BRAIN TUMOR CLASSIFICATION USING HYBRID CLASSICAL-QUANTUM TRANSFER LEARNING

Mukesh Kumar Pokharel[1 *], **Sunil Kumar Shrestha**[1], **Naresh Khatri**[1]

[1] Department of Computer and Electronics Engineering,
Khwopa College of Engineering, Tribhuvan University

Abstract

Magnetic Resonance Imaging (MRI) images reveal unique abnormal patterns in brain tumors. These patterns play an important role in diagnosis and therapy planning. This study proposed a new model that combines Convolution Neural Network (CNN) and Parameterized Variational Quantum Circuit (VQC) to better diagnose and categorize brain tumors. The model extracted features from MRI images using pre-trained systems such as VGG16, VGG19, and ResNet-18. Among these models of CNN, the base model was selected as VGG16 for feature extraction which yield better performance. The features were subsequently reduced via an affine transformation and passed through a VQC for the hybrid model. The VQC used quantum superposition and entanglement as tools for categorization. The hybrid model performed better than base model due to the representation of feature in large space called Hilbert space. Using n qubit of quantum, 2^n states were represented in the Hilbert space. Using VQC, the complex high dimensional relationship of features was learnt and also the performance of the hybrid model was optimized by integrating VQC to VGG16. The experiment was done integrating the pennylane simulator with pytorch.

Keywords: VQC, CNN, VGG16, VGG19, ResNet-18, Affine-transformation

1. Introduction

A brain tumor is one of the most lethal disorders that results from the uncontrolled growth of brain tissue inside the skull. It could be benign or cancerous. Malignant tumors can spread fast via the surrounding brain tissue, but benign tumors grow slowly. Malignant tumors are harmful since their growth might impact neighboring brain regions. Approximately 70% of tumors are benign, with the remaining 30% being malignant (Lapointe et al., 2018). Among 120 different types of brain tumors that have been discovered and identified so far, the three most frequent types are meningiomas, gliomas, and pituitary tumors. Meningioma tumors are the most typical type of primary brain tumor in the meninges, affecting the brain and spinal cord (Louis et al., 2016). One of the most dangerous types of brain tumor is high-risk glioma. Overgrowth of brain cells in the pituitary gland of the brain results in pituitary tumors. Therefore, early detection is critical. Global Cancer Statistics 2020 reports that there were 251,329 cancer-related deaths and 308,102 new instances of brain and Central Nervous System (CNS) tumours reported in 2020 (Sung et al., 2021). The National Brain Tumor Foundation (NBTF) reports that during the past three decades, the number of people who have died from brain tumors has increased by 300 % (El-Dahshan et al., 2014). Untreated brain tumors can result in death. It is challenging for medical experts to identify and treat infected people due to the complexity of brain tumors. The survival rate of these individuals is significantly impacted by early diagnosis of brain tumors and the start of treatment. A biopsy of a brain tumor is trickier than any other part of the body since it necessitates surgery. Scientifically speaking, tumor diagnosis based on imaging data is flawed and significantly reliant on the radiologist's training. Due to the wide pathological variation and probable weariness of human specialists, computer-assisted therapies and computational intelligence-oriented tactics can assist the di-

*Corresponding author: Mukesh Kumar Pokharel
Department of Computer and Electronics Engineering,
Khwopa College of Engineering, Tribhuvan University
Email: mukeshpokhrel662@gmail.com
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agnosis and classification of brain tumors. Machine learning methods, particularly deep learning, can be very helpful in the analysis, segmentation, and classification of cancer images; particularly those of brain tumors. The use of such techniques also paves the way for the accurate and error-free identification of tumors, allowing for their recognition and differentiation from similar disorders. This study incorporated the Convolution Neural Network (CNN) and Variational Quantum Circuit (VQC) to create a hybrid model for classification of the different class of brain tumors. The main concept behind this is transfer learning, which reuses previous learned model on a new problem. The main advantage of transfer learning is that it has capacity to increase the performance of model with less amount of medical data. Trained machine learning model is transferred to different but closely linked problem throughout transfer learning. Transfer learning uses the knowledge from the early and central layer where those layers are frozen and only remaining layers of model are retrained. In this study, a pre-trained CNN architecture was used on brain tumor dataset. In classification, some fully connected layer was replaced by quantum circuit. To perform classification by VQC, the extracted feature was passed on it.

