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Article

Implementing Magnetic Resonance Imaging Brain Disorder Classification via AlexNet–Quantum Learning

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Abstract: The classical neural network has provided remarkable results to diagnose neurological disorders against neuroimaging data. However, in terms of efficient and accurate classification, some standpoints need to be improved by utilizing high-speed computing tools. By integrating quantum computing phenomena with deep neural network approaches, this study proposes an AlexNet–quantum transfer learning method to diagnose neurodegenerative diseases using magnetic resonance imaging (MRI) dataset. The hybrid model is constructed by extracting an informative feature vector from high-dimensional data using a classical pre-trained AlexNet model and further feeding this network to a quantum variational circuit (QVC). Quantum circuit leverages quantum computing phenomena, quantum bits, and different quantum gates such as Hadamard and CNOT gate for transformation. The classical pre-trained model extracts the 4096 features from the MRI dataset by using AlexNet architecture and gives this vector as input to the quantum circuit. QVC generates a 4-dimensional vector and to transform this vector into a 2-dimensional vector, a fully connected layer is connected at the end to perform the binary classification task for a brain disorder. Furthermore, the classical–quantum model employs the quantum depth of six layers on pennyLane quantum simulators, presenting the classification accuracy of 97% for Parkinson's disease (PD) and 96% for Alzheimer's disease (AD) for 25 epochs. Besides this, pre-trained classical neural models are implemented for the classification of disorder and then, we compare the performance of the classical transfer learning model and hybrid classical–quantum transfer learning model. This comparison shows that the AlexNet–quantum learning model achieves beneficial results for classifying PD and AD. So, this work leverages the high-speed computational power using deep network learning and quantum circuit learning to offer insight into the practical application of quantum computers that speed up the performance of the model on real-world data in the healthcare domain.

Keywords: deep neural network; convolution neural network; classical network; transfer learning; quantum circuit; quantum transfer learning; brain disorder; Parkinson disease; Alzheimer's disease

MSC: 68T07

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1. Introduction

Today, healthcare has become an important part of the human way of life. Since then, changes and developments in the healthcare domain have become prevalent in terms of technology. Disease identification has been done via biomedical imaging technologies such as CT scans, MRI scans, and X-rays. With the increase in the use of technology, handling the excessive growth of imaging data is becoming a problem for healthcare specialists. However, high-power computational tools increase the speed at which biomedical imaging data are analyzed and minimize the workload for the radiologist. Beyond that, this development in technologies has permitted researchers to deal with more complex clinical models and data. Neurodegenerative disease (ND) recognizes the complications found in the brain and it is often referred to as cognitive impairments that affect the person's abilities of thinking, walking, speaking, and learning. Some neurological disorders affect the brain cell severely and cause permanent suffering that can threaten a person's life. So, awareness of this disorder becomes crucial to reduce the mortality rate.

Brain disorders such as Parkinson's disease (PD) and Alzheimer's disease (AD) are the most common NDs, that are usually diagnosed in older adults [1]. The symptoms in people with Alzheimer's are difficulty in performing normal tasks, loss of memory, unable to walk, speak, move or learn. Brain nerve cells become damaged along with neurofibrillary tangle accumulation that disrupts the functioning of the brain and are the main cause of Alzheimer's disease. PD is also common in older people and its major signs are slow movements, expressionless faces, muscle stiffness, tremors, trembling handwriting, and unable to speak [2,3]. The main cause of PD is the deficiency of dopamine due to the loss of nerve cells in the brain. The neurons in the substantia nigra are responsible for producing dopamine. These brain disorders are highly progressive and recursive in nature PD. Therefore, the diagnosis of AD and PD at an early stage will be beneficial in providing appropriate diagnoses to patients.

The early diagnosis and identification of neurodegenerative disorders is the most complex task and dealing with massive data manually by experts often takes much time to find the solution to the disease. But now, a computer-aided diagnosis (CAD) system has been implemented for neurologists to discern brain disorders from large biomedical imaging data. CAD systems help experts to evaluate the massive amount of medical imaging data and improve the classification accuracy and speed of the systems. Meaningful information extraction from imaging data is one of the basic elements of the CAD system and this feature vector is given as input to the classification model to classify the patient into normal or disease categories.

Compared with other imaging modalities (such as CT, PET, ultrasound, and X-rays), magnetic resonance imaging (MRI) scans are mostly chosen by doctors to diagnose brain diseases because MRI scans show accurate neuroanatomical biomarkers. MRI is a non-invasive biomedical image processing technique that measures and envisages the anatomy of the brain, evaluates abnormalities, locates diseased areas, recognizes, and classifies anomalies found in the human brain, and implements image-related procedures.

Machine and deep learning applications in the classification of brain disorders have proven to be very beneficial in recent years. Machine learning-based CAD systems that utilize imaging data and electronic healthcare records have proven to be very accurate in accurately classifying and predicting different brain diseases.

Neural networks and transfer learning methods are extensively used by scholars for their high efficiency and computational performance [4,5]. In neural networks and transfer learning models, there is no need to extract features manually, therefore, deep learning models fully automate the binary or multiclass classification task. However, these classical neural networks have some limitations when dealing with a large dataset, which can affect their performance in computer vision tasks. Therefore, to overcome the shortcomings of classical neural networks, quantum circuit networks are specifically designed for image-related tasks.

Quantum variational circuits (QVCs) are built using quantum bits that process the information, and quantum gates that change the quantum state, respectively. Hadamard and CNOT gates are the two most common gates that superposed and entangled the qubits. Thus, this work provides an algorithm based on a convolutional neural network and quantum circuit to detect neurological disorders. AlexNet from the hybrid classical-quantum model is a pre-trained classical model and it tends to learn good weights for feature extraction and image classification, as well as how to infer spatial pose parameters from images [6–8]. All of these attributes make AlexNet–quantum networks an ideal alternative to the classification of multiple types of neurodegenerative diseases and provide an optimal result against neuroimaging data. The main contributions of this study are as follows:

- A binary classification framework for brain disorders based on the AlexNet–quantum transfer learning network is proposed;
- The Quantum learning model is implemented with the depth of six quantum layers and this model leverages quantum simulator;
- To validate the robustness, and efficiency of the brain disease system in real-time, the PPMI dataset for PD classification and the ADNI dataset for AD classification was used for training and testing the model; and
- Lastly, the performance of the brain disease–quantum neural system is compared with other deep transfer learning models such as AlexNet, VGG-16, ResNet 50, and Inception v3 on the same brain disorder dataset.

The rest of the article is arranged as follows: Section 2 describes the detailed literature review related to the article. The AlexNet–quantum transfer learning algorithm for the binary classification of brain disorder is described in Section 3. The result and analysis using PPMI and ADNI datasets based on Classical neural network and quantum transfer learning is implemented in Section 4, which shows the evaluation of the proposed model. Section 5 presents the conclusion of the paper.

