



Intelligent Pediatric Epilepsy Detection using Quantum Computing

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Abstract: Epilepsy is a common neural disease among the children and in such cases, early and proper diagnosis is of paramount importance to en-sure a successful treatment. The signals of EEG in paediatrics are very unstable and noisy which complicates the process of automatic seizure detection in traditional systems. The paper presents a quantum-classical hybrid frame-work of the detection of epilepsy by EEG topographic map. EEG is processed in-to topographic representations on the scalp and de-composed in-to standard frequency bands. A light-weight convolutional neural network derives spatial features out of these maps and they are then classified by a Quantum Support Vector Machine with amplitude embedding. The framework can be used to evaluate paediatric EEGs, especially when compared to classical and quantum classifiers, which proves the potential of the framework.

Keywords: Pediatric Epilepsy, EEG Topographic Maps, CNN, Quantum SVM, QML, Biomedical signal pro-processing.

1. Introduction

Epilepsy is a neural disorder prevalent amongst children in most parts of the globe and is a non-standard process of un-initiated and recurrent seizures elicited by the irregular brain electrical activity. One of the most severe disorders is childhood epilepsy, and the fact that the dis-ease should be diagnosed as soon as possible has a dark-er side as the delay in identifying the disease may affect the cognitive and academic functioning, and overall the quality of life. EEG has been the most used original diagnostic tool of epilepsy as it does not involve any invasive procedure, and the opportunity of recording the dynamics of the brain in high time resolution[1]. The pediatric EEG records are however very hard to study due to age specific maturation of brain, high inter-subject variability, and high artifact occurrence in pediatric EEG records. Conventional automated epilepsy detect algorithms have experimented to a significant extent on features of the EEG signal developed by hand in the time, frequency, or time-frequency domain and then composed of classical machine learning classifiers[2]. Even though these techniques can provide reasonable performance when used in controlled set-tings, they are usually susceptible to issues in generalizing performance across patients and documenting settings [3]. This weakness is further reinforced in the study of pediatric EEG, since the brain activity at developing stages is not stationary, and due to the presence of the small hallmarks of seizure, difficult to differentiate during the separation of normal

developmental rhythms. Recent advances in the field of deep learning have given so-called convolutional neural networks [4] (CNNs) as effective tools of EEG analysis.

The CNNs may be trained on hierarchical representations, and have been demonstrated to do better when the EEG data is reconstructed into image-like data, e.g. spectrograms or scalp topographic maps. Topographic map-ping of a of-fer in particular provides a spatially significant visual representation of the brain activity, which enables neural networks to provide spatial associations between channels of EEG. However, deep learning [5] models are likely to require large sized labelled data sets and they are subject to overfitting in case of small sized pediatric EEG data. Another promising extension of classical learning techniques is quantum machine learning [12], which offers new representations and processing of high dimensional and complex data. Earlier studies have revealed that QSVMs would have the capability to do better than classical SVMs when it is trained on EEG spectral feature, which would be of possible use in seizure detection [6] tasks. Following these results, this pa-per will propose a hybrid quantum-classical model, which will be the integration of EEG topographic map-ping, features extraction through CNN and quantum-enhanced classification [7]. The proposed methodology will be aimed to promote the precision of pediatric epilepsy detection with the help of the



integration of spatial EEGs representations with the quantum kernel based learning and be feasible in clinical setting [8].

2. Literature Survey

The problem of automated epilepsy identification with the help of electro-encephalography is a well-investigated and the initial methods employed were the manual extraction of features and the utilization of the classical classifiers. The description of seizure activity was first done with the characteristics of the time domain (statistical moments, zero-crossing rates and energy measures). These characteristics are simple to calculate, compared to the frequency specific features , which are significant when detecting the occurrence of epileptic activities in the case of the pediatric EEGs [9]. Temporal frequency analysis and frequency-domain analysis was proposed in order to remove these shortcomings. Techniques (built on Fourier transform, wavelet trans-form and Stockwell transform) have been extensively applied in deriving spectral and time information of the EEG signals.