Despite significant effort in the field of artificial intelligence in this domain, medical image categorization remains one of the most difficult challenges. Similarly, in the field of brain tumor identification and classification, a lot of progress has been made using Classical CNN with numerous innovative approaches. Due to the unavailability of sufficient and wide range of medical image dataset, more accurate result from the CNN is challenging. In this study, a new approach is used to enhance the performance of CNN model by embedding quantum variational circuit on it for the classification of pattern of brain tumor.

The main aim of this study is to enhance the performance of CNN model by embedding quantum variational circuit and to compare the performance of hybrid model with classical model.

2. Review of Literature

A brain tumor is formed when a collection of abnormal brain cells join together. The brain tumor's synaptic growth is characterized by uncertainty. The potential increase of cranial volume is difficult to limit due of its strong stiffness and elasticity. This influence may impede human ability to think and feel, as well as cause swelling in other bodily parts. So far, more than 130 different forms of brain and central nervous system tumors have been discovered, ranging from benign to malignant, as well as exceedingly rare to very common (DeAngelis, 2001). As a substantial amount of medical MRI imaging data is obtained through picture acquisition, the researchers are currently putting forth different machine learning algorithms to recognize brain cancers. These procedures are built on techniques such as dimensionality reduction, feature extraction, feature selection, and classification. The majority of suggested machine learning algorithms focus on the binary classification of brain tumors.

Support vector machine (SVM) and genetic algorithm (GA)-based binary classification of brain images was proposed by (Kharrat et al., 2010). A discrete wavelet transform (DWT) was used for feature extraction in combination with a SVM classifier, resulting in a prediction accuracy of 98% on a dataset of 52 brain tumor images (Chaplot et al., 2006). In another study, a K-nearest neighbor (KNN) classifier was applied to a dataset of 70 images, achieving a slightly higher accuracy of 98.6% (El-Dahshan et al., 2010).

Deep learning is one of the most powerful techniques in data science and artificial intelligence that are used to train algorithms for making effective decisions based on data. These models aim at achieving an expected network through a reduction of the image and no loss of information needed to predict it. For tumor segmentation, deep learning algorithms are recognized to be the most efficient (Soomro et al., 2022). Since training algorithms are able to generate most precise results, computed tomography (CT) brain scan is one of the most widely used Deep Learning applications (Yeo et al., 2021). The concept of transfer learning was extended by performing feature extraction using pre-trained deep learning models, followed by classification through an embedded quantum variational circuit. This quantum transfer learning approach demonstrated effective classification of high-resolution images (Mari et al., 2020). CNN offers a segmentation-free approach that does not need manually created feature extractor methods. As a result, various CNN architectures have been suggested by various researchers.

3. Methodology

Feature extraction and claasification play a vital part in developing a model. Pretrained models were chosen in the methodology in such a way that they deliver the best features by implementing different pre-trained models. In a hybrid model, the quantum layer was embedded in the classification layer known as the fully connected layer of the best feature extracted pre-trained model. Here, Figure 1 represents the work flow and how the system works in classification. Algorithm of system workflow:

- Pre-processed medical datasets were used as input for a model that had already been trained to extract features which was resized to 224×224 pixels.
- The features were extracted using transfer learning with a pre-trained model of CNN. All layers were frozen, with the exception of final fully connected layer and the quantum layer in order to prevent the

weights on these layers from changing during model training.