2. Literature Review

For computer vision task analysis, machine learning models produced remarkable results in recent years. Various works have been employed for the binary and multi-classification of brain disorders. Initially, machine learning models have been implemented for the classification of brain disorders using neuroimaging data. In [9–12] they used different machine learning algorithms for the binary classification of AD. They extracted features using different techniques such as least absolute shrinkage, selection operator, and radial-based function support vector machine from T1 sequence MRI and utilized SVM as a classifier to yield 85% to 90% accuracy. These classifiers are trained on diffusion tensor image features and entropy features. In [13] they examined the resting state fMRI images taken from the ADNI dataset and trained this dataset on the SVM algorithm by using multiple kernel learning techniques to identify AD. Similarly, refs. [14–16] SVM algorithm is also trained on PET, MRI, and FDG-PET imaging modalities to perform binary classification of AD. Recently, deep learning techniques have been implemented to perform binary and multiclassification of AD. Generally, CCN algorithms are trained and tested using generic datasets downloaded from PPMI and ADNI. In [17] they created a CNN model based on leaky rectified linear unit and max pooling which is employed on MP-RAGE imaging modality on the local dataset to perform the classification and to provide an effective diagnosis of AD.

In addition, they aim in [18–21] to use different CNN models such as 3D neural network, Resnet-50, and Resnet-34 using a transfer learning approach based on PET and MRI datasets taken from ADNI and OASIS to perform the binary or multi-classification task. Furthermore, the hybrid model is constructed using a stacked convolutional neural network and a bidirectional long–short-term memory approach is proposed in [22] to discriminate AD from non-AD. Similarly, another hybrid approach [23] is designed by combining convolution neural network and support vector machines to classify the ADNI dataset. In [24,25] transfer learning method is implemented in which pre-trained network such as resNet-18, VGGNet, AlexNet, GoogLeNet, DenseNet, Inceptionv3, and Inception ResNet is trained on an MRI image dataset to perform the computer vision task.

In [26] the author investigates the performance of a machine learning classifier known as the least squares formulation of linear discriminant analysis to discriminate the PD from healthy controls based on an MRI dataset downloaded from the PPMI dataset. In [27–29] SVM based on multiple kernel classifier, a random forest classifier is proposed to detect PD using T1 weighted MRI and achieved reasonable accuracy. In addition, a transfer learning approach [30] has been used in which an already pre-trained network is implemented on an MRI dataset. The authors utilize VGG 16 and ResNet 50 to accurately classify PD from HC. In [31,32] 2D and 3D CNN have been proposed and trained on MRI datasets. Similarly, using T2-weighted imaging and MRI scans, a convolutional neural network [33,34] has been performed to identify PD with reasonable statistical measures. In [35] the authors aim to create a customize CNN network and diagnose PD more accurately. Pre-trained models such as AlexNet, VGG19, and VGG16 are performed based on a transfer learning approach using structure MRI scans [36] and SPECT images [37–39] for the detection of PD.

Moreover, the authors in [40,41] trained CCN on neuromelanin-sensitive MRI (NMS-MRI) and electroencephalography (EEG) datasets to detect and identify PD. Similar work [42,43] has been performed leveraging deep neural networks by applying various imaging modalities.

The authors in [44–46] employed SPECT scans, MRI, and DaTscan data to train the CNN model and in some studies, different mapping techniques such as quantitative susceptibility and R2 map [47], textured feature extraction techniques [48] and morphological characteristics [49] are considered for the prediction and classification of PD.

This literature shows the robustness of the CNN model using various feature extraction techniques and different imaging modalities to classify brain disorders. However, there are some challenges and limitations in terms of slow training speed, large datasets, and high GPU requirements that directly affect the performance and efficiency of the model. So, in this work, the AlexNet–quantum transfer learning approach has been implemented to improve the speed and classification accuracy of the model. This method leverages quantum gates and parameterized circuits to transform and process the classical–quantum information [50]. We particularly focused on hybrid models containing neural networks for informative feature vector extraction and amalgamated them with QVC circuits to perform binary classification [51–53]. Moreover, hybrid models also utilized the method of transfer learning with quantum circuits [54–56] to maximize the performance measures and offer impressive speed up for computer vision tasks.

3. Materials and Methods

In this work, we implemented a new hybrid model by amalgamating classical layers of CNN with quantum layers of variational circuits followed by a fully connected layer. The schematic diagram of the proposed network is shown in Figure 1. Classical layers are constructed by convolutional followed by nonlinear Relu activation function and adaptive pooling layers that are used as feature extractors and provide meaningful patterns. The feature extraction techniques aim to transform the rich information from the wide data into a few score vectors. The CNN architecture used in this work is AlexNet as shown in Figure 1. This model is used as a feature extractor and provides the 4096 features as input to the quantum variational circuit (QVC). QVC utilizes the qubits and quantum gates to construct a quantum circuit to take benefit from a speedup in computational requirements.

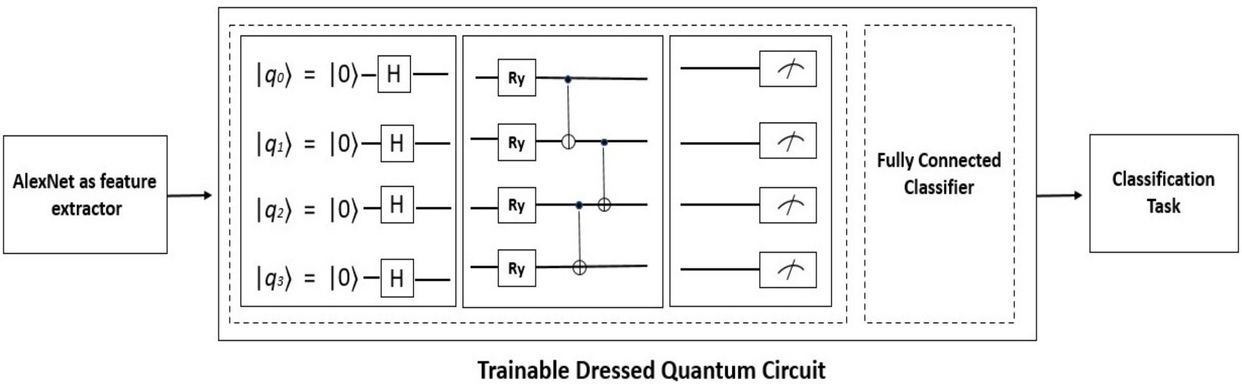

Figure 1. AlexNet–quantum transfer learning network [53].

First, we used the Hadamard gate to initialize the qubit and then use the superposition phenomena to transform the qubits into another state, and then we used CNOT gates to entangle the qubits. To convert it into the classical state, we use the measurement layer to find the expectation values using the z-operator. Dressed quantum circuits can be constructed by combining the classical layers of CNN at the start and the end of the quantum variation circuit. The equation for the dressed quantum circuit is given as:

$$\mathbf{Q\tilde{V}C}^* = \mathcal{C}_{\ell}\mathrm{q}{\to}_{\ell}\mathrm{out} \cdot \mathbf{Q\tilde{V}C} \cdot \mathcal{C}_{\ell}\mathrm{in}{\to}_{\ell}\mathrm{q} \tag{1}$$

where $\mathcal{C}_{\ell}{\to}_{\ell}{}'$ is presented in the form of an equation in which φ is an activation function, w is called weights, X is an input vector and b denotes the bias term.

$$\mathcal{C}_{\ell}{\to}_{\ell}{}'{:}\mathrm{X}{\to}\mathrm{Y} = \varphi(\mathrm{wX} + \mathrm{b}) \tag{2}$$

The 4096 input features extracted from the classical network and 2 output features can be written as follow:

$$\mathcal{C}4{\to}2 \cdot \mathbf{Q\tilde{V}C} \cdot \mathcal{C}_{4096}{\to}4 \tag{3}$$

where $\mathcal{C}4096{\to}4$ represents a feature extracted layer, $\mathbf{Q\tilde{V}C}$ denotes a variational circuit, and $\mathcal{C}4{\to}2$ is used as a classifier that provides the binary classification.

