

# Quantum Computational Techniques for Prediction of Cognitive State of Human Mind from EEG Signals

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**Abstract:** The utilization of quantum states for the representation of information and the advances in machine learning is considered as an efficient way of modeling the working of complex systems. The states of mind or judgment outcomes are highly complex phenomena that happen inside the human body. Decoding these states is significant for improving the quality of technology and providing an impetus to scientific research aimed at understanding the functioning of the human mind. One of the key advantages of quantum wave-functions over conventional classical models is the existence of configurable hidden variables, which provide more data density due to its exponential state-space growth. These hidden variables correspond to the amplitudes of each probable state of the system and allow for the modeling of various intricate aspects of measurable and observable physical quantities. This makes the quantum wave-functions powerful and felicitous to model cognitive states of the human mind, as it inherits the ability to efficiently couple the current context with past experiences temporally and spatially to approach an appropriate future cognitive state. This paper implements and compares some techniques like Variational Quantum Classifiers (VQC), quantum annealing classifiers, and hybrid quantum-classical neural networks, to harness the power of quantum computing for processing cognitive states of the mind by making use of EEG data. It also introduces a novel pipeline by logically combining some of the aforementioned techniques, to predict future cognitive responses. The preliminary results of these approaches are presented and are very encouraging with upto 61.53% validation accuracy.

**Keywords:** Cognitive state of mind; hybrid quantum-classical neural network; variational quantum classifier; quantum annealing; EEG signals

## 1 Introduction

Quantum computing is expected to have a high and beneficial impact on many computational disciplines [1]. This field has the potential to model complex scientific phenomena using the resources more efficiently, including modeling of events that occur in nature, since most of these are based on quantum phenomena at their core. In the recent past, with the development of quantum computers that are accessible to the public via cloud interfaces, it is now feasible to develop novel solutions using the quantum approach. The introduction of quantum frameworks has had an impact on the performance and the modeling of a variety of real-time applications.

The development of a representative, complete model for human cognition has been a goal of scientists for several decades. One recent finding that provides a new direction to this form of research is that the human brain functions in a manner similar to that of quantum computers [2]. This indicates that a quantum mechanical modeling of the brain would be required to develop a functional representative model of the



human brain. Thus, the inclusion of the quantum approach is imperative to contain and represent all the relevant information pertaining to the human brain.

The current research work comprises of an amalgamation of these concepts and aspires to develop a pipeline for using quantum computing to model human judgement outcomes. A few sample preliminary models that use a hybrid quantum neural network model have also been created. The approach relies on the latest advancements in hybrid quantum-classical computing, particularly in quantum neural networks, research on the modeling of cognitive states of the human mind, and is inspired by the application of other quantum principles in tackling various aspects of understanding the complexity of this structure.

### ***1.1 Developments for Studies of Cognitive State of Mind***

A cognitive state is a representation of a thought process based on past experiences and current situations of the subject. Extensive studies have been performed that define the various states of mind [3] and establish the differences between the human brain and the theoretical mind [4]. Analysis of these states of mind are done on the basis of electroencephalography (EEG) readings, and can also be done with fMRI brain scans [5–6].

Various theoretical models have been written to study cognition [7] and practical models based on machine learning techniques have also been developed to understand and predict cognitive processes. Frameworks have been designed which simulate the behavior of the brain [8], and these modeling methods are extensively used to analyze and study disease-related information from EEG signals [9–10].

Thus, while there is extensive research aimed at understanding cognitive states using neural networks and EEG signals as input, most of these do not focus on the involvement of the underlying quantum mechanical principles while constructing these models. Hence, it is necessary to combine quantum mechanical principles with neural networks.

### ***1.2 Applications of Quantum Neural Networks***

Quantum neural networks as a variant of feed-forward neural networks were first designed about twenty years ago [11]. However, in the recent past, the various methods for simulating quantum neural networks were explored [12]. As simulation tools and frameworks began to develop, many studies were conducted that began to describe the various architectures and approaches [13] that could be used to develop these models, and comparative analysis of these with respect to neural networks was started [14].

There were efforts on the application of machine learning methods over quantum information [15]. The introduction of the feature of memory also indicated that quantum networks could perform better if they were able to hold information of previous quantum states [16]. Neural networks that use quantum states have been created for a multitude of applications, being used for noise filters [17], brain image segmentation [18], and in rolling bearing fault predictions [19]. These quantum neural networks have been used to classify click counting data [20], predicting optimal parameters [21], and in image recognition systems [22]. This variety of applications shows the prowess of the quantum mechanical approach to design neural networks.