- Linear Layer also known as pre-processing layer converts the 4096-feature vector into required dimension by utilizing affine transformation and Rectified Linear Unit (ReLU) as activation function to achieve non-linearity.
- In Quantum layer: All the qubits were initialized from $|0>$ state.
  - Hadamard gates were used to embed the feature elements in the quantum circuit, bringing all of the quantum bits into a state of superposition. Rotational Y gate were used to rotate the qubit by the angle of the input feature. The quantum vector were created by the embedding layer from the classical vector.
  - Learnable parameters were trained in the VQC utilizing the rotation around y-axis gate sequence and controlled NOT gates for entanglement.
  - All qubits in the measuring layer were measured using a Pauli-z matrix to determine the present state of the qubit. Following measurement, quantum data were transformed into classical data.
- Following measurement on the classical register, the output from the quantum layer were transmitted to the linear layer, which serves as the model's final prediction layer.
- The loss function used as categorical cross entropy, and Adam optimizer opted to update the model's weights at every training step, and a scheduler is configured in the model to decay the Learning Rate (LR) by gamma with each step size.
- The model was trained using number of epochs and different quantum depths and number of qubit as hyper-parameters.

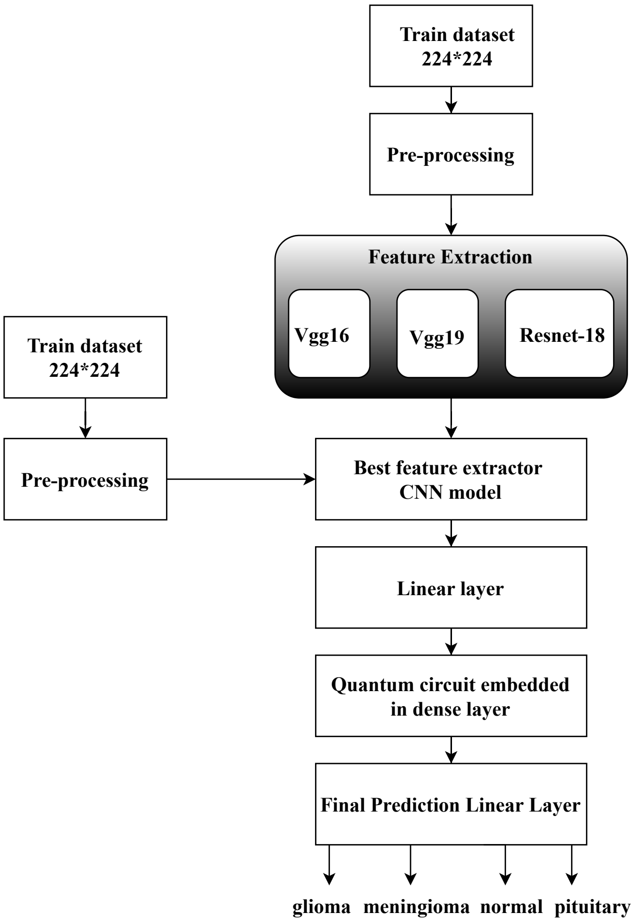


Figure 1. System Block Diagram

3.1. Data Description

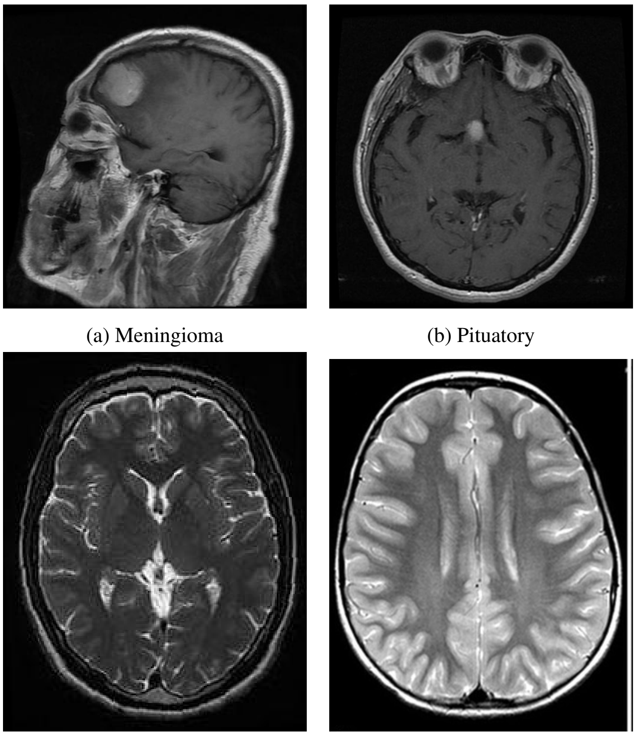
A total of 3264 T1-weighted, contrast-enhanced MRI images comprised the data that utilized image-based dataset .There were 500 images of a healthy brain in this collection, 937 images of meningiomas, 901 images of pituitary tumors, and 926 images of gliomas. These dataset are publicly available and taken from kaggle. These dataset were verified and validated by (Saeedi et al., 2023) for the detection of MRI based brain tumor using CNN. In this study, dataset were splitted into training, validation and testing set in the ratio of 0.75, 0.15 and 0.1 respectively for training and evaluation of the model. Figure 2 represents the sample image of brain tumor pattern and normal image used for the classification.