It has been demonstrated that the band power properties of the traditional EEG frequency bands are effective in seizure detection processes, whereby, epileptic activity is likely to be seen as an abnormal distribution of energy in a frequency band. Nonetheless, they are also stereotypically based on the selected features [10] and parameter optimization that predisposes them to other datasets and populations of different ages. Some examples of machine learning classifiers that have been widely applied in the EEG-based epilepsy detection are support vector machines, k-nearest neighbors, decision trees and ensemble machines [11]. They have resorted to use of the support vector machines as it is capable of working with high dimensional feature space. Although this is an advantage, classical SVMs use fixed number of kernel functions and the functions could be too simple to identify the non-linear, complex structure of children EEG data, in particular in such cases when noise is present in recording. Convolutional neural networks and the creation of deep learning have significantly been used to analyze EEG signals [12].

The CNN-based methods have been identified to be better where the discriminative features are trained with the original signals or the transformed representations like spectrograms and topographic maps [13]. Topographic mapping methods retain spatial correlations of the EEG channels in such a way that the CNNs can utilize the spatial and spectral features of the brain activity. Deep models are however large, annotated datasets and are intensive to compute and thus may not be made available in a pediatric clinical environment [14]. Later quantum

machine learning became an area of research as the extension of classical learning models. The quantum Support Vector Machines based on quantum Kernel estimation and amplitude embedding have demonstrated desirable results in the study of high dimensional and complex biomedical data [15]. On the basis of research, it has been suggested that the tests QSVMs on EEG spectral characteristics result in a higher class separability when compared to classical kernels. Despite this, a study with deep learning [16] based feature extractions and quantum classifiers has not been performed to detect pediatric epilepsy yet in this regard, the need to involve hybrid-structure which harnesses the strengths of the two paradigms exists.

3. Proposed Work

The suggested framework adheres to a sequential processing pipeline that aims at deriving meaningful spatial and spectral data of pediatric EEG recordings and conduct trustworthy seizure classification [11] in a hybrid quantum [9] classical framework. The process of methodology involves EEG preprocessing, frequency decomposition / topographic mapping generation of features, deep features generation, and the ultimate classification of the classical and quantum models.

Table.1 Standard EEG Frequency Bands

Frequency Band	Range (Hz)	Clinical Relevance
Delta	0.5 – 4	Dominating during deep sleep; an unusual occurrence could be a sign of pathology.
Theta	4 – 8	Characteristic of childhood; too much power associated with convulsions.
Alpha	8 – 13	Resting brain activity
Beta	13 – 30	Active thinking and attentiveness.
Gamma	>30	Cognitive and epileptic activity of the high level.

First, unprocessed multi-channel EEG records are obtained on paediatric patients and pre-processed to enhance signal [14] quality. Normal band-pass filtering is implemented to eliminate low frequency drift and high frequency noise. The notch filtering is used to attenuate power-line interference, and the segments that have been contaminated with excessive artifacts are not to be analyzed further. The resulting cleaned EEG data are further separated into fixed length, non-overlapping time windows in order to facilitate the extraction and labelling of consistent feature patterns [17].

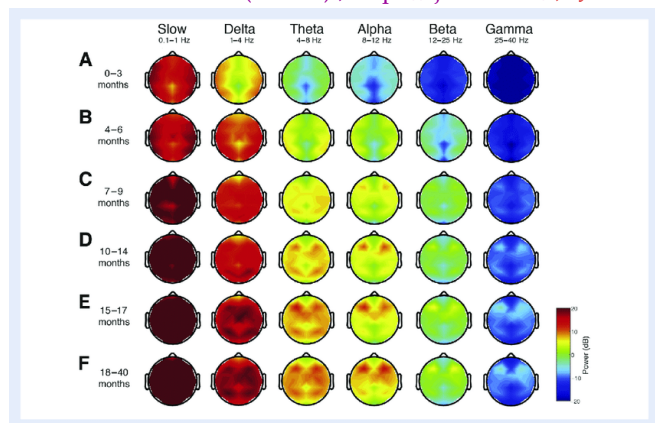


Figure.1 EEG Data Analysis

The EEG segments are divided into typical frequency bands with delta, theta, alpha, beta, and gamma. Band power in every channel and frequency band is calculated because epileptic activity is frequently linked with unnatural energy distribution in these bands. The extracted band power values are mapped on to two-dimensional scalp topographic maps in order to maintain spatial relationships between EEG channels [18].

