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Hybrid Classical Quantum Deep Learning Model For The Classification of Interstitial Lung Diseases

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Abstract
Interstitial lung disease (ILD) is associated with certain abnormal imaging patterns seen in computed tomography (CT) images. The correct classification of these patterns plays an important role in making accurate clinical decisions about the extent and nature of the disease.In this research,we train hybrid classical-quantum neural network that combines classical and quantum neural network for the classification of abnormal CT attenuation patterns of interstitial lung diseases using transfer learning(TL).we use VGG16 to extract the features from the image and those extracted features were reduced using affine transformation and embed on the Variational Quantum Circuit(VQC) which is composed from different quantum gates and have characteristics of superposition and entanglement of qubits for classification. We implement the parameter shift rule for the gradient of quantum layer and optimatization is done by classical computer. With the implement of parameter shift rule , gradient of quantum circuit is found with the use of same quantum circuit.Experiment were run on quantum simulator and result were compared with the classical pre-trained vgg16 architecture.we found that hybrid classical-quantum neural network enhance the performance of pre-trained VGG16 architecture from our experiment.

Keywords
Quantum Computing, Transfer Learning, Interstitial Lung Disease, Hybrid Classical-Quantum Model,Parameter-Shift Rule

1. Introduction

Interstitial lung disease is a term used to describe a group more than about 200 chronic lung disorders that are characterized by inflammation and scarring, making it difficult for the lungs to get enough oxygen.These diseases symptoms and progression can differ from person to person. The common thread connecting the various forms of the disease is that they all start with inflammation. High- resolution (HRCT) is a essential tool for the assessment of patients with suspected idiopathic pulmonary fibrosis which may also offer a certain diagnosis without the requirement of a surgical test[1].Computer-aided detection (CADe) or computer-aided diagnosis (CADx) is a computer-based system that supports doctors in making decisions quickly in the field of medical imaging[2].CADe systems are used to enhance the image quality, which help in appropriately interpreting medical imaging and processing the images to highlight the portions that exposed the information of the images.Nowadays, interstitial lung disease (ILD) is the most common, most common categories. The progressive scarring of lung tissue brought on by ILD will eventually impair a patient's capacity to breathe and absorb enough oxygen in their blood. In all likelihood, if a person has a respiratory problem they may have an ILD disorder. Therefore, the precise classification of ILD is very important. Because of its unique lung-attenuation qualities, HRCT is widely recognized as the best of the many methods. The quality and distribution of distinct ILD text patterns on a CT scan of the lungs are used to translate image data. Emphysema, fibrosis, honeycombing, ground glass opacity (GGO), and micro nodules are common ILD patterns seen on CT scans[3].

The previous recent study of computer aided classification of ILD was based on CNN architecture.CNN is one of the best algorithms when it comes to visual content identification and demonstrated definitive performance.However,its complexity is one of its major drawbacks[4].Due to the inter-connection of node from one layer to the node of next layer, the algorithm of the model become complex.In this reserch paper, new approach of hybrid classical-quantum neural network is used for the classification of CT attenuation pattern of five classes of ILD .

The main objectives of research paper are to : (i) detect the CT attenuation pattern of interstitial lung diseases using hybrid classical-quantum model, and (ii) compare the performance of CNN and hybrid classical-quantum model.

2. Literature Review

First, utilizing CT scans, computer-assisted automatic detection and classification of ILD was performed. They employ densitometry metrics such skewness, kurtosis, and the mean of the histogram of lung density distribution[5].Gray level co-occurrence matrices, run length matrices, and fractal analysis were created to extract handcraft aspect[6].Deep learning models are being employed instead of manual handcrafting to extract features directly. To generate a set of learnt features, unsupervised learning methods such as the restricted Boltzmann machine (RBM) or k-means and k-SVD were utilized[7].To forecast and diagnose diseases, a variety of in-depth research methodologies have been applied. Convolutional Neural Networks (CNN) have been trained for a variety of tasks, including pulmonary artery-vein isolation, biomarker regression, pulmonary fissure identification, and emphysema data utilizing data CT from the COPDGene project, a large multidisciplinary investigation with over 10,000 studies. In 2018, full-image classification of ILD with thier CT attenuation classes using deep learning neural network was done to address the patch based image classification where some information was lost due to the extract of small size of image with refion of ineterest(ROI) of each abnormal pattern[8]. In CNN based architecture, the algorith of model become complex due to the interconnection of node from one one layer to the node of next layer. With the increasing of hidden layer in the CNN, node and trainable parameter of CNN architecture get increased and hence the interconnection of artificial node from one hidden layer to the next layer get increased. So these interconnection made the algorithm complex.