3.2. Hybrid Classical Quantum Model

The proposed model consists of thirteen layers of convolution from a pre-trained vgg16 model for feature extraction, followed by three fully connected layers for classification. The VQC was embedded into the second layer of the fully connected layer of VGG16. The model was trained by freezing the trainable parameter except the last layer of fully connected layer. Following the first fully connected layer, the feature map was reduced via an affine transformation to input the number of qubits used in the Quantum layer. The reduced features were made non-linear by the ReLU activation function. The final linear layer was responsible for predicting the class of abnormal pattern.

3.3. Quantum Layer

In quantum computers, data can either be represented by a single 1 or a single 0 or by a single 1 and a single 0 simultaneously. Superposition, a form of quantum computing,



(a) Meningioma (b) Pituatory

(c) Normal (d) Glioma

Figure 2. Sample image of Meningioma tumor, Pituatory tumor, Normal brain and Glioma tumor

is the coexistence of a 1 and a 0. The core components of quantum computers are qubits, or quantum bits. The ground states $|0>$ and $|1>$ are combined into linear vector representations of the qubits. The<bra | ket> notation also called Dirac notation is used to identify quantum systems. A qubit can be mathematically represented as in Equation (1).

$$|\psi >= \alpha|0 > +\beta|1 > \tag{1}$$

Where, $|\psi>$ represent the state of qubit, $|0>$and $|1>$ are two orthogonal vectors.

$$|\mathbf{0}> = \begin{bmatrix}1\\0\end{bmatrix}, |\mathbf{1}> = \begin{bmatrix}0\\1\end{bmatrix}, \quad |\Psi >= \begin{bmatrix}\alpha\\\beta\end{bmatrix} \tag{2}$$

When a qubit is measured, it will either measure as a $|0>$ or $|1>$. These probabilities show how likely it is to measure $|0>$ or $|1>$. Bloch's sphere is a typical method of a qubit representation which can be sphere of unit radius.The outer sphere points on the Z axis, represented by the vectors $|0>$ and $|1>$. Only measurements of $|0>$ and $|1>$ will be used in this study because we will only be measuring against the Z-axis. Quantum gates are used to change quantum states, whereas quantum states are in function of encoding data. Quantum gates allow for the conversion of one quantum state into another. VQC was used in fully connected layer as a fine tuning layer for classification. It consists of three layers i.e Data embedding, Quantum circuit and Measurement layer which is shown in Figure 3. Data encoding was done using the concept of amplitude encoding method. In amplitude encoding method, classical data i.e. feature vector extracted from pre-trained model were converted into quantum data i.e. n qubits were used to represent 2^n states. In VQC, number of depth of linear CNOT gate and RY-gate was used. A number of depth is the number of linear layer of CNOT and RY gate used in QVC. CNOT gate is used to create the entanglement of qubit.

After various gate operations, the final state of qubit is determined using quantum measurement. The measuring layer of a quantum circuit behaves like a convolution neural network's non-linear activation function. Pauli-Z measurement is used to obtain the expected value following a quantum measurement. Expectation values were collected, and these values were fed into the final prediction layer of the classical linear layer. Pauli-Z measurements have an anticipated value range of -1 to 1. The state of qubits were collapsed into a single state during quantum measurement. There is no need to include an activation function for non-linearity in a hybrid model that uses quantum measurement. The function of non linearity was present in quantum measurements.