The flowchart for the proposed method is shown in Figure 2 in which low-level and high-level features are extracted using the AlexNet model and the classification task is performed by a fully connected layer. The quantum circuit is connected between the feature extraction layers and classification layers to construct the dressed quantum circuit as shown in Figure 2. This dressed quantum circuit is trained with an MRI dataset to classify the brain disorder using MRI scans.

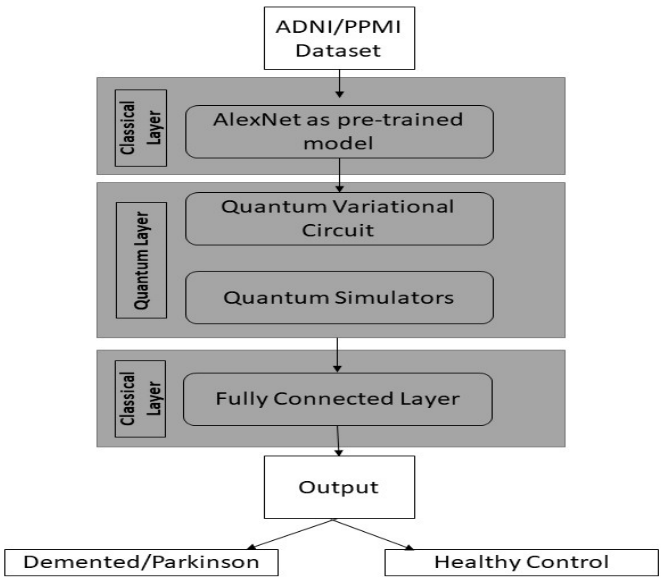

Figure 2. Flowchart for AlexNet–quantum transfer learning model.

3.1. AlexNet Architecture Using Transfer Learning

A convolutional neural network (CNN) has three main blocks: convolutional layers, and pooling layers followed by a fully connected layer. The image is given as input to the convolution layers to take the pixel value from the image data and then convolve this with learnable filters to produce a feature map. Pooling layers are used as a dimensionality reduction technique and reduce the dimensions of the given feature maps. Lastly, a fully connected layer is used as a classifier to yield an output vector. It is designed to hold and use the information between pixel values when it takes two- or three-dimensional input images. Given the efficiency and performance of the model, we have chosen the AlexNet model to extract the features and classify the output. Training the AlexNet model requires less computation and it reduces the training time on a large dataset with improved accuracy. The architecture of the AlexNet CNN model is presented in Figure 3.

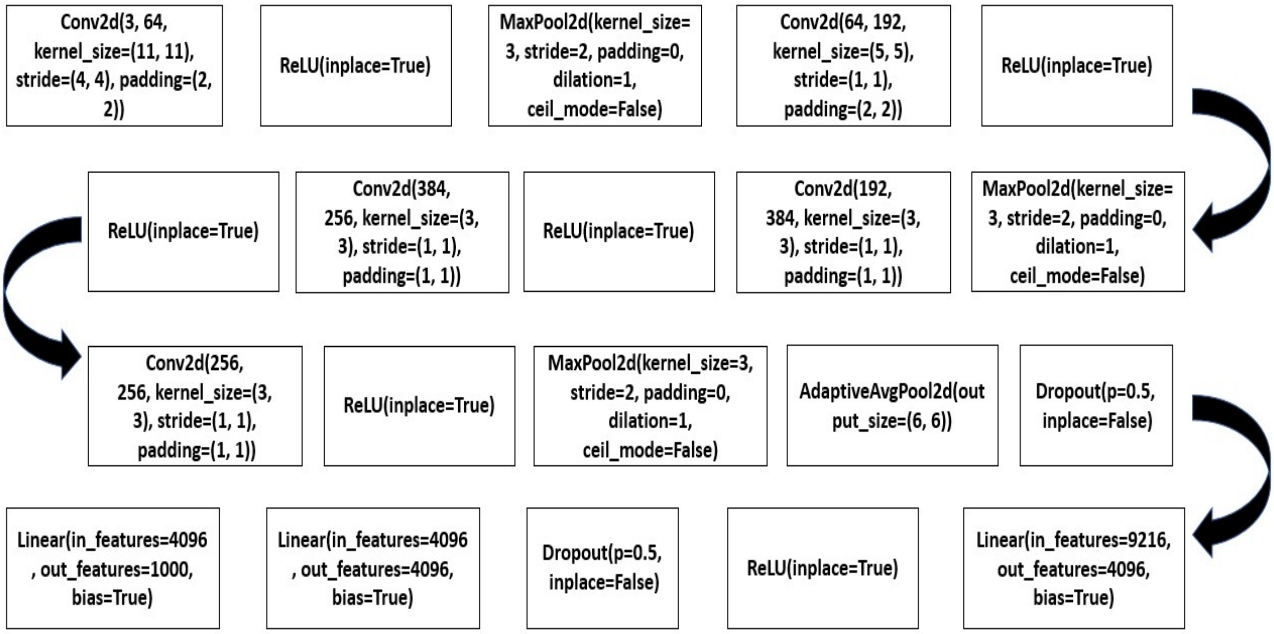

Figure 3. Schematics of AlexNet architecture.

There are eight layers present in the architecture of AlexNet which further comprises five convolutional layers and three fully connected layers as shown in the figure. Nonlinearity based on the Relu function, multiple GPUs made available for training large datasets, and overlapping pooling are the new features used in the CNN algorithm which help in improving the performance of the model on a large dataset. AlexNet used rectified linear units (ReLU) activation function instead of a tanh function to introduce non-linearity, and lessen the training time and it was the optimal solution for the vanishing gradient difficulty. It also helps in reducing the training time by utilizing multiple GPUs on a bigger model. It approximately takes 4–5 min to train the dataset. This network introduces the concept of overlapping pooling to prevent the model from overfitting and helps in reducing the error of the network. This model also used data augmentation techniques such as image translation, image flipping, image scaling, and horizontal reflections to augment the training data samples and dropout techniques to lessen the overfitting and makes the model help in a learning meaningful pattern.

3.2. Quantum Variational Circuit

Quantum computing depends on the properties of quantum mechanics such as quantum data, superposition, entanglement phenomena, and the concept of interference. It helps in solving problems faster than traditional computers and provides beneficial results in particular applications. Quantum data are given in the form of a qubit to process the given information. A Quantum bit can be present in one, zero state, or both states are present simultaneously and this phenomenon is called superposition in which a linear combination of states is presented at the same time and it is a vector state represented in Hilbert space:

$$\mathrm{b}|\varphi\rangle = \begin{pmatrix} \theta \\ \delta \end{pmatrix} = \theta\ |0\rangle + \delta\ |1\rangle \tag{4}$$

where θ and δ are denoted by a complex number, also called probability amplitudes and it is given in the form of $|\theta^2| + |\delta^2| = 1$.

Entanglement is another feature of quantum mechanics. It represents a strong and resilient connection between qubits. When two qubits are separated from each other and placed at a longer distance, the change in the state of one qubit affects the other qubit's state and this shows that the two qubits get entangled.

