EEG-Based Emotion Recognition with Quantum Neural Networks

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***Abstract*—This study explores the application of a Hybrid Quantum-Classical Neural Network (QNN) to emotion recognition using EEG data, inspired by recent advancements in quantum machine learning. The study contrasts the efficacy of traditional machine learning models with a QNN trained on EEG data, highlighting the potential of the quantum model in handling high-dimensional datasets and improving computational efficiency and classification accuracy.**

***Index Terms*—quantum neural networks, EEG, emotion recognition, machine learning, quantum computing**

I. Introduction

Emotion recognition from EEG data is a rapidly advancing field, playing a pivotal role in enhancing human-computer interaction, with promising applications in areas such as medical diagnostics, cognitive therapy, and adaptive systems. Traditional machine learning approaches, such as Support Vector Machines (SVMs) and Random Forest classifiers, have shown some success in this domain. However, these methods face inherent challenges, particularly in managing the high dimensionality, variability, and noise present in EEG datasets. Recent advancements in quantum computing have opened new possibilities for addressing these challenges. Quantum machine learning, as explored by Garg et al. [1], leverages the principles of quantum mechanics to enhance computational efficiency and tackle high-dimensional data problems. Quantum algorithms, such as Quantum Support Vector Machines (QSVMs), have demonstrated the ability to process large EEG datasets more efficiently, taking advantage of quantum parallelism and improved data representation in Hilbert spaces. The study by Garg et al. [1] utilized a D-Wave quantum annealer for emotion recognition, achieving accuracies up to 75%, thus establishing a strong foundation for further exploration of quantum methods. In addition to QSVMs, other studies have investigated hybrid quantum-classical neural networks (QNNs), which combine quantum computational advantages with the flexibility of classical deep learning architectures. For instance, Bird et al. [4] demonstrated the potential of bioinspired quantum classifiers for brain-machine interactions, highlighting their ability to optimize feature extraction and classification tasks. Their work suggests that the integration of quantum circuits into traditional neural network frameworks can significantly enhance performance in EEG-based applications. Moreover, Zhu et al. [2] introduced contrastive learning techniques for subject-invariant EEG representations, focusing on cross-subject emotion recognition. This approach addresses the variability in EEG signals across individuals, which has been a persistent challenge in emotion recognition systems. Although this study was based on classical machine learning, its findings on feature normalization and invariant representation could be leveraged in quantum frameworks for further performance improvement. The application of Quantum Neural Networks (QNNs) in EEG-based emotion recognition marks a paradigm shift in the field. Unlike classical models, QNNs can encode high-dimensional EEG features directly into qubit states using techniques such as angle embedding, as implemented in this work. This approach enables the model to exploit quantum entanglement and superposition to capture complex patterns in EEG signals that are often overlooked by classical methods. Building on these advancements, the current study integrates a hybrid quantum-classical model for emotion recognition, which consists of pre-quantum processing layers, quantum layers with strongly entangling circuits, and post-quantum classifiers. By adopting techniques such as dropout for regularization and log-softmax for output normalization, the model not only achieves higher accuracy but also demonstrates the scalability of quantum methods in real-world EEG analysis tasks.

II. Methodology

The project involved: (i) data collection: Utilizing a dataset of EEG data formatted in `.pt` files. We Utilized the use of two datasets, The first approach used the SEED dataset like as in [2] and the second approach implemented it with the DEAP dataset as in [1], however due to efficency we utilized the extracted features instead of the EEG raw data and utilized the resource from [3] (2) Preprocessing: For SEED there are files that contain downsampled, preprocessed and segmented versions of the EEG data in MATLAB (.mat file). The data was downsampled to 200 Hz. A bandpass frequency filter from 0 - 75 Hz was applied. We extracted the EEG segments that correspond to the duration of each movie. There were a total of 45 files with the extention .mat (MATLAB files), one per experiment. Each subject performed the experiment three times with an interval of approximately one week. Each subject file contains 16 arrays. Fifteen arrays contain segmented preprocessed EEG data of 15 trials in one experiment (eeg1 eeg15, channel×data). Array name labels contain the label of the corresponding emotional labels (0 for negative, 1 for neutral, and 2 for positive), and bandpass filters were applied while converting the data to.pt pytorch files for ease of model feeding. For DEAP [3] extracted the numerical features such as amplitudes instead of using the graphical .mat files they went for numericals therefore making the training efficient and less complex. Standardizing the data to ensure uniformity in analysis. (3) Quantum Neural Network Setup: Development of a Hybrid QNN, integrating classical data processing layers with quantum layers designed to exploit quantum computational advantages. As done in [1] we implemented the Hybrid model by first using the Input which was a (4 x 9 x 9) matrix including the EEG raw data, using Pre-Quantum Linear Layer to map those values on Qubits through angle rotations