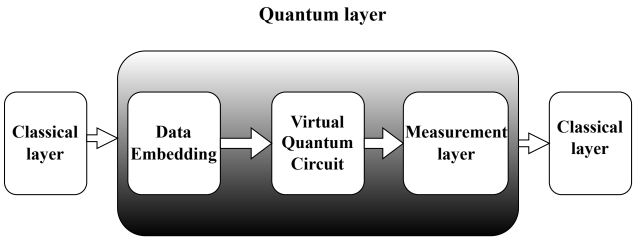


Figure 3. Variational Quantum Circuit

3.4. Amplitude Encoding Method

Amplitude encoding method is another method used to encode the classical feature into quantum circuit. A vector of length x is encoded via amplitude encoding, creating N distinct amplitude levels represented by n-qubit quantum state with $n = log_2(N)$:

$$|x >= \sum_{i}^{N} x_i|\mathbf{i}> \tag{3}$$

where $|i>$ is the computaional basis of hilbert space. In amplitude encoding method, the classical feature is amplitude in quantum circuit. Hence the amplitudes must follow the condition of normalization such that $|x|^2 = 1$. For instance:

$$x^T = \begin{bmatrix}\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2}\end{bmatrix}$$

The state vector $|x\rangle$ can be represented as:

$$|x\rangle = \frac{1}{2}|00\rangle + \frac{1}{2}|01\rangle - \frac{1}{2}|10\rangle - \frac{1}{2}|11\rangle$$

In the above mentioned equation, 4 state are represented by 2 qubits and summation of the square of amplitude of quantum state must be equal to 1.

Using the basic concept of amplitude encoding method, the quantum features were encoded. From the second layer of fully connected layer, 16 features were encoded just using 4 qubit. i.e 2^4=16. That means 16 state of quantum are represented by 4 qubits. Before feeding into the quantum circuit, normalization of 16 fatures was done such that their square of summation is equal to one. Using 4 qubit of VQC, 4 expectational value after quantum measurement were obtained. Quantum entanglement is the phenomenon when two quantum states interact in a way that prevents the quantum states from being described independently of one another. Typically, this implies that the outcome of a measurement on one qubit reveals information about the other. Controlled operation using Controlled Not (CNOT) gates can be used to entangle qubits. The CNOT gate operates on two qubits and accepts two inputs, namely a controlled qubit and a target qubit. The general expression of CNOT gate for matrix representation can be defined by Equation (4).

$$CNOT = \sum_j |input_j >< output_j| \tag{4}$$

The CNOT gate matrix of two qubit operation is represented as:

$$CNOT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

It is necessary to evaluate the expectation values of those states in order to measure the qubit state following its transformation via quantum gates, including a number of CNOT gates. The anticipated value of the state is assessed after N times of repeated measurement. A measuring operator is employed with the Pauli Z gate. The general expression of expectation value of ψ state is represented in Equation (6).

$$< Z > = < \psi|Z|\psi > \tag{6}$$

4. Results and Discussions

The Experiment was done using hyper-parameters mentioned in Table 1. The best feature extractor model was found as VGG16 among VGG19, VGG16 and Resnet-18 (Khaliki and Başarslan, 2024) and used as base model of feature extraction for hybrid model. After that, Classical-Quantum model with same hyper-parameters was implemented for the classification of brain tumor.

Table 1. Hyper-parameter

Hyper-parameters	Remarks
Number of epoch	20
Batch size	8
Learning rate	0.001
Loss function	Categorical cross entropy loss function
Optimizer	Adam optimizer
Gamma LR schedular	0.9 per every 10 epoch

In hybrid model, Parameterized Quantum circuit was embedded on second layer of fully connected layer. After the quantum circuit had been introduced, two new hyper-parameters for the hybrid model were added: the quantum-depth and the number of qubits. In this experiment, the 4-qubit quantum circuit was developed and 2 layer of entanglement was made using CNOT gate. Setting the hyper-parameter mentioned in the Table 1 , experiment of hybrid classical-quantum model was carried out. Here quantum circuit was implemented to enhance the performance of model obtained from previous base model. Quantum circuit was embedded after the second fully connected layer. In Quantum circuit, superposition and entanglement operation was done using hadamard gate and CNOT gate respectively. Using quantum entanglement process, the model learnt the complex high dimensional feature which is the advantage of quantum over classical model. Model was trained with 15 number of epochs where loss gradually decreased and converged as shown in Figure 4. In the same manner, the training accuracy and validation accuracy were smoothly increased and found to be 87.67% and 89.84% respectively as shown in Figure 5.