Values between locations of electrodes are estimated using interpolation techniques and smooth and spatially consistent representations of brain activity are obtained. These topo-graphic maps are the image-based inputs on deep learning. To extract discriminative spatial features on the topographic images generated, a lightweight convolutional neural network is created [18]. The network design is purposefully designed small to minimize the problem of overfitting as well as computational complexity, which is appropriate in small paediatric datasets. Convolutional layers learn localized spatial features whereas pooling layers decrease the features dimensions and amplify their robustness.

The final convolutional or fully connected layer yields feature embeddings which are high level spatial-spectral characteristics of the EEG values. The embeddings obtained are then classified [19]. The classical Support Vector Machine is used as a benchmark model to test the linear and non-linear separability and traditional kernels. To achieve quantum enhanced classification, a Quantum Support Vector Machine associated with amplitude embedding is used. The feature vectors are coded into quantum states and a quantum kernel is calculated in order to encode complicated relationships in the data.

Moreover, a Quantum Neural Network setup is also investigated to evaluate the opportunities of variational quantum circuits to EEG classification. The clinically relevant metrics are used to conduct performance evaluation to compare a classical and quantum classifier, and determine how effective the proposed hybrid framework is in the detection of paediatric epilepsy [20].

4. Modules and Implementation

The suggested system is adopted as a modular pipeline to make it clear, flexible, and easy to evaluate. All the modules do a certain task and can be tested or edited separately without influence on the entire structure. EEG data acquisition and preprocessing is done in the first module [21]. Filtering of Raw pediatric EEG recordings is done to remove noise and artifacts after which they are segmented into fixed-length windows. This is a module that makes sure that the quality of input at later Processing steps is uniform, and has the ability to scale across various datasets.

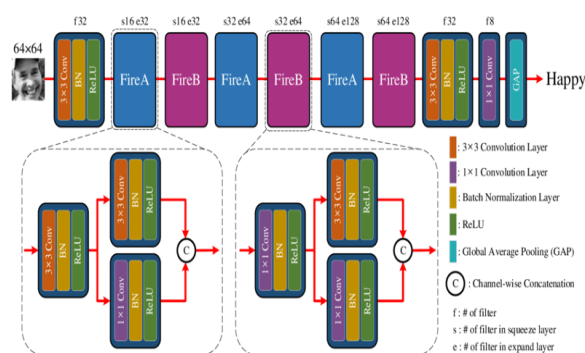


Figure. 2 Internal EEG segments Frequency Data Analysis

The second module has frequency band decomposition and feature generation. EEG segments are separated into regular frequency bands and band power values are calculated per channel. The values are then mapped on to the two-dimensional scalp topographical maps through spatial interpolation methods [22].

The result images maintain the patterns of spatial brain activity and are used as inputs of deep learning. Deep feature extraction is done by the third module. A convolutional neural network with a small number of filters is used to take the topographic maps and learn the discriminative space features [23].

EEG data are labelled and the network is trained, after which feature embeddings are obtained at intermediate layers and used to classify them. The last module is the classification and evaluation. Both classical and quantum models are used to classify feature embeddings and include Support Vector Machine and Quantum Support Vector Machine with amplitude embedding [24].

A comparison is also made with a Quantum Neural Network configuration. Evaluation of model performance relies on sensitivity, specificity, F1-score, and false alarm rate because they allow objective assessment of the offered framework [25].

5. Results

The given hybrid [15] quantum-classical model was tested to explore its usefulness in the application to paediatric EEG data to detect epileptic activity. The comparisons of performances were performed among three configurations, which are CNN-SVM, CNN-QSVM, and CNN-Quantum Neural Network [26]. The analysis was based on clinically important measures, such as sensitivity, specificity, F1-score, and false alarms per hour, that are essential in the context of systems of practical seizure monitoring. The CNN-SVM setup was used as a control to determine the input of classical machine learning [4] after deep feature extraction [27]. This method showed consistent results and validated that topographic EEG representations together with convolutional feature learning is an effective blend of spatial patterns of brain activity. But, the classical SVM was found to be weak when it came to separating seizure and non-seizure classes when there is dirt in the noise, or when the patterns of seizure are fine.

involved, which emphasizes the practical interest of the suggested method in clinical scenarios where a full-channel setup might not be possible [28]. The CNN-Quantum Neural Network architecture showed good performance but showed greater variability across the trials. Although the QNN had promising learning on non-linear decision boundaries, it was more prone to parameter initialization and stability in training. Such behaviour is indicative of up to date constraints of variational quantum circuit optimization, especially in regimes where the circuit depth is constrained, as are the number of available qubits.