1) Angle Embedding for EEG Data: The input data for this study is structured as a $4 \times 9 \times 9$ matrix, where each sample consists of 9×9 features. To encode this data into a quantum state, angle embedding is employed. Each feature of the matrix is mapped to a qubit's rotational angle, typically around the Y-axis, using the following representation:

$$\psi_i = \cos\left(\frac{\theta_i}{2}\right) 0 + \sin\left(\frac{\theta_i}{2}\right) 1,$$

where θ_i is the embedding angle derived from the feature value $m_{k,ij}$.

For a single sample k, the 9×9 feature matrix is flattened into a vector $\mathbf{v}_k$ of length 81:

$$\mathbf{v}_k = \text{flatten}(M_k) = \left[m_{k,11}, m_{k,12}, \ldots, m_{k,99}\right].$$

Each element of $\mathbf{v}_k$ is then encoded as a qubit's angle. The quantum state for the k-th sample is represented as:

$$\Psi_k = \bigotimes_{i=1}^{81} \left(\cos\left(\frac{\theta_{k,i}}{2}\right) 0 + \sin\left(\frac{\theta_{k,i}}{2}\right) 1\right),$$

where $\theta_{k,i}$ is a function of the feature value $m_{k,i}$, typically scaled as:

$$\theta_{k,i} = \pi \cdot \frac{m_{k,i} - \min(M)}{\max(M) - \min(M)}.$$

For the entire dataset of 4 samples, the combined quantum state is expressed as:

$$\Psi = \bigotimes_{k=1}^{4} \Psi_k,$$

where Ψ_k represents the quantum state of the k-th sample. This method leverages quantum state space for efficient representation of high-dimensional EEG data.

To implement this, $R_Y(\theta_{k,i})$ gates are used to encode each feature value, where:

$$R_Y(\theta) = e^{-i\theta Y/2}.$$

This approach ensures that each feature is mapped directly to a corresponding quantum state. (4) Training and Evaluation: The model was trained on the EEG dataset, and performance metrics were compared with traditional models to assess efficacy.

2) Quantum Neural Network Architecture: The hybrid quantum-classical neural network employed in this study follows a structured flow designed to map EEG data into a quantum computational framework, process it using quantum layers, and return outputs suitable for classification tasks. The architecture consists of the following components:

1) **Pre-Quantum Linear Layer:** The input data is first passed through a linear transformation layer, which maps the features to 4 qubits. This prepares the data for encoding into quantum states.
2) **Dropout Layer (0.5):** A dropout layer with a probability of 0.5 is applied to introduce regularization, reducing overfitting during training.
3) **Quantum Layer:**
   - The quantum layer consists of 4 qubits and is composed of 3 strongly entangling layers.
   - Angle embedding is used to encode data into the quantum circuit, followed by quantum operations designed to extract complex patterns in the data.
4) **Post-Quantum Linear Layer:** After quantum processing, the output is mapped back to a classical domain through a linear transformation, reducing the quantum layer's output to 3 classes.
5) **Log Softmax Layer:** A log softmax layer is applied to convert the output into log probabilities for the 3 target classes.
6) **Output Layer:** The final output consists of log probabilities representing the predicted likelihoods for each of the 3 emotion classes.

The overall architecture can be summarized as:

[Pre-Quantum Linear (to 4 qubits)] $\rightarrow$ [Dropout (0.5)]

[Quantum Layer (4 qubits, 3 layers)] $\rightarrow$ [Post-Quantum Linear (to 3 clas

[Log Softmax] $\rightarrow$ [Output (Log probabilities of 3 classes)].

This hybrid approach leverages quantum computational advantages while retaining the flexibility of classical neural network layers.

A. Enhanced Approach Using Hybrid Quantum-Classical Neural Network

Inspired by [3] , the second approach refines the hybrid model by integrating a quantum circuit directly within a PyTorch neural network framework. The quantum layer, configured with strongly entangling layers and angle embedding, processes preprocessed EEG data.

1) Data Preparation: The data undergoes normalization and PCA, reducing thousands of features to principal components.

