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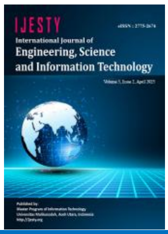

Quantum Machine Learning for Enhancing Signal Processing Applications

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Abstract

In neuroscience and therapeutic practice, electroencephalography (EEG) is a vital instrument for tracking and analysing brain activity. While traditional neural network models, like EEG-Net, have made significant progress in interpreting EEG signals, they frequently encounter difficulties due to the great dimensionality and complexity of the data. Quantum machine learning (QML) techniques offer new ways to improve machine learning models, thanks to recent developments in quantum computing. As a forward-looking approach, we present Quantum-EEG Net (QEEG Net), a novel hybrid neural network that combines quantum computing with the classical EEG Net architecture to improve EEG encoding and analysis. While the results may not always outperform conventional methods, it demonstrates its potential. In order to capture more complex patterns in EEG data and maybe provide computational benefits, QEEG Net integrates quantum layers into the neural network. Using the benchmark EEG dataset, BCI Competition IV 2a, we test QEEG Net and show that it consistently performs better than standard EEG-Net on the majority of participants and has other robustness to noise.

Keywords: *Quantum Machine Learning, Significant Potential, Quantum Layers.*

1. Introduction

In several industries, human dependability is becoming more and more crucial for preventing accidents [1].By using methods like an electroencephalogram (EEG) to monitor human biological parameters like metabolic agents, data analysis can identify patterns that point to drowsiness, a major source of fatigue that can affect tasks in a variety of industries, including oil and gas, aviation, the navy, the railway, and others that require shift work [8]. While conventional machine learning techniques, like Multilayer Perceptron (MLP), have been investigated in the literature for EEG-based drowsiness detection, quantum mechanics concepts have been introduced by computing technology advancements, potentially providing benefits in computational efficiency for problem-solving [11].This study investigates the use of Quantum Machine Learning (QML) for sleepiness detection [3] [10].In addition to statistical parameters like mean, variance, root mean square, peak-to-peak, and maximum amplitude, EEG signals are pre-processed to extract properties unique to this kind of data, such as Higuchi Fractal Dimension, Complexity, and Mobility. We use various quantum circuit topologies that include entangling gates (CNOT, CZ, and iSWAP) and rotation gates (Ry, Rz, Ry). Using parameterized quantum circuits of relatively shallow depths operating on a quantum device, VQAs are hybrid classical-quantum algorithms [2]. The parameter optimization process is then delegated to a classical machine using one of the many highly effective machine-learning/optimization techniques that have been developed over the years [4].In order for the parameters obtained by the previously mentioned hybrid routine to specify the optimal circuit with respect to the learning goal, a given algorithm is written in terms of a set of standard elementary operations implemented on quantum hardware [16].Because systematic errors may be automatically adjusted for throughout the process, this is especially helpful in the NISQ age.By allowing a combination of estimating and detection methods to attain optimal performance for every speech signal, a structured framework has been established for broad signal processing applications [12]. This thesis introduces quantum signal processing (QSP), which uses various mathematical structures of quantum mechanics, including vector algebra, analytical geometry, functional analysis, calculus of variations, etc., to create new or modify existing signal processing algorithms.It suggests that a new model for a range of signal processing applications is produced by bridging the gap between quantum measurement and signal processing algorithms. In order to represent the potential replication of the original speech signal as sent with linear complexity (in data length), a modified Projected Orthogonal Matched Filter (POMF) receiver was designed [5].

2. Literature Review

Probability of a system not failing in a given environment for a specific amount of time. There are no absolute assurances in the execution of reliability; it is just a likelihood. Increasing the chances of achievement within a specific reason is the primary theme or goal. A alternative mechanism can be used to achieve detection reliability. The primary purpose of redundancy is to improve system availability and dependability. N-Self-Checking Programming Software Redundancy System shown in Fig 1.