In this paper, we approach the hybrid classical-quantum model with the use of quantum variational circuit as classifier to address the limitation of CNN architecture.Our idea is influenced by Mari et al.(2019) research on TL in hybrid classical-quantum neural networks[9].Our goal was to categorize full-image scans with pretrained conventional neural networks that had been previously trained and were utilizing a quantum upgraded TL technique.Our hybrid models for this research contain circuit-based quantum layers in the neural network.

3. Methodology

Because it's miles distinctly uncommon to have a dataset big enough to train a Convolutional Network from the beginning, Transfer learning is the most widely used for the classification of the images. To re-use the pre-trained convolution neural network was the main aim of transfer learning. In this experiment, transfer learning will be used, and load pre-trained model of Vgg16. Later, model will be modified by replacing fully connected layer of VGG16 with a Quantum circuit.The basic image classification method is split into two steps: feature extraction and classification. The CNN method's most appealing feature is that it learns end-to-end feature extraction and classification simultaneously. At first, the feature will be extracted from the pre-trained model of VGG16 and the output feature from a model will be embedded in the quantum layer using different Quantum Gates.Figure 1 describe the overall system workflow how it perform on classification of abnormal patterns of interstitial lung diseases.

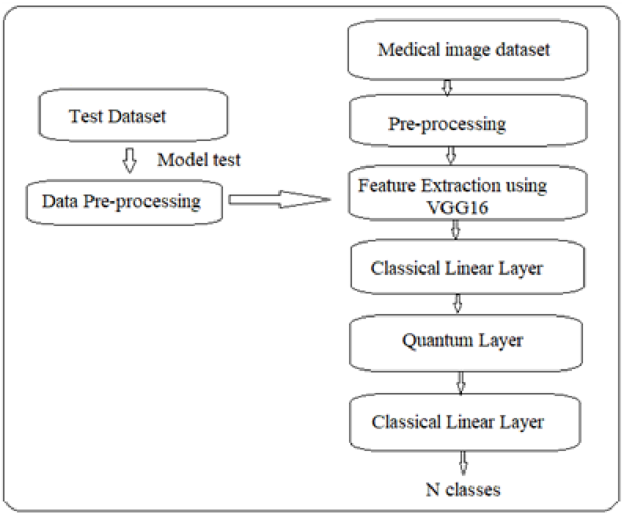

Figure 1: system workflow

3.1 Dataset Description

The datasets were collected from the university Hospital of Geneva(HUG) which is made available to public for researrch on request after signing the liscense agreement.The data was in medical image format (.dcm format) of 512*512 pixels.There was an HRCT image of 120 patients,each patient consist of about 24-30 Slices. The medical image of ILD consist of five class of abnormal pattern called Emphysema,Fibrosis,Honeycombing,Ground-Glass Opacity(GGO),and Micronodules.

3.2 Data preprocessing

The HRCT image of ILD contain a lot of information in which the range of pixel intensity is very large in between [-2000,2000].In order to rescale the pixel intensity into [0,255],different windowing for each pattern is set using their respective Hounsfield Unit(HU) for the better capture of each abnormal pattern after converting the pixel into HU. Since different scanner was used to capture the HRCT image of patients lung, the different scanner have different pixel spacing. In order to make pixel spacing uniform, resampling was done to make the pixel spacing into [1,1] mm. After resampling, data augmentation was done to overcome the overfitting of model.

3.3 Hybrid Cassical Quantum Model

Our model consist of thirteen layer of convolution layer of vgg16 pre-trained model for feature extraction followed by three fully connected layer for classification task. In second layer of fully connected layer, Quantum Variation Circuit is inserted.And the model is trained freezing the trainable parameter before the layer of first fully connected layer.After first fully connected layer,the feature map is reduced using affine transformation for the input into the number of qubits used in Quantum layer.The reduced feature is made non-linearity introducing into the Rectified Linear Unit(ReLU).The last linear layer is used for the predicting class of abnormal pattern.

