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Quantum Machine Learning for Drowsiness Detection with EEG Signals

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Human reliability is increasingly important in accident prevention, and monitoring biological parameters can help detect patterns indicating behaviors that may lead to accidents. Electroencephalogram (EEG) data has been used to identify drowsiness, a major cause of fatigue in machine operators in the oil and gas industry. While classic machine learning methods like Multilayer Perceptron (MLP) have been used with EEG data, quantum computing has shown promise in solving complex problems efficiently. Variational Quantum Algorithms are one example of quantum concepts applied to classical structures for data training. This study aims to classify operator drowsiness using Quantum Machine Learning (QML) models. EEG signals are preprocessed to extract relevant features such as Higuchi Fractal Dimension, Complexity, and Mobility, as well as statistical features. QML models are trained with various quantum circuit layers, rotation, and entanglement gates. Results will be compared with classical MLP models. This work contributes to exploring the context of drowsiness in QML, which has not been extensively studied in the literature. It serves as a proof of concept that QML models are suitable for this type of data and can be further improved as Quantum Computing continues to evolve.

Keywords: EEG. Quantum Machine Learning. Drowsiness Detection. Diagnosis. Variational Quantum Algorithm.

1. Introduction

Quantum mechanics presents a new paradigm for solving computational problems, sometimes with a significant advantage over classical methods, such as in prime factorization or quantum system simulation (Maior et al., 2023). In this study, we utilize Quantum Machine Learning (QML) through Variational Quantum Algorithms (VQA) to analyze a practical issue - detecting drowsiness using real-world electroencephalography (EEG) time series data. We analyze in this extended abstract the subject #8 from the ULg multimodality sleepiness database, also known as DROZY (Massoz et al., 2016).

Accurate detection of drowsiness from EEG data is critical for ensuring safety in industries and critical processes. Fatigued workers can pose significant risks in workplaces, particularly in industries involving hazardous operations and equipment. Drowsiness can impair operators' judgment, concentration, and productivity, leading to errors and decreased work quality, as well as an increased risk of accidents. Utilizing a drowsiness detection model based on EEG data can provide valuable insights into operators' wakefulness, enabling the implementation of preventive measures to avert serious incidents (Ramos et al., 2022).

2. Methodology overview

The VQAs models are based on the methodology used by (Maior et al., 2023). These models were developed using the TensorFlow Quantum library and were executed on the Cirq quantum simulator without consider the quantum noise. The algorithms are constructed through four main steps. Firstly, the classical data is preprocessed by normalizing and extracting features due to the qubit limitation (30 qubits consume 8 GB of RAM). We consider three features related to EEG specifically (Higuchi Fractal Dimension, Complexity, Mobility), and five statistical (Mean, Variance, Root Mean Square, Peak-to-peak, Kurtosis, and Maximum amplitude). Subsequently, the data is encoded into qubits using the angle encoding method, where N qubits are initialized in a $|0\rangle$ state.

Secondly, we define Parameterized Quantum Circuits (PQC) using different architectures. The first architecture includes only rotation gates (R_y, R_z, R_y) for each qubit with parameterized angles. Additionally, we explore a circuit configuration with the same Euler rotation (R_y, R_z, R_y) followed by nearest-neighbor qubit couplings using a single type of entanglement gates per circuit. In this study we use three: CNOT, CZ, and *i*SWAP. PQCs with different numbers of layers (1, 5, and 10) are constructed, with a maximum of 10 layers due to computational limitations.

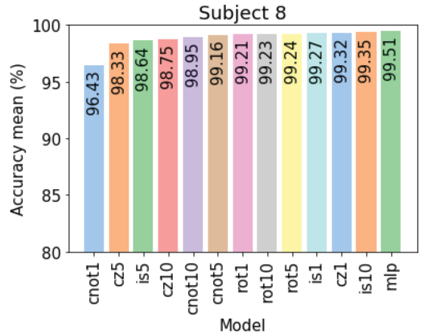
Thirdly we perform the measurements resulting in processed quantum data that is converted back into classical data. Finally, the extracted features from the quantum measurements are collected and fed into a classical neural network (with a dense layer composed by 100 neurons). Error backpropagation and classification analyses are performed, where we can assess if the subject is awake or drowsy.

3. Results

Our results were generated based on the aforementioned architectures, which gave 12 different quantum models. Furthermore, we used a classical Multilayer Perceptron (MLP) with the same configuration of the neural network inserted in the QML models. We ran each model 10 times and extracted the mean value of the accuracy for comparison purpose.

In Figure 1, we can observe an increasing visualization of the average accuracy results. As a positive highlight, the classical model still outperforms the quantum models, with an average accuracy of 99.51%, while the lowest accuracy was observed for the CNOT entangling gate configuration with one layer (96.43%). The quantum model with the highest result was the *i*SWAP gate (99.35%) with 10 layers, which was very close to the classical MLP, followed by the CZ gate with one layer (99.32%).

Figure 1. Subject 8 accuracy mean by model.



We used a Kruskal-Wallis statistical test to assess whether there was a significant difference in accuracies among the 13 models studied. The test was conducted at a significance level of 0.05, and we obtained a p-value lower than 0.01 and a test statistic of 98.60, indicating that there were significant differences among the models.

4. Conclusion

In this study, we applied QML models to test their applicability on EEG drowsiness data. For subject 8, we found that the MLP model performed better on average than the quantum models, although the *i*SWAP gate with 10 layers of circuit also showed promising results. As quantum computing advances, it is important for experts to stay informed about the potential improvements these technologies can offer. Our future research will expand to include more subjects and different QML models to further investigate their performance in this context.

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