Quantum circuits can be constructed using different quantum gates and quantum gates are further categorized depending on the number of qubits. There are 1-qubit, 2-qubit, and multiple-qubit gates available to manipulate the quantum information. The most important and widely used gate is the Hadamard gate which creates superposition states. In quantum mechanics, a Unitary matrix can be used to transform the quantum state into another state and this transformation is performed using different quantum gates. A unitary matrix must meet the following condition:

$$\grave{U}\grave{U}\dagger = \grave{U}\dagger\grave{U} = \text{Ị} \quad (5)$$

where Ị is called the identity matrix and $\grave{U}\dagger$ is called the transpose of the matrix. Unitary transformation can be performed using multiple quantum bits such as the CNOT gate and swap gate.

In this work, we have trained the brain disorder dataset on the AlexNet–quantum learning method. The Quantum learning method is implemented using quantum variational circuits and this approach has shown remarkable results in image classification and detection and improved the challenges of the classical learning method. The variational quantum circuit has three main parts as shown in Figure 4. First is the state preparation layer, in which the quantum data is initialized and embedded into the quantum state to process the information. To transform the quantum data into a superposition state and entanglement state, we use various quantum gates such as the Hadamard gate, Rotational gates, and CNOT gates. The second is the variational circuit which entangles the quantum data by utilizing rotational and CNOT gates. The quantum circuit depth is set to six and which means there are six layers of rotational and CNOT gates as shown in Figure 4. We can build various variational circuits using different quantum gates to solve image classification tasks. Lastly, we use the measurement layer to collapse the quantum data into a classical state. A detailed explanation of these layers is given below.

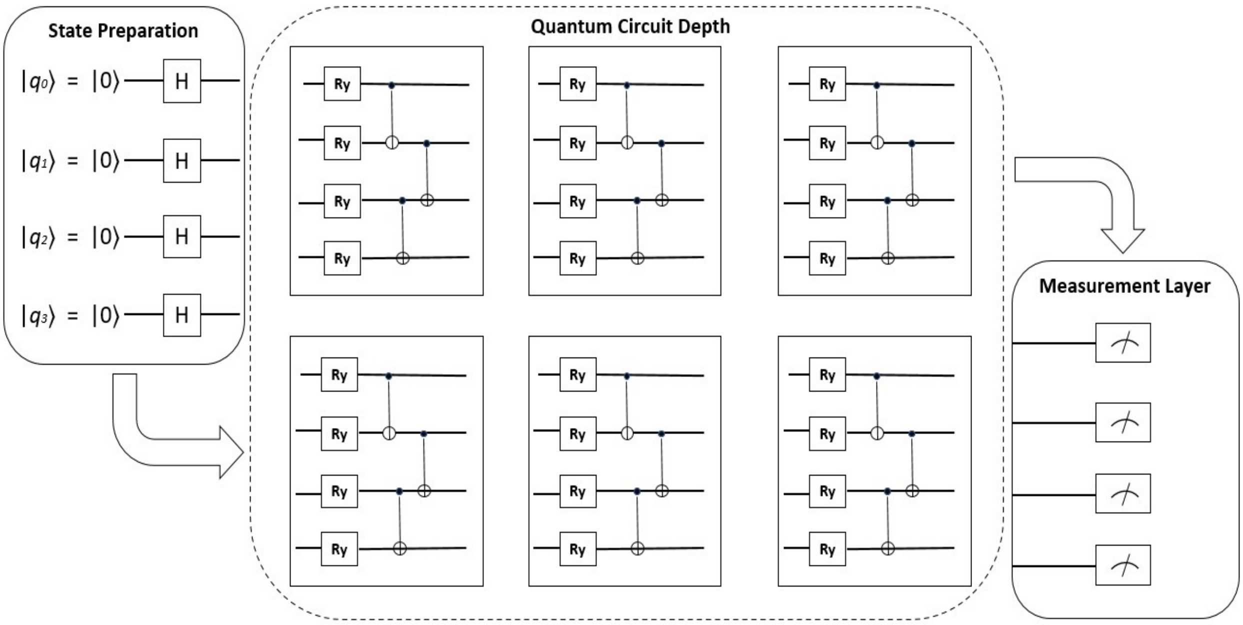

Figure 4. Quantum variational circuit with qubits, quantum gates, and measurement states.

Encoding Layer:

The encoding layer is used to transform the classical data into quantum states. This layer utilizes a single qubit Hadamard gate and rotational gates. Qubits are initialized with the ground state and then we use the Hadamard gate to convert the state into superposition states.

$$Ꝁ\text{:}X \rightarrow |X\rangle = E(X)|0\rangle \tag{6}$$

where Ꝁ represents the quantum bits in superposition states, X is the classical vector, and $|X\rangle$ is the quantum vector.

Rotational gates have been employed to transform the quantum states. Rx, Ry, and Rz are the gates containing a single qubit rotated around the x, y, and *z*-axis. This quantum vector represents the Hilbert space of quantum systems.

Variational Circuit:

The variational quantum circuit is also known as a parameterized quantum circuit. The circuit consists of a single-qubit gate called a rotational gate and two-qubit gates called CNOT gates to train the network.

Also, CNOT gates entangle the quantum bits and it has a controlling parameter θ which helps in the learning process and also improves the speed of the model by providing parallel computation. The variational circuit can be written as:

$$Ụ(\theta)|\varphi\rangle = \left(\prod_{k=1}^{m} \mathrm{U}_i \right)|\varphi\rangle \tag{7}$$

where $Ụ(\theta)$ represents the quantum circuit and $|\varphi\rangle$ is the quantum vector in Hilbert space.

Decoding Layer:

The decoding layer is used to decode the quantum states into classical states using the measurement layer in which the expected value is measured using the Pauli z-operator and yields a classical state vector.

$$ş : \; |X\rangle \; \rightarrow \; Y = \langle X|Y|X\rangle \tag{8}$$

where ş represents the decoding state, $|X\rangle$ is the quantum vector and Y is the classical vector.

The complete QVC can be written in the form of an equation:

$$\mathbf{Q\tilde{V}C} = S{\cdot}L{\cdot}Ꝁ \tag{9}$$

where $\mathbf{Q\tilde{V}C}$ represents the quantum variational circuit, Ꝁ represents the encoding layer and ş represents the decoding layer.

In the end, QVC feeds the feature vector to the fully connected layer, and the backpropagation learning procedure is done via the classical network that utilized the loss function and updates the parameters through the Adam optimization technique.

Algorithm 1 is given below for AlexNet–quantum deep network in which the dataset is prepared, preprocessed, and given as input to the hybrid AlexNet–quantum deep network. AlexNet generates the output of the 4096-feature vector and fed this vector to QVC. QVC encodes the feature vector into a quantum learning circuit and creates superposition and entanglement states to transform the quantum states. Lastly, a measurement layer is implemented to decode the quantum state into the classical vector and further ed his vector to a fully connected classical layer to classify the MRI imaging dataset.