Quantum neural networks for prediction of the cognitive state of mind have not yet been developed. This research aims to build a foundation and eventually bridge the gap that exists in the understanding of human cognition and its quantum modeling.

### ***1.3 Focus of the Present Research***

Some new approaches which have utilized quantum rules and methods to study the human mind have begun emerging in the recent past. One of the most significant advances is using black hole physics to mimic human memory [23]. Based on the natural working of the brain, quantum associative learning models have been created which can be used to achieve memorization [24]. Classification of EEG signals has been done using recurrent neural networks that are inherently quantum in nature [25]. These discoveries were used to create an information processing model [26].

These researches focus on a pure quantum-based approach. Additionally, they focus on the classification or modeling of natural information by quantum techniques. The presented research work not only proposes a variety of hybrid quantum-classical approaches, but also utilizes the models to perform the task of prediction of some specific cognitive states of mind. Hence, providing an initial path to realize the feat.

This paper employs a quantum encoding followed by a variety of hybrid neural network models for the classification of two distinct states of cognition through the neuromarketing dataset [27]. This was achieved using a hybrid quantum convolutional neural network, a variational quantum classifier, and a quantum annealing classifier. The results of all these approaches are presented.

This paper explores the detailed theory and methodology of the above-mentioned approaches in Section 2, captures the setup of the experiment in section 3, and the results and their discussion in Section 4. Section 5 presents a brief conclusion of the findings from this research work. The primary novelty of this research work is the proposal of a new hybrid quantum-classical pipeline for prediction of judgement outcomes, as well as the development of possible quantum methods to tackle this problem.

## 2 Quantum Machine Learning Techniques

This section introduces the various theoretical concepts that have been applied during the research. It provides details on the encoding scheme applied as well as the conceptual basis and design of various quantum neural network architectures.

### 2.1 Encoding Classical Values into Qubits

*Qubits* or *quantum*-bits are the fundamental building blocks of a quantum system. Unlike a classical bit that can represent data most efficiently by using only a binary basis, a qubit can represent a numeric value by various techniques like basis encoding, amplitude encoding, and dynamic encoding [28].

Basis encoding is a one-to-one correlation of quantum states with classical bit values (Example: Classical value 3 is encoded as  $|0011\rangle$ ), whereas in amplitude and dynamic encoding, exponentially large number of values can be encoded in a set of qubits. Basis encoding is used only in cases where a one-to-one correlation is necessary.

Dynamic encoding utilizes the gate-model of quantum computing to apply transformations using quantum gates represented as high dimensional Hilbert space matrices. A detailed study of dynamic encoding can be found in the papers by Mottonen et al. [29–31], which employ uniformly controlled rotations to encode classical data. A recursive approach for dynamic encoding involving the use of CNOT gates by Martin et al. [32] also discusses a similar approach. Though this method is very powerful in representing data, it is not best suited for Noisy Intermediate-Scale Quantum (NISQ) devices due to its exponential increase in circuit depth with linear upscaling in the number of qubits.

The encoding scheme used here is inspired by Xia et al. [33], employing a form of amplitude encoding with Variational Quantum Circuits (VQC), which is in-turn based on the work by Maria et al. [34]. VQC consists of  $R_x$  and  $R_z$  rotation gates, symbolizing rotation about *the x – axis* and *z – axis*, respectively, of the Bloch sphere representation of a qubit. This type of encoding scheme has a linearly increasing circuit depth with increase in the number of qubits and is suitable for the problem statement at hand.

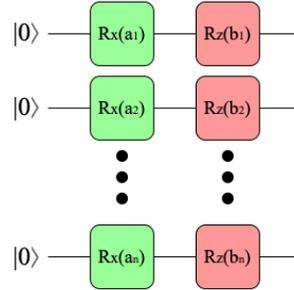
The raw EEG data undergoes three steps for encoding, within the data state-space of the quantum system: (i) Normalization of data to set the range of data points  $x \in [0,1]$ ; (ii) Converting the data into probability values for each state in the quantum system by employing (1); (iii) Converting the probability values for each quantum state into probability value for each qubit by (2), and using single-qubit rotation gates to encode it into the system by using (3) to get appropriate rotation angles; for an N-qubit system,