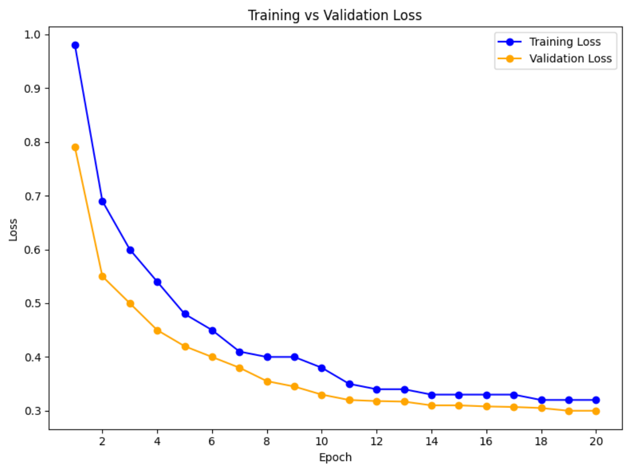


Figure 4. Loss Curve

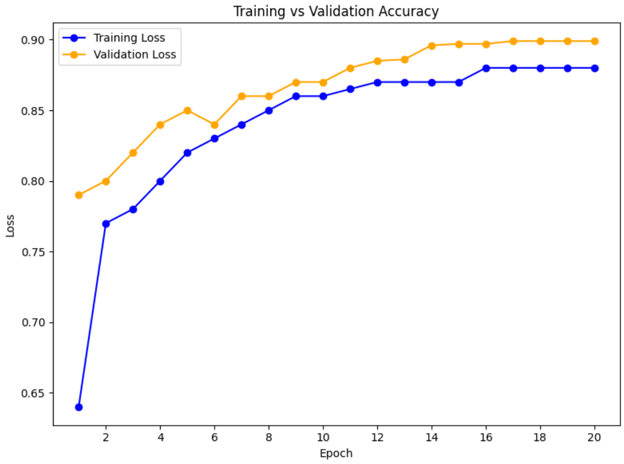


Figure 5. Accuracy Curve

4.1. Comparison of Models

From the comparison of chart performance of hybrid model shown in Table 2, the overall performance of hybrid model using amplitude encoding method was found better than CNN model. Due to the superposition and entanglement properties of Quantum, it was able to find the complex high dimensional relationship of features. One state of qubit get affected than another state of qubit due to entanglement. Qubits relationship was developed due to the entanglement using CNOT gate. In this study, variational quantum circuit was used to enhance the performance of pre-trained model i.e VGG16. All performance evaluation metrics like accuracy, precision, recall and F1-score of hybrid model of amplitude encoding method was better than all other experiments. From these experiments, it was found that the quantum circuit enhanced the performance of pre-trained model and also, adding some hyper parameter (number of qubit, number of depth etc) helped to optimize the performance of the model.

Table 2. Comparison of Model Performance

	Accuracy	Precision	Recall	F1-score
VGG19	86.950	86.275	86.208	86.241
ResNet-18	89.120	88.110	88.039	88.075
VGG16	89.360	88.720	88.824	88.772
Hybrid	90.780	89.690	89.770	89.732

5. Conclusion

From the experiment using amplitude encoding method in quantum circuit, the model achieved better result and was able to enhance the performance of classical CNN model. In hybrid model, amplitude encoding method was used to encode feature in the quantum circuit. From the experiment, it was found that embedding quantum circuit in the CNN model, the performance of pre-trained model was enhanced. However, it should not be concluded that the hybrid model is better than CNN, but it was able to enhance and optimize the result of pre-trained model. In this study, training was hampered by the intricacy of the program created by merging PyTorch and PennyLane Simulator; as well as the lack of readily available genuine quantum devices. This experiment would have taken less time to complete if it had been carried out on an actual quantum hardware operating parallel processing.

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