Algorithm 1: AlexNet–quantum deep network

Input: The brain disorder dataset consists of MRI images of brain disease and normal controls
Output: Binary classification of Brain disease using MRI scans based on the AlexNet–quantum model

Steps: Organize the brain disorder dataset by downloading it from the PPMI and ADNI databases.
Preprocess the MRI images.
Using AlexNet, Extract features to give as input to quantum learning circuit whose steps are given as:

Quantum learning Circuit

$V = (\mathcal{X}_n, \mathcal{Y}_n)$ Feature vector dataset
$\frac{1}{\sqrt{k}} \sum_{i=1}^{k} |i\rangle\, \mathcal{X}_i$ Inserting the feature vector dataset into the quantum learning circuit
$\frac{1}{\sqrt{k}} \sum_{i=1}^{k} |i\rangle\, |m(\mathcal{X} \cdot \mathcal{X}_i)\rangle$ Taking inner product by creating superposition and entanglement state
$|m^*\rangle = \frac{1}{\sqrt{\mathcal{F}}} \sum_{i=1}^{k} |i\rangle\, m(\mathcal{X} \cdot \mathcal{X}_i)$ Measurement state for decoding the vector into a classical state
Return value m^*

Classifier: Using AlexNet fully connected layer to classify the vector into two classes.

4. Results and Analysis

In this work, we have proposed the AlexNet–quantum transfer learning approach to discriminate between different brain disorders for neuroimaging analysis. This work performed the binary classification task on neurological disorders such as PD and AD from a healthy control. For PD, the dataset was taken from PPMI database (http://www.ppmi-info.org/ (accessed on 6 June 2022)) [57]. For AD, the dataset was downloaded from ADNI database (adni.loni.usc.edu) [58]. The goal of ADNI to measure the evolution of early AD using magnetic resonance imagining, biological markers and clinical assessment. Detailed information is given on ADNI website.

The demographic details for the brain image dataset are given in Table 1 with the total no. of participants, their gender, and age group details with the given modality and disease type, respectively. The PD dataset contains 423 MRI scans and the healthy control (HC) dataset consists of 198 MRI scans. Similarly, The AD dataset consists of 358 MRI images, and the HC dataset contains 229 MRI images. The AD and PD dataset is further divided into 80% training dataset and 20% testing dataset. The brain disorder dataset is given as input to the network for training the proposed AlexNet–quantum model. After training, we will test the model on 20% testing dataset separately. Before training the network, the MRI dataset has been pre-processed using the normalization technique and data augmentation techniques. In the normalization process, the input image sample is normalized and measured in the range of 0 to 1. Also, the normalization process was first performed on the training dataset and then performed on the testing dataset separately. In the data augmentation process, we resize, crop, rotate, and flip the input samples to prevent the network from overfitting and improve its efficiency and robustness.

Table 1. Details of the brain disorder Image database.

Dataset	No. of Participants	Healthy Control	Disease	Male/Female	Age (Years)	Disease Type
PPMI MRI Images	621	198	423	412M/209F	33–70	Parkinson
ADNI MRI Images	787	229	358	423M/364F	61–90	Alzheimer's

In this paper, experiments have been performed using a classical network such as AlexNet and a classical-quantum network which consists of AlexNet and variational circuits on AD and PD datasets. In AlexNet–quantum learning, a feature map is taken from a pre-trained model and given the output of the pre-trained model to QVC to classify the brain disorders. To train the proposed method, hyperparameter values need to be set to improve or increase the performance of the model. The various hyperparameters are used for training the AlexNet–quantum neural network on neuroimaging dataset to diagnose AD and PD. The learning rate is set to 10^{-2} and it is used to calculate the minimum cost function. The batch size represents the training data given to the network and it is equal to 32. The number of times the entire dataset has been trained on the network is called epoch and is set to 30. During backpropagation, the loss function is calculated and this should be minimized to achieve the best accuracy. Cross entropy has been used as a loss function and the learning parameters will be updated by using the Adam optimization algorithm on the AlexNet–quantum learning network for the AD and PD datasets. The number of quantum bits is four and it is used for the initialization and state preparation layer. The quantum circuit layer is set to six and it represents the depth of the quantum circuit. The hyperparameter values are presented in Table 2.

Table 2. AlexNet–quantum transfer learning hyperparameter values.

Hyperparameters	Qubits	Quantum Depth	Cost Function	Batch Size	Learning Rate	Epochs
Values	4	6	Cross-entropy	32	10^{-2}	30

To evaluate the performance of the proposed model based on neuroimaging dataset, statistical parameters such as accuracy, precision, F1-score, and Recall are considered for the binary classification task. These metrics for binary classification task on the AD and PD dataset are calculated as:

$$ACC = \frac{\mathrm{T}p + \mathrm{Tn}}{\mathrm{T}p + \mathrm{Tn} + \mathrm{F}p + \mathrm{Fn}} \tag{10}$$

$$RECALL = \frac{\mathrm{T}p}{\mathrm{T}p + \mathrm{Fn}} \tag{11}$$

$$PRECISION = \frac{\mathrm{T}p}{\mathrm{T}p + \mathrm{F}p} \tag{12}$$

$$F1 - SCORE = \frac{RECALL \times PRECISION}{RECALL + PRECISION} \times 2 \tag{13}$$

where $\mathrm{T}p$ is a true positive that accurately classifies the brain disorder and is labeled with AD and PD, Tn is a true negative that accurately discriminates the normal case and is labeled with healthy control, $\mathrm{F}p$ is a false positive that inaccurately classifies normal control and Fn is false negative that inaccurately determines PD and AD. The confusion matrix for the proposed AlexNet–quantum learning model is presented in Figure 5 for the AD and PD datasets.