$$(p_1, p_2, \dots, p_{2^N}) = \frac{1}{\sum_{i=1}^{2^N} x_i} (x_1, x_2, \dots, x_{2^N}) \quad (1)$$

$$P_k = \sum_{i=1}^{2^N} (p_i \times (i \cdot 2^{k-1})) \quad (2)$$

$$\theta_k = 2 \times \arcsin(\sqrt{P_k}) \quad (3)$$

where  $(x_1, x_2, \dots, x_{2^N})$  represent the input EEG signal data points;  $(p_1, p_2, \dots, p_{2^N})$  are the probabilities of each state in the set  $S = (|00 \dots 0\rangle, |00 \dots 1\rangle, \dots, |11 \dots 1\rangle)$ ;  $P_k$  is the probability of each qubit in the system and  $\theta_k$  is the input angle to the single-qubit rotation gate for each qubit, where,  $k = 1, 2, \dots, N$ . Fig. 1, shows a representation of the data encoding circuit.

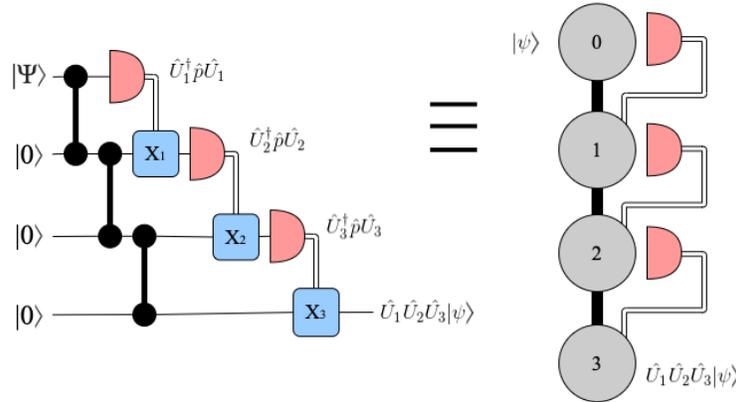


**Figure 1:** Amplitude encoding circuit using  $R_x$  and  $R_z$  gates. Here  $a_k$  and  $b_k$  are angles for amplitude and phase rotation respectively for each qubit, where  $k = 1, 2, \dots, N$  in an  $N$ -qubit system. Also,  $a_k$  corresponds to angles  $\theta_k$  in (3), and the set of angles  $(b_k)$  can be neglected as there is rotational symmetry about the  $z$  - axis

## 2.2 The Quantum Layer Architecture and Hybrid Networks

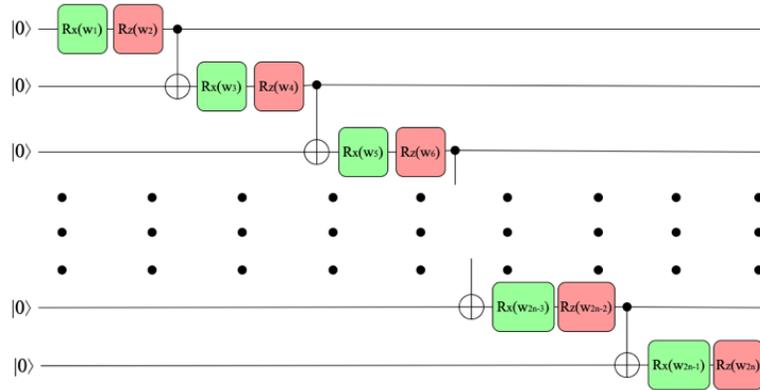
The quantum layer of the neural network consists of a combination of two parts:

- *Cluster-state circuit:* A graphical approach to simulate quantum circuits more efficiently on classical hardware [35], as seen in Fig. 2. The cluster-state circuit allows the usage of a hybrid neural network model (mentioned in the next sub-section) which involves the use of both quantum and classical parts to seek the advantages of both types of architectures. Running the quantum layer in a simulated quantum environment on a classical machine provides the flexibility for seamlessly connecting both parts.



