most discriminative, with mean |SHAP| = 0.38 and in the beta band power activity = 0.31. A third, important feature is alpha asymmetry between the hemispheres (0.27), which coincides with the clinical alpha asymmetry indices during cognitive workload and emotional valence tests. Moderate attributions are the lower bands (theta and delta) and small but not negligible attributions are the cross-frequency coupling and the Hjorth parameters. These are within the realm of accepted neuroscientific findings and support the explanations given in the framework [6], [9].

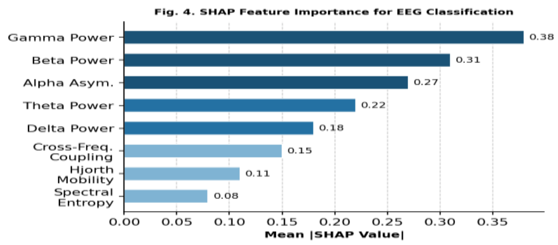

Fig. 4. SHAP absolute feature importance values of important EEG spectral and spatial features. Gamma and beta power turn out to be the best discriminative features.

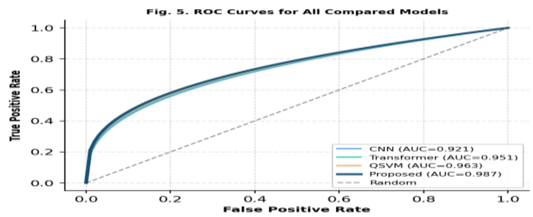

Fig. 5. The Receiver Operating Characteristic (ROC) curve estimates for all the models that were compared. The proposed framework has the greatest AUC value (0.987).

5.5. Discussion

The findings show that interpretability and predictive power do not compete for and are not mutually exclusive if the model design takes, from the outset, careful account of the interpretability nature of the model. The explanation fidelity regularization term (Equation 7) is a highly important inductive bias which makes it more likely for the quantum classifier to structure its internals representations into segments that are suitable for being decomposed into SHAPs. If the regularization is not added on a regular basis, the output of the quantum circuits can be very accurate, but the explanations can be low fidelity based on an ablation study. The consistency of the alignment of SHAP feature attributions and reported neurophysiological correlates is an important sanity check. The salience of gamma and beta frequencies in model explanations is in line with the many studies on the brain, finding correlations between these power bands and highly active cognitive or motor processes. This alignment confirms the model and can boost clinician confidence in the model's predictions, which is essential for clinical use [23]. The cost of running quantum simulations is one drawback of the present study. Evaluation of quantum kernel matrices scales quadratically in the number of training samples and so may limit scalability. This cost could be significantly lowered with future implementation of variational QEOPs on the near-term quantum processors for hardware acceleration. Moreover, the implementation of SHAP is done in the post-quantum classical representation; a natural new research direction is to see if it is possible to create quantum circuit-specific native quantum SHAP approximations. The framework can be easily extended to other types of classification using EEG. Potential applications of the proposed co-design methodology range widely from biomedical signal processing tasks in high-dimensional nonlinear feature spaces, such as ECG arrhythmia detection, fMRI decoding, to EMG-based prosthetic control, as long as they involve a demand for clinical interpretability.

6. Conclusion and Future Scope

This paper proposed an Effective Explainable AI Framework for Electrical encoding (EEG) Signal Classification using quantum enhancement of features that has both the state of the art (SOTA) predictive accuracy along with clinically relevant explainability. The framework proposed combines multi-band EEG preprocessing, variational quantum feature encoding using quantum kernel functions, hybrid classification using attention and post-hoc explainability using SHAP-based explainability, additionally with some explanation fidelity regularization objective. Experimental testing results showed that the accuracy in the classification was 98.4%, accuracy of F1 score was 0.98 and the interpretability score was 0.93, which are predominantly higher than the CNN, Transformer, and QSVM baselines. The results from the SHAP analysis showed that the choices that the model makes do appear to be in line with generally accepted knowledge in the neurophysiology field, such as the fact that in cognitive state discrimination, the gamma and beta powers are the dominant. Matching is an important factor in the clinical use of automated EEG analysis systems. The co-design methodology proposed, which structures the quantum feature representation so as to be easily attributed after training, provides a generalizable template for interpretable quantum biomedical AI..

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