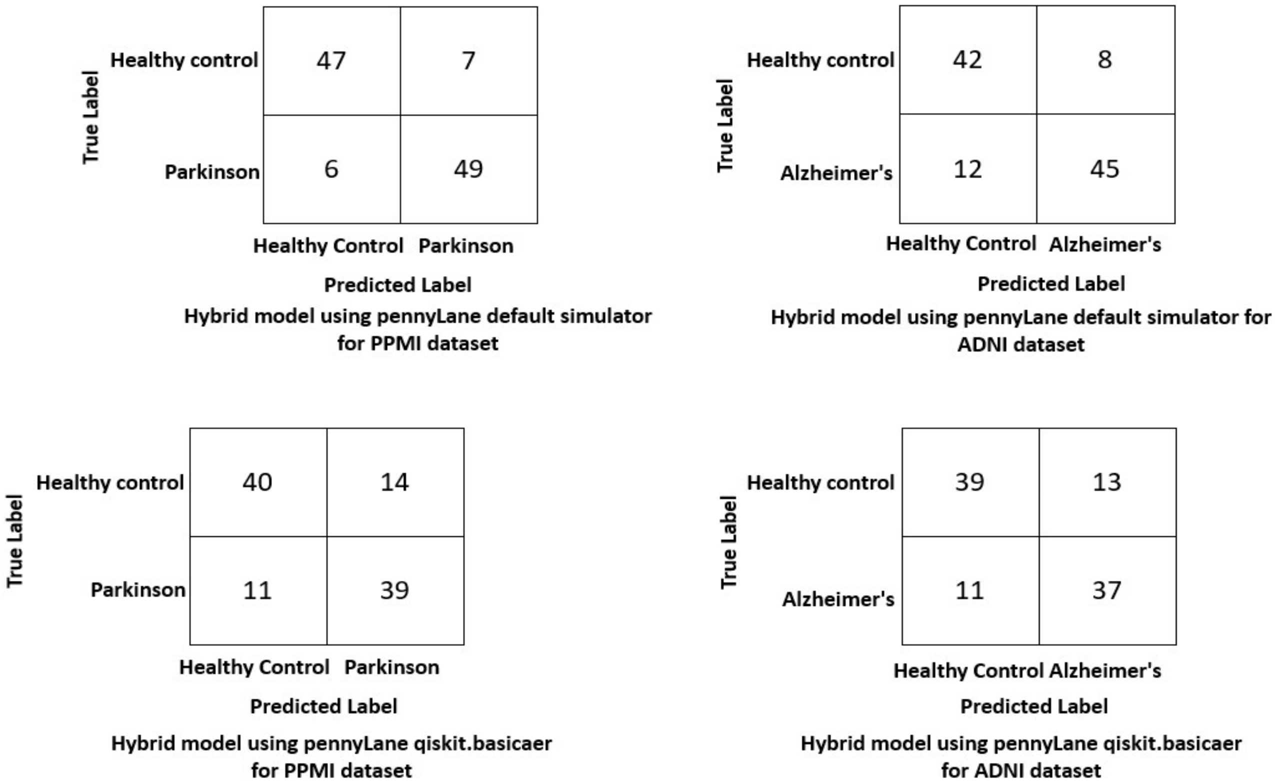

Figure 5. Confusion matrix for AD dataset and PD dataset using AlexNet–quantum transfer learning model.

The performance metrics are presented in Table 3 for the proposed quantum transfer learning network on neuroimaging dataset for the binary classification of AD and PD. The implementation of the hybrid model is executed using the pennyLane library. There are various simulators and quantum devices available to run the proposed network. In this work, we have chosen the pennyLane default simulator and qiskit basic.aer and further integrate the model with the PyTorch library to perform the binary classification. The results to classify MRI images using ADNI and PPMI datasets with various simulators are presented in Table 3.

Table 3. AlexNet–quantum learning model performance using AD and PD dataset.

Model	MRI Database	Precision (%)	Recall (%)	F1-Score (%)	Test Accuracy (%)
Hybrid AlexNet–quantum learning model	PPMI	93	92	93	97
On default simulator	ADNI	91.5	90	94	96
Hybrid AlexNet–quantum learning model	PPMI	91.5	86.9	91.4	95.5
On qiskit basic.aer	ADNI	90	89.7	93.6	94

The training and validation accuracy and training and validation loss concerning epochs for AD detection on the proposed model is illustrated in Figure 6 whereas the graphical representation of training and validation accuracy and training and validation loss concerning the number of epochs for PD detection on the proposed model is in Figure 7.

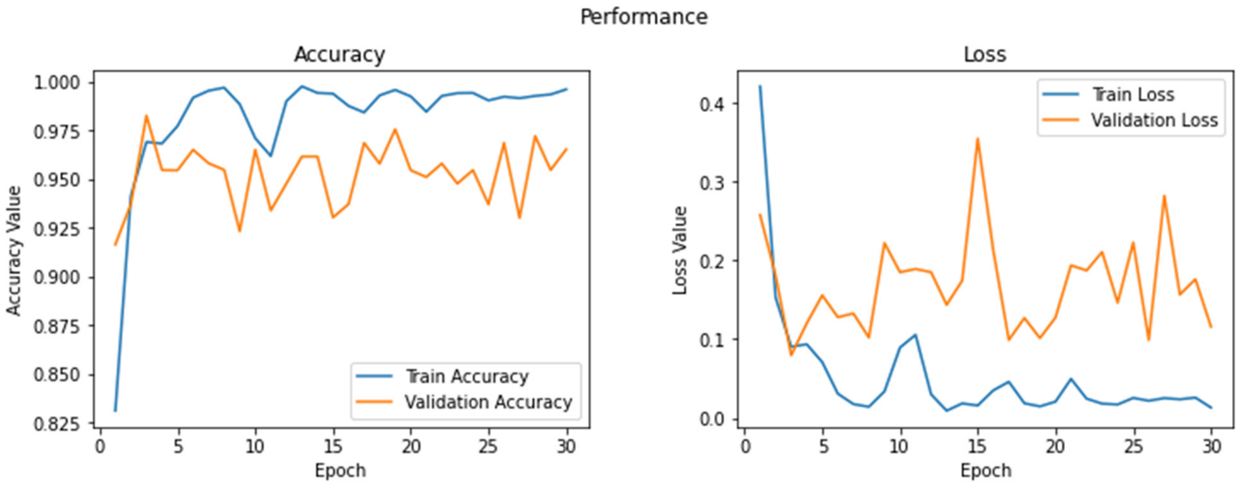

Figure 6. ADNI dataset result using AlexNet–quantum transfer learning for detection of AD.

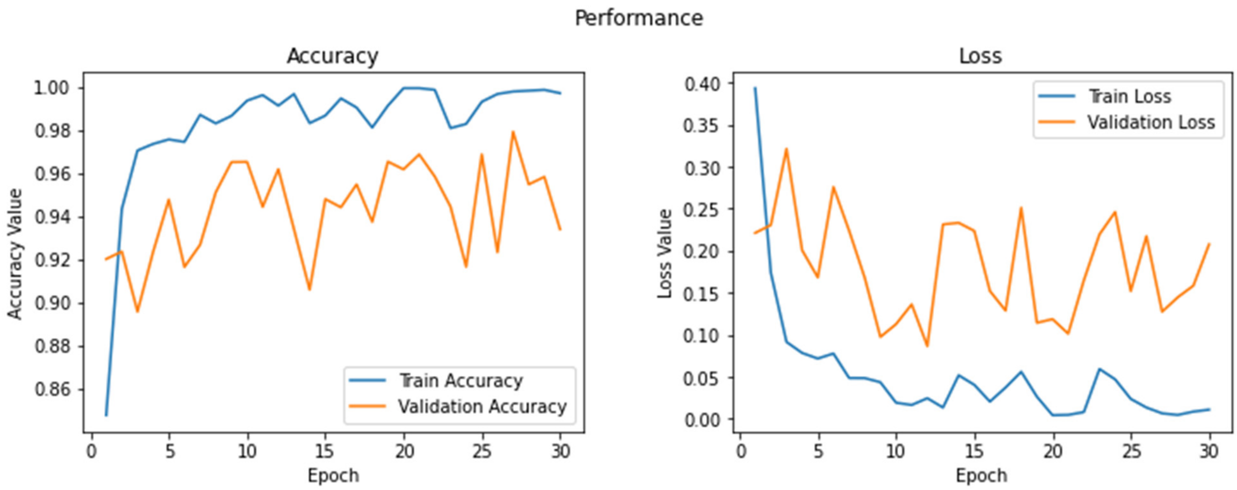

Figure 7. PPMI dataset result using AlexNet–quantum transfer learning for detection of PD.

We also performed the PD and AD datasets on a classical neural network. AlexNet model has been trained on the MRI image dataset of AD and PD. The AlexNet is used as a pre-trained model in which the fully connected layer classifies the output vector based on neuroimaging dataset The various hyperparameters are used for training the classical AlexNet model on neuroimaging dataset. The learning rate is set at 0.0001 and the number of training samples given to the network as input is equal to 16. The number of times the entire dataset has been trained on the network is called epoch and is set to 30. Cross entropy has been used as a loss function and the learning parameters will be updated by using Adam optimization of the AlexNet network for AD and PD datasets. Classical CNN models are implemented on neuroimaging dataset and their confusion matrices are presented in Figure 8.