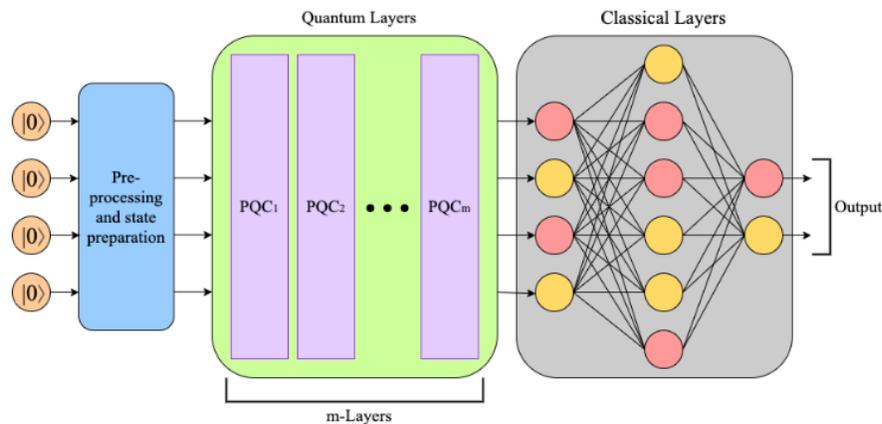
**Figure 2:** An example of a cluster state circuit to implement arbitrary operations  $\widehat{U}_1$ ,  $\widehat{U}_2$ , and  $\widehat{U}_3$  on a wavefunction  $|\psi\rangle$ . Here,  $\hat{p}$  is the probability with which the respective operation is applied

- *Parameterized Quantum Circuit (PQC):* A collection of rotation and CNOT gates. The parameters to the rotation gates can be varied to train the neural network model as can be observed in [28] and [33]. The parameters of the PQC act as the quantum counterpart of “weights” and “biases” of a classical neural network. Here, the  $R_x$  gates act as the “weights”, by changing the qubit amplitude and the  $R_z$  gates act as the “bias” values, by altering the qubit phase, as seen in Fig. 3.



**Figure 3:** Structure of Parameterized Quantum Circuit (PQC) using rotation gates. The parameters to the rotation gates  $w_i$  are the weights and biases of each layer, where  $i = 1, 2, \dots, 2n$  for an N-qubit system

The hybrid quantum-classical neural network refers to a logical combination of quantum and classical layers to build the neural network model. This method provides extreme flexibility as the quantum layer provides efficient data encoding and exponential speedup for calculations whereas, the classical layers provide the necessary non-linearity when applying optimizers and activation function to the model.



**Figure 4:** Block diagram of a hybrid quantum-classical neural network

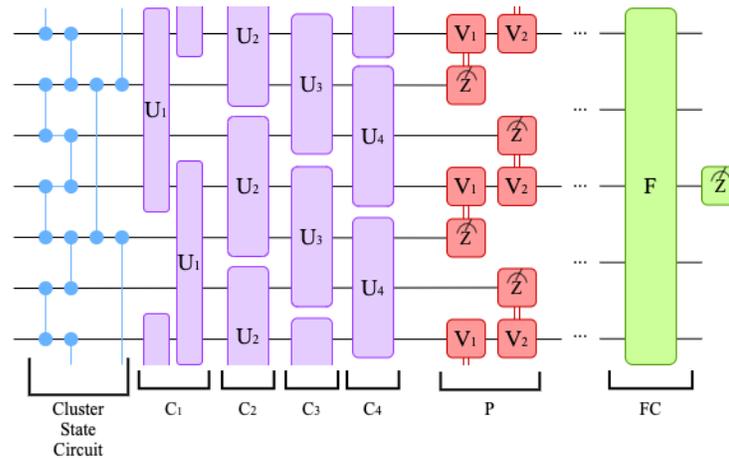
Fig. 4 portrays a block diagram of such a hybrid neural network. The initial step involves state preparation to encode the data values within the qubits. Once the qubit states are prepared, they act as input to the Quantum Layers consisting of a series of PQCs with tune-able parameters. The output from the quantum layer goes to the classical neural network layer to implement optimizer and activation function and introduce nonlinearity within the model. The final output from the classical layer represents the best prediction/solution to the input.

### 2.3 Quantum Convolutional Neural Networks

Quantum Convolutional Neural Networks (QCNN) is another application for quantum machine learning. A theoretical implementation of a QCNN has been discussed in the paper by Cong et al. [36] which uses the concept of cluster-state circuits [37] to achieve a highly entangled state of the quantum system. Cong also portrays a method to build a quantum counterpart for convolution and pooling layers in a convolutional neural network by using one and two-qubit unitary matrices mentioned in the paper by Tucci et al. [38].