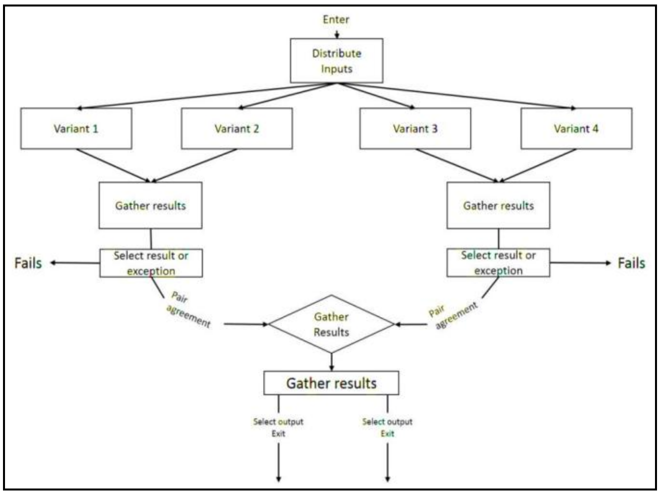


Fig 1. N-Self-Checking Programming Software Redundancy System

Backup redundancy is another name for standby redundancy. The backup system for the primary system is an identical secondary system. Without requiring primary system supervision, the secondary system is utilized as a backup [13]. In order to take over, the standby system has to receive input and output signals from the primary system because it is not synced with it. When the secondary system takes over, a bump is required so that the secondary system can send output signals to the devices attached to the primary system output. This strategy requires a third system to act as a watchdog in order to keep an eye on things and make the appropriate switchover decisions. In order to provide the standby system complete control, this third system also transmits a command signal. Both when the switchover must occur and which subsystem must assume control are determined by the voting system. The price is doubled by a factor of two under this standby redundancy scheme, but it is independent of the cost of software development. [7].

3. Methods

The receiver's performance is measured by the likelihood of error correction and the likelihood of input signal detection. The Bit Error Rate (BER) level enhances the receiver system's performance because communication is the main environment in which the POMF receiver is used. Specifically, a novel approach to matched filter detection has been developed, which generates the idea of using a covariance-shaping least square estimator to study the quantum detection problem as an estimation problem [14]. For any bounded Hilbert space sequences, the technique performs the best among all estimators in its class. The approach has been used with a range of parameter values for trigonometric, exponential, and autoregressive moving average (ARMA) models. Speech signals with additive white Gaussian noise and coloured noise are also included in the analysis. Improving channel dependability, data rate, and user capacity are the primary goals of wireless communication. Channel fading, frequency selective distortion, and Multiple Access Interference (MAI) are the main challenges [9]. Proposed Model shown in Fig 2.

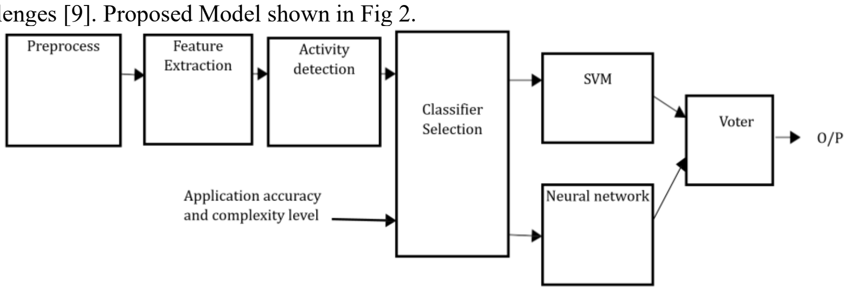
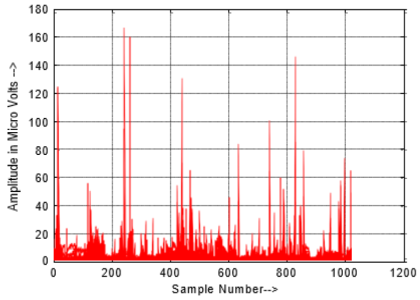