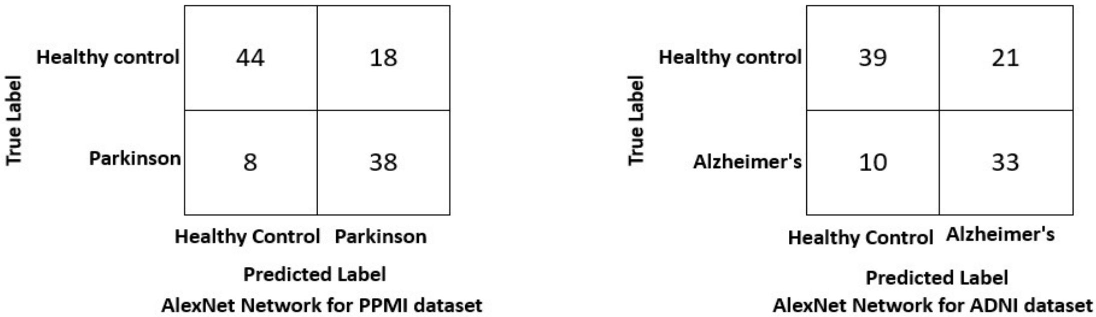

Figure 8. Confusion matrix for AD dataset and PD dataset using CNN models.

The performance outcomes on the AD and PD datasets using a classical neural network which is based on a transfer learning approach are presented in Table 4. The training and validation accuracy and training and validation loss for AD detection on AlexNet pre-trained model is illustrated in Figure 9 whereas the graphical representation of training and validation accuracy and training and validation loss for PD detection on the AlexNet pre-trained model is illustrated in Figure 10.

Table 4. AlexNet pre-trained model performance using AD and PD dataset.

Model	MRI Database	Precision (%)	Recall (%)	F1-Score (%)	Test Accuracy (%)
AlexNet using classical neural network	PPMI	91.5	92.5	90	93
	ADNI	92	89	89.7	91.9

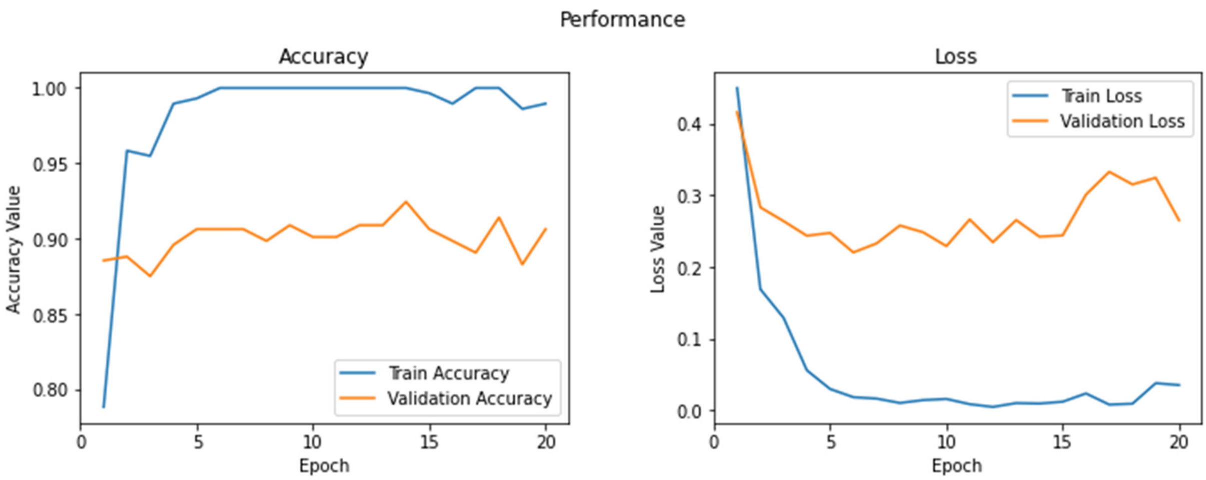

Figure 9. ADNI dataset result using AlexNet pre-trained model.

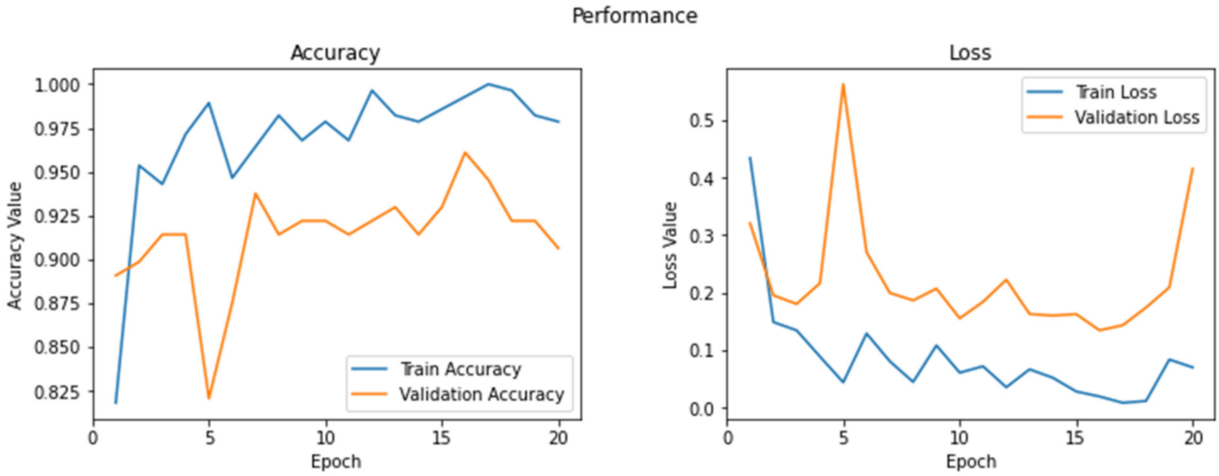

Figure 10. PPMI dataset result using AlexNet pre-trained model.

For comparison with other CNN models, the neuroimaging dataset is also utilized on the classical model such as inception3, resnet18, and VGG16 for the binary classification of AD and PD. The performance metrics results are presented in Table 5 on PPMI and ADNI datasets for the detection of neurological disorders using the classical CNN model to compare it with the proposed method. This shows that the proposed method based on AlexNet and QVC model outperforms the classical CNN models in terms of accuracy, precision, f1-score, and recall on the MRI database.

Table 5. The performance outcomes on neuroimaging dataset using classical CNN transfer learning model.

Model	MRI Database	Precision (%)	Recall (%)	F1-Score (%)	Test Accuracy (%)
AlexNet	PPMI	91.5	92.5	90	93
	ADNI	92	89	89.7	91.9
Inceptionv3	PPMI	85	90	83	92
	ADNI	91	87.4	85.9	89
ResNet18	PPMI	85.5	93.5	86	90.5
	ADNI	91	89	90	91
VGG16	PPMI	88.8	91.7	85.4	92.5
	ADNI	90	90.9	94.5	89
Proposed method	PPMI	93	92	93	97
	ADNI	91.5	90	94	96

Moreover, the proposed AlexNet–quantum transfer learning model is compared with other state-of-the-art models on neuroimaging datasets and this is presented in the given Table 6. For PD detection, SVM [49] has been employed on an MRI dataset that yields an accuracy of 85.78%. Various CNN models such as 2D-CNN [50], GCNN [51], and 3D CNN [52] have been trained on different image modalities to provide reasonable accuracies for PD detection.