Brain waves are considered as a time series data. Due to their continuous nature, the EEG readings and the temporal locality of the current reading are correlated. This phenomenon makes a Hybrid Quantum-

Convolutional Neural Network (HQCNN) model suitable method to process such data as the readings in the temporal locality can be pooled together. An example of a HQCNN can be seen in Fig. 5.



**Figure 5:** An example of a Quantum Convolutional Neural Network. The cluster state circuit provides maximal entanglement within the qubits. The layers  $C_x$  are the quantum convolution layers (QConv), where  $x \in [1,4]$ . The layer  $P$  is the quantum pooling layer (QPool) and  $FC$  is the fully connected layer

## 2.4 Quantum Annealing

Quantum annealing [39] is a meta-procedure for attaining the lowest possible cost of a system by employing phenomena like quantum tunneling [40] and quantum entanglement [41] to get to the most optimized solution of a problem. It is faster than classical algorithms. It is similar to the classical phenomenon of simulated annealing [42], in which a particle always tends to go into its lowest energy state by accumulating energy from its surroundings to go over an energy barrier.

In quantum annealing, a particle can take advantage of the quantum mechanical principles and can employ quantum tunneling to pass through a high but narrow energy barrier in order to reach the global minimum. This technique does not allow for precise control of the qubits as the user only has access to the initial conditions system. Once the process is started, the parameters cannot be changed mid-way like a gate-model quantum computer. The natural evolution due to interference between the quantum states brings out the most optimized solution. Hence, it is very useful for optimization and probabilistic sampling problems.

Quantum annealing based quantum computers make use of more resources in terms of qubits and couplers. However, their ease of scalability makes them more useful than the gate model NISQ computers.

## 3 Methodology

This section provides the experimentation details which includes using three completely different techniques to train on the EEG signal data obtained from an open-source dataset called the ‘‘Neuromarketing Dataset’’ explained in the next subsection.

### 3.1 The Neuromarketing Dataset

The dataset used for this experiment is the Neuromarketing dataset generated by Yadava et al. [27]. The response of a consumer towards a product was recorded in terms of like/dislike, and a predictive model was created based on EEG signals. This dataset has 14-channel signal data from 25 subjects by showing them pictures of various products and then recording their response to the product. The binary nature of classification in the dataset is beneficial as it needs a smaller number of readout qubits as compared to a multilevel classification.

The 14-channel data is preprocessed to separate the different brain-wave components, i.e., *alpha*, *beta*, *gamma*, *delta*, and *theta* waves. Discrete Wave Transformation (DWT) is applied to obtain the aforementioned components from each channel. Yadava et al. also mention in their paper that the *theta* waves play a decisive role in the prediction of the like/dislike response from the subject. To keep the complexity and realizability of the quantum circuit within the limits of available quantum computing technology, only the *theta* waves have been used to train the models subsequently discussed in the paper.

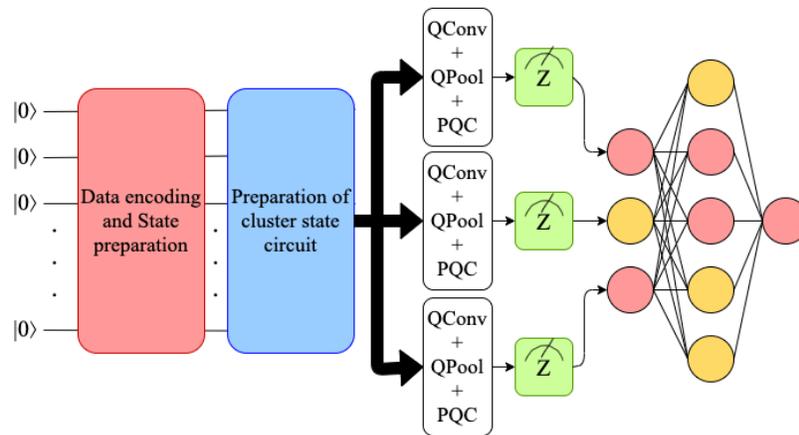
The EEG data is taken channel-wise, i.e., each EEG channel's data is trained separately. This provides two advantages:

- Channel-wise training of EEG data helps to analyze the contribution of each channel in generating the like/dislike response within the brain. This can further be used in the future to make more efficient EEG headsets with a smaller, but precise number of electrodes.
- The number of data points per reading decreases, which makes the model use a smaller number of qubits, facilitating the program to run on the current NISQ hardware.