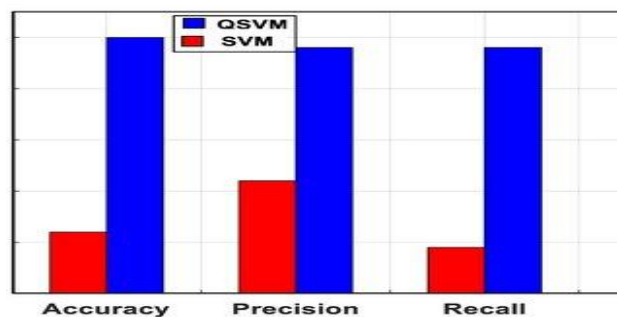


Figure. 4 SVM-QSVN Channel Patterns of Brain Activity

On the whole, the findings suggest that converting EEG signals to topographic maps would improve the spatial learning of features and classification reliability. The separability of seizure and non-seizure states is further enhanced by the integration of quantum-enhanced classification of the circumstances of tough paediatric EEG applications [29]. The improvements observed in spite of the fact that the framework is not based on large-scale quantum hardware prove the applicability of hybrid quantum-classical solutions to biomedical signal analysis. Irrespective of these encouraging results, there are some limitations. The assessment was an assessment on a small paediatric EEG data set, and additional confirmation through large multicentre datasets is necessary. Also, in this study, real-time im-implementation and physical quantum hardware implementation were not investigated. However, the findings justify the possibilities of the suggested frame-work as a step in the right direction of more precise and clinically viable paediatric epilepsy detection systems.

6. Conclusion and Future Scope

In this paper, quantum-classical model of parathyroid epilepsy detection in children was presented on the basis of EEG topography representations. The frame-work is important because it combines frequency-based EEG analysis and spatial topographic mapping to obtain the patterns of important brain activity. Convolutional neural network with lightweight is an efficient method of obtaining discriminative features, but

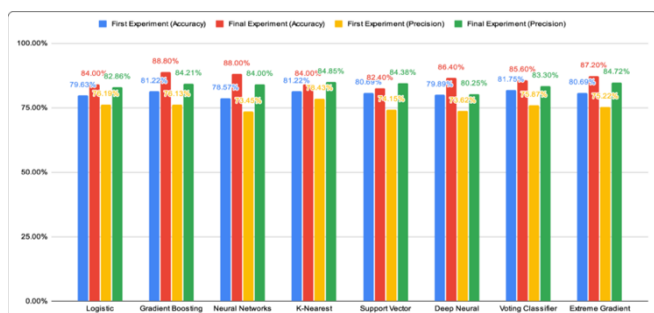


Figure. 3 Spatial Patterns of Brain Activity

The CNN-QSVM setup has recorded better results in most of the evaluation measures. A quantum kernel was used, which allowed the feature embeddings in high dimensions to be separated more effectively, which increased sensitivity and F1-score and minimized false alarm rates.

Table.2 Performance Comparison Of Classifiers

Model	Sensitivity (%)	Specificity (%)	F1-Score	False Alarms/hr
CNN-SVM	90.2	91.5	0.91	0.35
CNN-QSVM	94.6	95.1	0.95	0.18
CNN-QNN	92.1	93.0	0.93	0.26

These findings indicate that amplitude-dependent quantum kernels are more useful in Modeling non-linear relationships in paediatric EEG data that are more complex than the classical kernels. Better robustness was also found to be in those cases when less EEG channels were



quantum-enhanced classifiers are more efficient in increasing separability of classes under noisy conditions. The value of the quantum kernel of the paediatric EEG analysis is highlighted as compared to classical and quantum models. The proposed solution can potentially be more accurate and less reliant on the channels and, as such, may be applied to clinical practice. This can be further improved by its validation on bigger datasets and live set-tings in the future.

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