3.4 Quantum layer

The Quantum layer is used in the place of second fully connected layer. It consists of three steps. i) Data Embedding ii) Variational circuit,and iii) Measurement.Figure 2 define the quantum variational circuit.

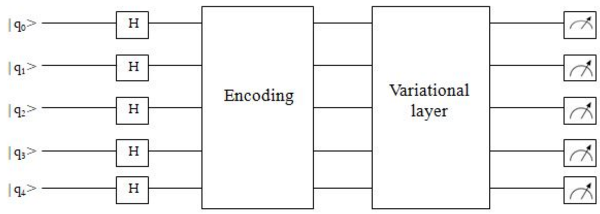

Figure 2: Vairiational Quantum Circuit

At first,all quibits are placed at initial state in |0>.Hadamard gate is used to make all the qubits in superposition state.After that,the input feature called classical data is embedded on the quantum circuit converting into the quantum data by using angle encoding method.In angle encoding method,the classical data is rotated by using Y Rotational gate(Ry).The Ry gate is a single-qubit rotation around the y-axis through angle θ in radians.The Ry transformation gate is defined by matrix as given below:

$$R_y(\theta) = \begin{bmatrix} cos(\frac{\theta}{2}) & -sin(\frac{\theta}{2}) \\ sin(\frac{\theta}{2}) & cos(\frac{\theta}{2}) \end{bmatrix}$$

In Quantum Variational Circuit, controlled operation is performed to made the entanglement of qubit using Controlled Not(CNOT) gates.In quantum variational ciruit, qubit behave like node in the artificial node in CNN and we initialized the weight to each node randomly.Similarly,randomly initialized weights were also embedded in each qubit using RY gates and controlled operation is performed. The number of initial weight were depend on the quantum depth.Here, the quantum depth in quantum circuit represent the hidden layer of CNN.

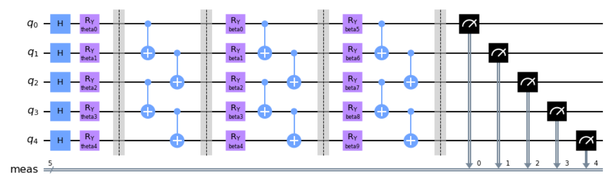

Figure 3: Vairiational Quantum Circuit of Depth Two

Figure 3 represent the Quantum variational circuit of depth two which was used in our experiment.The last part of quantum layer was measurement layer.Quantum measurement is used to get the final state of qubit after different gate operation. We get the expectation value after the measurement using Pauli-Z measurement. The proposed hyrid classical-quantum neural network replaces the linear part of the classical neural network with quantum circuits and the nonlinear part with measurements.The measurement layer of Quantum circuit behaves as non-linear activation function like in Convolution Neural Network[10].The expectation value of qubits gives the expected value of each qubits which either collapes to $|0>$ state or $|1>$ state after Pauli-Z measurement. The pauli-Z measurement is single qubit measurement operator and we used it to find the expectation value of each qubit.If the qubit is in state Ψ,way to calculate expectation value is defined as:

$$<z> = <\Psi|Z|\Psi> \tag{1}$$

The above Dirac Bra-ket notation is a convenient way to represent the expected value of a qubit in Ψ state.

3.5 Quantum Gradient

Parameter shift rule is used to find the quantum gradient[11]. Expectation value of each qubit are cost function and their gradient are found using same quantum circuit by shifting the value to the right and left side and the difference of output serves as gradient.

$$\Delta f = f(\theta + s) - f(\theta - s) \tag{2}$$

In equation 2, Δf represents gradient,θ represent expectation value and S represent shift constant. Shift constant for Pauli gate is used as $\pi/2$. Using parameter shift rule, there is no need to use chain rule for finding gradient of quantum layer. At last layer, again linear layer is used which gives the final output by predicting the sample of data to their respective class. It simply takes the five expectation value of quantum layer as input and converts the outputs features into number of classes.