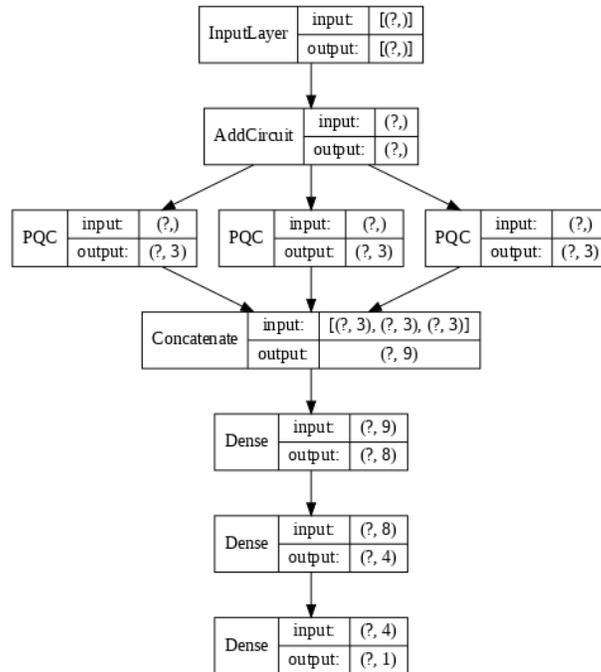
### 3.2 Hybrid Quantum Convolutional Neural Network

To realize the HQCNN as discussed above, the TensorFlow Quantum (TFQ) library [43] has been used as it provides seamless connection and data interchange between the classical and quantum layers of the neural network. TFQ utilizes tensors to simulate qubits and quantum gates. It transforms the quantum circuit into a resultant tensor-based neural network structure. A block diagram for the model is given in Fig. 6.

In Fig. 7, the “*AddCircuit*” layer consists of the encoding circuit based on the aforementioned encoding scheme and a cluster state circuit to implement the Quantum Convolution (QConv) and Quantum Pooling (QPool) transformations before the input goes to the PQC layers. The “*Concatenate*” layer concatenates the output from each of the three PQC blocks and forwards it to the fully connected layers “*Dense*” layers. At the last layer, the output is a binary classification of a like/dislike opinion for a set of items.



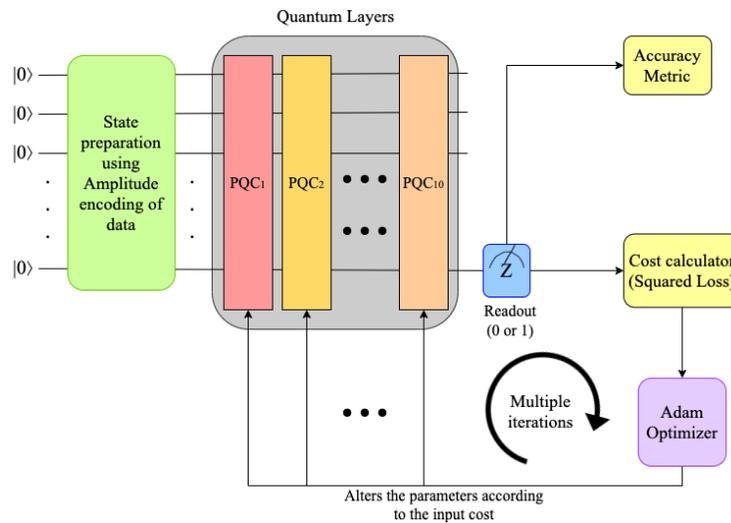
**Figure 6:** Block diagram of the Hybrid Quantum Convolutional Neural Network. The state preparation is done using amplitude encoding as discussed in the section 2A. The cluster state circuit is prepared by entangling the adjacent qubits to maximize connectivity. QConv and QPool are implemented using the technique mentioned by Cong et al. [36]. The neural network architecture is extended by employing a fully connected classical neural network to induce nonlinearity to the model



**Figure 7:** The actual HQCNN architecture used to train the model Variational Quantum Classifier

### 3.3 Variational Quantum Classifier

The Variational Quantum Classifier (VQC) used in this paper is implemented using PennyLane [37]. The neural network follows the architecture described in Fig. 8 and utilizes the aforementioned encoding scheme. PQC is used to implement the quantum segment. The classical part consists of an optimizer based on the ADAM optimization algorithm [44]. The quantum circuit uses a 6-qubit system to encode up to 64 values per channel of EEG data.