Fig 2. Proposed Model

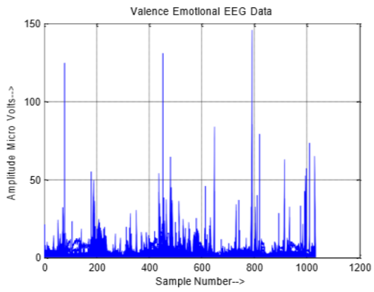
Four feature-based models were tested with three neural network (NN) models over six different window lengths: long short-term memory (LSTM), convolutional neural network (CNN), and a combination of LSTM and CNN. The most noteworthy outcomes were shown by the CNN, LSTM, and LSTM-CNN models; the LSTM-CNN hybrid model had an average accuracy of 85.6%.

4. Result and Discussion

We examine two models' embedding performance using the uniform manifold approximation and projection (UMAP) method. The feature embeddings generated by the EEG Net and QEEG Net models are graphically represented by the UMAP projections that are supplied. Understanding the underlying structure and separability of the data as it is altered by each model is made easier with the aid of these 3D scatter plots [15]. Input ECG data shown in Fig 3.



(a)



(b)

Fig 3. Input ECG Data

These studies highlight the potential to transform a range of machine learning tasks, including those that include high-dimensional, complicated data like EEG [6] [7]. Histogram of Second Order Statistic 20 shown in Fig 4.

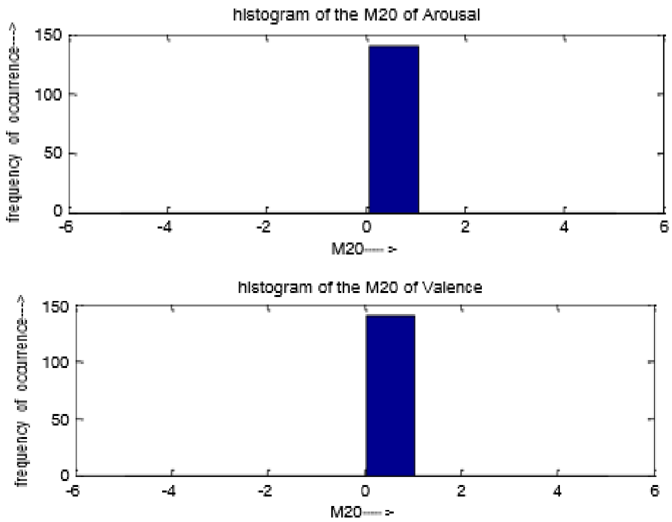


Fig 4. Histogram of Second Order Statistic 20

According to their findings, standard neural networks' representational capacity and efficiency can be greatly increased by quantum algorithms, opening the door to a more reliable EEG analysis model. Different Channel Data of Arousal shown in Fig 5.

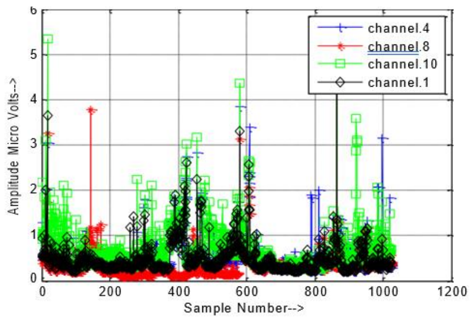


Fig 5. Different Channel Data of Arousal

Together, this research demonstrates how EEG analysis is developing and how significant performance improvements may be achieved by combining cutting-edge neural network architectures with quantum computing methods. Different Channel Data of Valence shown in Fig 6.

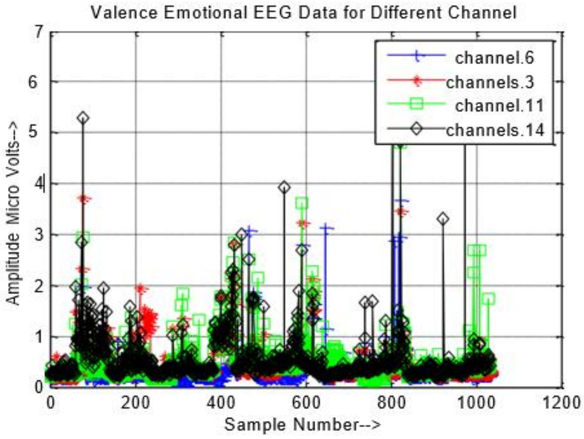


Fig 6. Different Channel Data of Valence

Our study builds on these foundations and distinguishes itself from the previously stated works by integrating VQC directly into the EEG Net architecture to produce QEEG Net. Classification Output shown in Fig 7.

