QEEGNet: Quantum Machine Learning for Enhanced Electroencephalography Encoding

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***Abstract*—Electroencephalography (EEG) is essential in neuroscience and clinical practice for brain activity analysis. While traditional models like EEGNet decode EEG signals well, they struggle with data complexity. Quantum computing advancements offer new ways to enhance these models through quantum machine learning (QML). This paper introduces Quantum-EEGNet (QEEGNet), a hybrid network combining quantum computing with EEGNet to improve EEG analysis. Despite potential limitations, QEEGNet incorporates quantum layers to capture complex EEG patterns, showing computational advantages. Tested on the BCI Competition IV 2a dataset, QEEGNet consistently outperforms EEGNet and demonstrates robustness to noise, highlighting the promise of quantum-enhanced neural networks for EEG analysis.**

I. Motivation

Electroencephalography (EEG) is a non-invasive method used to measure brain activity, aiding in understanding brain functions, diagnosing neurological disorders, and developing brain-computer interfaces. Traditional EEG analysis methods, such as EEGNet, have achieved notable success but struggle with the complex nature of EEG signals. Quantum machine learning (QML) offers new possibilities by leveraging quantum mechanics for potentially greater computational efficiency and larger solution space exploration [1]. Combining QML with classical neural networks may address some limitations of traditional deep learning models [2]. We propose QEEGNet, a hybrid neural network integrating QML with EEGNet [3] to enhance EEG data encoding and analysis. QEEGNet incorporates quantum layers to capture intricate EEG patterns, improving performance and robustness. Evaluated on a benchmark EEG dataset, QEEGNet consistently outperforms traditional EEGNet in accuracy and noise robustness. These results highlight the potential of quantum-enhanced neural networks for advancing EEG analysis in neuroscience and clinical applications.

II. Approach

In this section, we detail the architecture and methodology of QEEGNet, our proposed hybrid quantum-classical neural network model that leverages quantum machine learning to enhance EEG encoding and analysis.

A. Architecture of EEGNet

In the field of brain-computer interface (BCI) and EEG signal processing, EEGNet [3] is a popular method, it a compact CNN model specifically designed for the analysis and classification of EEG data. The network consists of only a few layers, each designed to capture different aspects of the EEG signal, including temporal and spatial features.

B. Architecture of Quantum-EEGNet

The integration of quantum circuits into classical neural networks enables the creation of hybrid models that combine the strengths of both paradigms. We provided a novel classical-to-quantum Data encoding on EEG signal processing. The quantum encoding layer serves as a bridge, allowing the network to learn quantum-encoded features while being trained using classical optimization techniques. The input EEG data will first encoding by the classical EEGNet, then the output features will encoding into the qubits through the quantum encoding layer module to exploit the high-dimensional information inherent in Hilbert space. The last stage of the model is output the quantum measurement result into fully connected layer to do the downstream classification task.

III. Result

The experiment results are shown in TABLE I. The results highlight QEEGNet's consistent performance advantages over EEGNet in both validation and test datasets. This performance disparity can be attributed to the quantum layer integrated into QEEGNet, which likely enhances its ability to capture complex patterns and features within EEG data. The substantial improvements in test accuracy for multiple subjects suggest that QEEGNet can generalize better across different data variations. Moreover, the noticeable improvement in subjects with lower accuracies using EEGNet (e.g., Subject 2) emphasizes QEEGNet's robustness and potential for broader applicability.

TABLE I: Comparison of the highest test accuracy results of EEGNet and QEEGNet on the BCIC-IV-2a Dataset.

	Subject 1	**Subject 2**	**Subject 3**	**Subject 4**	**Subject 5**
EEGNet	47.9%	22.9%	**46.5%**	32.6%	26.4%
QEEGNet	**49.3%**	**30.2%**	44.1%	30.6%	**26.7%**
	Subject 6	**Subject 7**	**Subject 8**	**Subject 9**	**Average**
EEGNet	28.8%	33.7%	32.3%	62.2%	37.7%
QEEGNet	**31.9%**	**36.8%**	**28.1%**	**65.3%**	**38.1%**

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