**Figure 8:** Block diagram of the VQC. The state preparation stage encodes the classical data into the qubits. The quantum layer consists of 10 PQC layers. The classical layer consists of an ADAM optimizer that gets the cost. Input from the cost calculator. The parameters to the PQC are varied by the optimizer for training the hybrid neural network. This process goes on for many iterations until an acceptable accuracy score is given by the accuracy metric

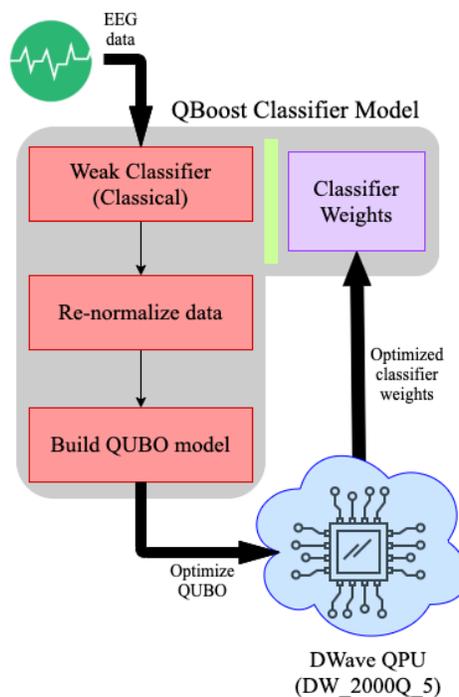
### 3.4 Quantum Annealing Classifier

The Quantum Annealing Classifier is designed using the QBoost technique by Neven et al. [45–46]. This technique uses more resources in terms of the number of qubits but is faster than the aforementioned two techniques during training phase.

Rather than employing a quantum computer simulator like the former two techniques, the Quantum Annealing classifier makes use of a Quantum Processing Unit (QPU) by DWave Systems Inc. The QPU which has been utilized here is the *DW\_2000Q\_5* which has access to 2030 qubits, capable of solving a multitude of optimization and probabilistic sampling problems through quantum annealing.

The QBoost classifier works by combining a weak classical classifier and the process of sampling the solution space using quantum annealing to find the lowest cost solution to the problem. Fig. 9 describes the process of training a model on the QPU.

The inherent use of quantum annealing ensures that the QPU always returns the most optimized solution for the problem. Once the classifier is trained, the most optimized weights are returned to the model and stored. These weights can then be used for predicting output for new input data.



**Figure 9:** Quantum Annealing classifier architecture. The raw data is taken as the input and is fed into a weak classifier and a preliminary classical model is trained. This model is used to build a Quadratic Unconstrained Binary Optimization (QUBO) model, which is then run on the QPU for sampling the problem space using quantum annealing. Most optimized weights are then returned to the model and stored. These weights can then be used to predict the test data labels

## 4 Results and Discussions

Three distinct hybrid quantum-classical models were created to experiment with the ability to predict the state of mind of each subject from their EEG signals. It was observed that some channels had better prediction accuracy than the others. This was due to the fact that not all areas of the brain are utilized while generating an opinionated response. Each aforementioned approach was trained for each EEG data channel. The results of these models were captured and are displayed in the sections ahead.

The validation accuracy is used as the primary metric for evaluation since any developed model should be able to generalize well. Validation accuracy represents this ability.

#### 4.1 Hybrid Quantum Convolutional Neural Network

To explore the findings from Pennylane, as well as to try a different method for solving this complex problem, a hybrid quantum convolutional network was designed on the TFQ [44] platform. The results found are tabulated in Tab. 1.

**Table 1:** Results from HQCNN

Channel	Hybrid Quantum Convolutional Neural Network (TFQ)		
	Training	Testing	Validation
1	54.67%	52.65%	53.48%
2	49.59%	47.34%	46.12%
3	51.64%	51.34%	52.88%
4	48.56%	49.33%	47.11%
5	53.67%	53.23%	54.78%
6	45.62%	45.21%	44.66%
7	56.34%	55.93%	55.82%
8	51.15%	51.23%	52.88%
9	52.25%	51.51%	52.88%
10	49.16%	48.13%	47.11%
11	47.15%	44.32%	45.18%
12	47.64%	46.32%	46.42%
13	44.18%	43.84%	43.36%
14	54.36%	53.87%	53.43%

It was observed that the channels 1, 3, 5, 7, 8, 9, and 14 show marginally better validation accuracies. However, the values were around below 55%, i.e., approximately between 52-54%. Thus, the model does not respond well to the data.