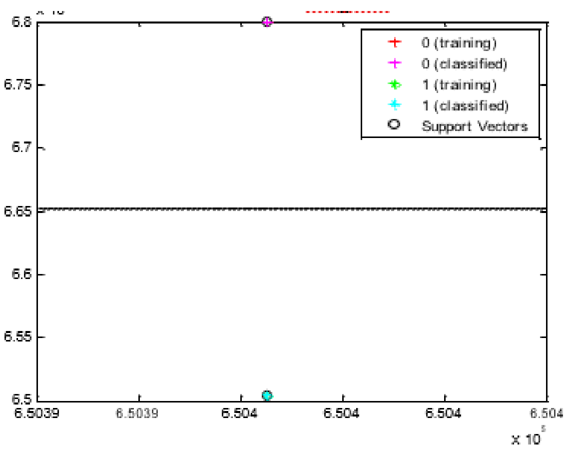


Fig 7. Classification Output

The system, which contains redundancies are costly and much more complex. It may not require for all the systems but an important one for a critical system like medical diagnostics, where the reliable diagnosis of diseases is very much important. Performance Plot shown in Fig 8.

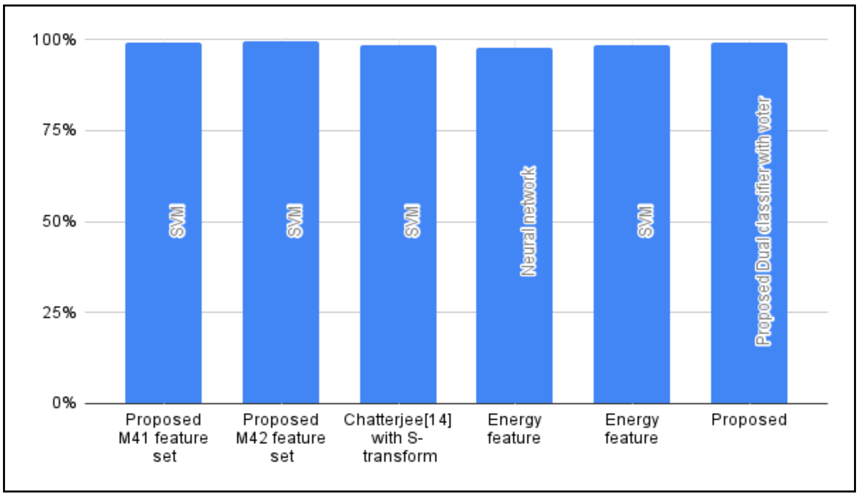


Fig 8. Performance Plot

So, in this EEG signal analysis research work, the redundancy mechanism is used. Redundancy deals with the duplication of critical components or functions of a system for the purpose of increasing the reliability of the system. It is used as a backup or fail-safe, or to improve actual system performance.

5. Conclusion

Our method is on using quantum layers to improve EEG encoding and analysis, even if earlier studies have demonstrated the potential of QML in a number of fields, such as time series analysis and medical imaging. By doing this, we hope to solve the particular difficulties presented by EEG data, including its complicated temporal-spatial correlations and high dimensionality. Being the first quantum-classical hybrid model to include VQC quantum encoding layers at the conclusion of the model, QEEG Net is innovative. Because of its special architecture, QEEG Net can identify more complex patterns in EEG signals, which enhances the robustness and performance of EEG-based applications. The substantial potential of quantum-enhanced neural networks in the field of EEG analysis is highlighted by our experimental results, which show that QEEG Net continuously outperforms conventional EEG Net models.

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