Table 6. Comparison of the proposed method with another state-of-the-art-model.

MRI Database	Reference	Modality	Model	Test Accuracy
PPMI	[59]	MRI	support vector machine based on Muti Kernel (SVM)	85.78
	[60]	SPECT	2D-CNN	89
	[61]	sMRI	GCNN	92
	[62]	SPECT	3D-CNN	95
	[30]	MRI	VGG16 and ResNet 50	82
	[63]	T2-Weighted MRI	CNN	95
	Proposed Method	MRI	AlexNet–quantum transfer learning	97
ADNI	[64]	PET	SAE	82.5
	[65]	sMRI + PET	3D-CNN + GAN	89
	[66]	rs-fMRI	DCAE	80
	[67]	MRI	DemNet	95.23
	[68]	MRI	MobileNet	85
	[69]	MRI	3DCNN	88
	Proposed Method	MRI	AlexNet–quantum transfer learning	96

Similarly, a hybrid model based on 3D-CNN and GAN [56] has been implemented on MRI and PET scans to distinguish AD. DemNet [58], MobileNet [59], and 3DCNN [60] using a transfer learning approach have been employed on the MRI dataset to provide 95%, 85%, and 88% accuracies. Moreover, the comparison of the proposed approach with other models is also presented in the form of a graph in Figures 11 and 12.

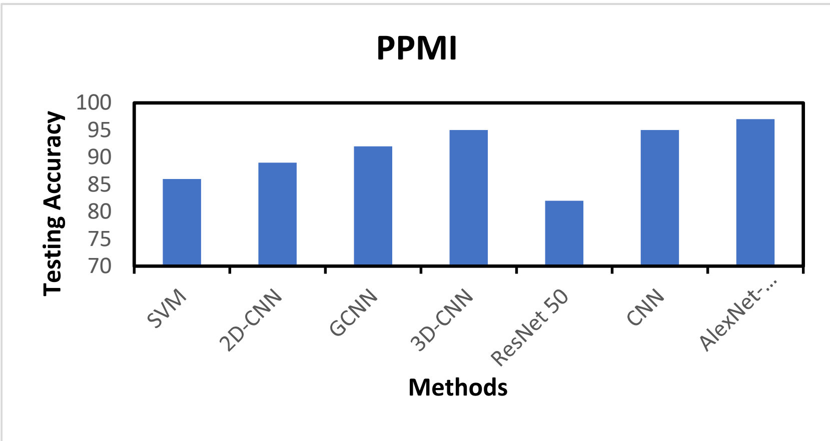

Figure 11. Comparison of the proposed method with a state-of-the-art model for the PPMI database.

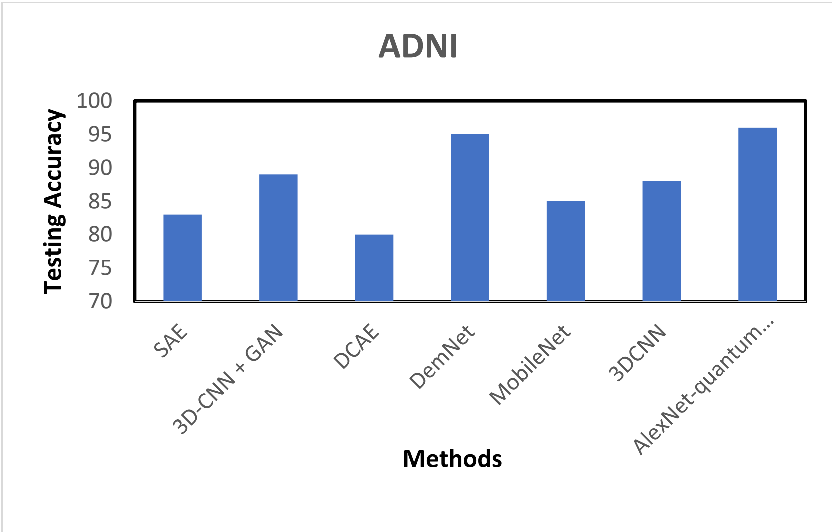

Figure 12. Comparison of the proposed method with a state-of-the-art model for ADNI database.

In this study, the proposed method is trained on an MRI dataset for AD and PD detection. To classify PD from HC, our model achieves 97% testing accuracy and for the binary classification of AD from HC, our model achieves 96% accuracy. This shows that a hybrid classical–quantum network improves the accuracy and performance of the model by amalgamating AlexNet with the variational circuit.

In this study, two experiments have been performed named classical models and classical–quantum models to classify AD and PD. Then, we compared the performance of both networks which clearly shows that the classical–quantum transfer learning approach has improved the performance of the model by reducing the learnable parameters and minimizing the complexity of computational parameters by automatically improving the accuracy and speed of the model.

Quantum neural networks endeavor the features and properties of quantum mechanics and are used to develop quantum computing algorithms to further integrate and use the advantages in the application of deep neural networks. Combining two developing fields helps to solve the image-related task accurately and improves the performance. The neural network leverages the quantum computing circuits which help in extracting rich and meaningful representation from the high dimensional dataset and reduce its computing power which helps in improving the speed of the network. The medical field has also started utilizing the benefit given using the application of quantum computing in the CAD system to speed up the diagnosis process, provide better healthcare services, improve the e-health systems, and optimize prices. Bio-medical data are present in complex form and processing this large dataset is computationally complex to find hidden patterns and information from this complex data, it should be helpful to use the advantages and benefits provided by using the application of quantum computing to solve the particular task in the health care industry.

5. Conclusions

This work focused on the classification of neurodegenerative diseases such as PD and AD using neuroimaging data. With the development of high-speed computational techniques, we implemented the hybrid model that integrated the two computing technologies known as classical transfer learning and quantum transfer learning for predicting brain disorders. AlexNet–quantum learning model is employed against neuroimaging data based on dressed quantum circuit and dimensionality reduction techniques to discriminate the disorder from normal cases and we also leveraged AlexNet, a classical pre-trained model for comparison purposes. The classical-quantum model helps in improving the classification accuracy and performance of the model by extracting a rich informative feature vector from the high dimensional MRI data utilizing quantum parameterized circuits and this network is further validated by quantum simulators. The proposed method will help in offering viable and feasible solutions in the healthcare domain as it provides beneficial results with notably improved classification accuracy to identify brain disorders when compared with the classical network. In the future, the quantum transfer learning method can be implemented on real quantum hardware devices. Further, the hybrid quantum–classical transfer learning method can be used to solve multi-classification tasks in computer vision.

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Abbreviations

AD	Alzheimer's disease
ADNI	Alzheimer's disease neuroimaging initiative
ANN	artificial neural network
CAD	computer-assisted diagnostic systems
CNN	convolutional neural network
CPU	central processing unit
DNN	deep neural network
EEG	electroencephalography
GPU	graphics processing unit
MRI	magnetic resonance imaging
NC	normal control
NDD	neurodegenerative Disease
PD	Parkinson's disease
PET	positron emission tomography
PPMI	Parkinson progression marker initiative
QML	quantum machine learning
QPU	quantum processing unit
TPU	tensor processing unit

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