#### 4.2 Variational Quantum Classifier

Tab. 2 showcases the results obtained from the VQC using the ADAM optimization algorithm [43] and being implemented on the Pennylane [37] platform. It was observed that channels 1, 3, 5, 7, 9, and 14 performed marginally better than the others. However, most of the accuracy values were saturated approximately between ~53-55%. Hence, although it shows that modeling may be possible, this approach does not appear much promising.

**Table 2:** Results from VQC

Channel	Variational Quantum Classifier (Pennylane)		
	Training	Testing	Validation
1	51.53%	51.30%	52.88%
2	54.26%	53.69%	47.11%
3	51.51%	51.28%	52.88%
4	49.31%	49.44%	47.11%
5	56.61%	54.50%	55.43%

6	47.12%	48.56%	46.21%
7	54.67%	53.23%	53.34%
8	51.20%	52.34%	51.10%
9	52.47%	52.31%	52.88%
10	52.40%	51.43%	51.14%
11	49.66%	48.71%	47.11%
12	51.24%	50.34%	49.35%
13	44.18%	43.84%	43.36%
14	54.36%	53.87%	53.43%

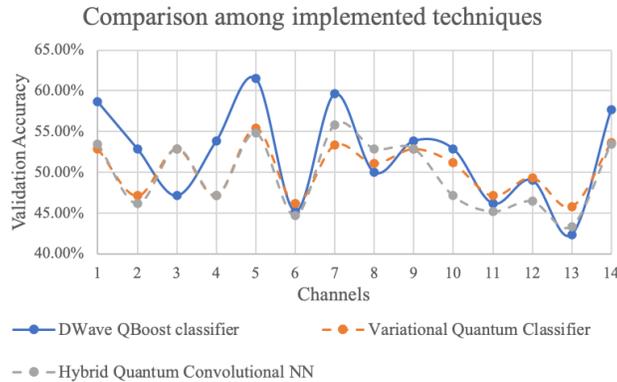
### 4.3 Quantum Annealing Classifier

While performing training of the neural network, the dataset used is quite restricted. Additionally, quantum constructs are complex and must be designed with the ability to hold all the relevant parameters. Keeping the ultimate goal of classification in mind, experiments were conducted on quantum annealing classifier using the QBoost algorithm [45–46], on the *DW\_2000Q\_5* QPU by D-Wave Systems Inc. This particular approach yielded encouraging results, with a high increase in training accuracy. The values are showcased in Tab. 3.

**Table 3:** Results from Quantum Annealing Classifier

Channel	Quantum Annealing Classifier (DW_2000Q_5 QPU)		
	Training	Testing	Validation
1	84.69%	57.89%	58.65%
2	83.06%	55.50%	52.88%
3	86.61%	48.80%	47.11%
4	82.78%	59.33%	53.84%
5	82.92%	55.02%	61.53%
6	83.46%	53.11%	45.19%
7	83.74%	51.19%	59.61%
8	84.28%	57.41%	50.00%
9	84.01%	56.45%	53.84%
10	82.92%	57.89%	52.88%
11	85.79%	55.02%	46.15%
12	87.15%	55.50%	49.03%
13	87.02%	50.23%	42.30%
14	83.19%	55.50%	57.69%

The results of training with each specific channel were compared. The variation in validation accuracies across the three techniques is visualized in Figure 10. It is seen that the channels 1, 5, 7, 14 perform the best with validation accuracies above 55%. Their values tend towards ~60%, which is a good and encouraging initial result from this work.



**Figure 10:** Graph for comparison of variation in validation accuracies from the aforementioned three techniques

## 5 Conclusion

The primary contribution of this work is the creation of three potentially novel pipelines for the prediction of judgement outcomes on the basis of cognitive states of mind. The research showcased in this paper demonstrates the ability to use hybrid quantum-classical approaches to model cognitive states of the human mind. The encouraging initial results obtained from the Quantum Annealing Classifier show that this approach is viable, and can perform better when large amounts of high-quality data are used for its training. In all approaches, it was observed that some channels outperformed others. Hence, it can be concluded that the process to generate an opinionated response to visual stimulus is controlled by specific regions of the brain.

This work effectively puts together initial modeling of the cognitive state of mind by using the powerful mechanisms of quantum information handling and quantum neural networks.

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**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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