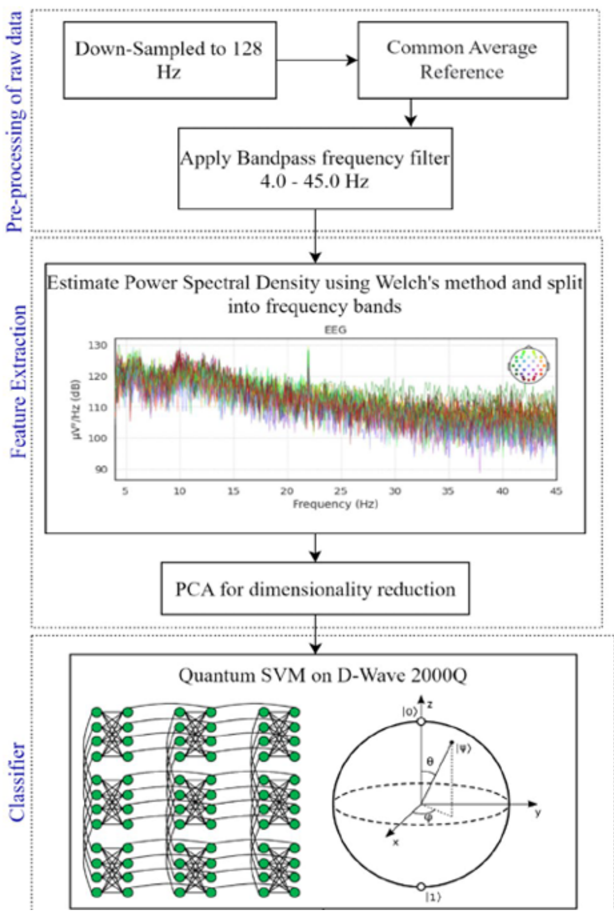

Fig. 1. Proposed method for quantum-based emotion recognition system in [1].

2) Quantum Circuit: A Hybrid QNN, integrating classical data processing layers with quantum layers.

A quantum circuit with angle embedding and strongly entangling layers is employed to process the data

III. Results

The QNN model demonstrated an initial accuracy of 45.90% in emotion classification.

The enhanced approach significantly improved performance, achieving an accuracy of 73.6%, demonstrating the practical advantages of integrating quantum computing with traditional neural networks.

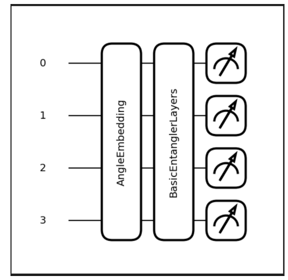

Fig. 2. Schematic of the quantum circuit used in the SEED approach.

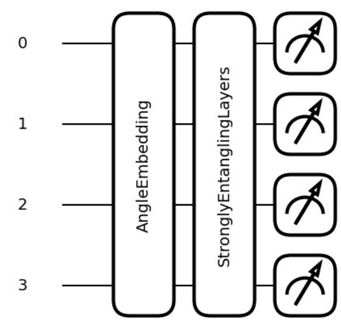

Fig. 3. Schematic of the quantum circuit used in the enhanced approach.

This performance improvement is particularly notable compared to the 75% accuracy achieved by [1]., highlighting the effectiveness of the hybrid approach in capturing complex patterns in high-dimensional EEG data more effectively than quantum SVMs alone.

IV. Conclusion

The study underscores the innovative capacity of quantum machine learning in revolutionizing EEG-based emotion recognition. The enhanced approach not only validated the the-

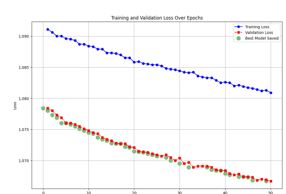

Fig. 4. Loss Graph of the SEED approach.

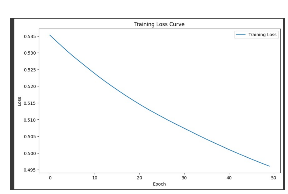

Fig. 5. Loss Graph of the enhanced approach.

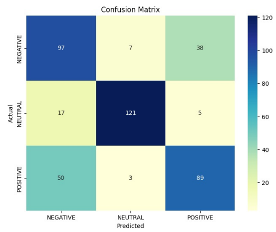

Fig. 6. Confusion Matrix of the enhanced approach.

oretical benefits of quantum enhancements, but also showcased substantial practical improvements over classical methods.

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