4. Experiments And Results

4.1 Experimental Setup

Pytorch connecting with PennyLane is used to develop the hybrid classical quantum model to classify the pattern of CT attenuation of Interstitial Lung diseases.Since using a quantum physical computer for quantum computing was not feasible, so lightning qubit simulator is used for classification task. Qiskit framework is also used to draw the quantum variational circuit.The model is run in Jupyter Notebook on google colaboratory on GPU runtime.

Colab Configuration:
GPU device: Tesla T4
GPU memory: 16 GB
RAM memory: 12 GB

To classify the abnormal pattern of interstitial lung diseases, two types of model is implemented. Classical CNN model and hybrid classical-quantum model is used for the classification task using pretrained model of vgg16.In hybrid classical-quantum neural network,model is trained using different number of quanatum depth.Also quantum gradient is used for estimating the gradients of quantum layer using same quantum circuit.The dataset is split into training,validation and testing set in the ratio 0.6,0.3,and 0.1 respectively. Learning rate of 0.001 with 25 number of epochs and optimizer called Adam optimizer with categorical cross entropy loss function is used hyper-parameter of models.

4.2 Result

In this section,we present:

- test and outcomes from the classical CNN architecture of pre-traained model of vgg16 using transfer learning.
- test and outcomes from the hybrid classical-quantum model using different quantum depth to increase the performance of classical CNN architecture.
- Comaparison of perfomance of classical CNN model and hybrid classical quantum model of different quantum depth.

In the experiment of CNN architecture, Table 1 shows hyper-parameter set in order to train the model.

Table 1: Hyper-parameter used in CNN model

Number of epoch	25
Batch Size	15
Optimizer	Adam
Loss function	Categorical-Cross entropy
Learning rate	0.001
gamma lr scheduler	0.1
step size	10

In the experiment of CNN architecture,the pre-trained model of Vgg16 was used in which thirteen convolution layer for feature extraction was there followed by three fully connected layer for classification.The trainable parameter of all layer were freeze expect the layer of last two fully connected layer.Hence there were 16797696 trainable parameter in order to classification of five class of abnormal CT attenuation pattern of ILD.The Model of CNN architecture was run upto 25 epochs with 0.001 learning rate and the 0.9399 model accuracy was found.

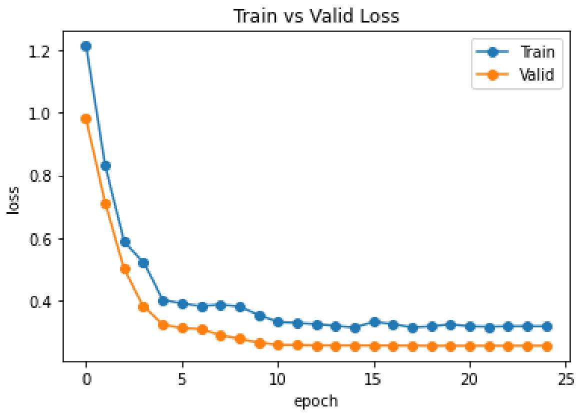

Figure 4: Training loss vs Validation loss

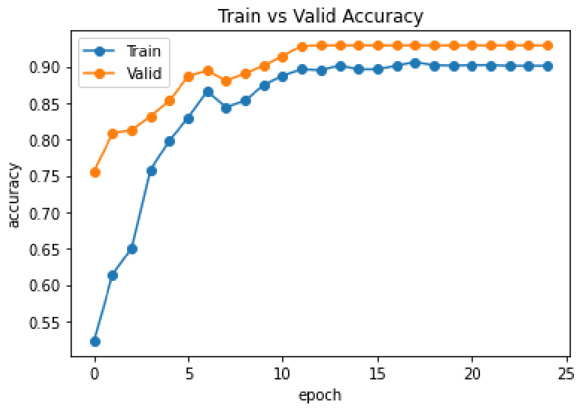

Figure 5: Training accuracy vs Validation accuracy

The training loss of the CNN model was started from 1.2135 and converges into 0.3172 on 25 epochs while validation loss was started from 0.98 and converges into 0.2558. And the training accuracy and validation accuracy was started from 0.5234 and 0.756 respectively and converge into 0.9009 and 0.9294 on 25 epochs respectively.
In Hybrid classical Quantum neural network, two experiment was done.First,using single Quantum depth in which single layer of weights are embedded was performed.Secondly,hybrid model with quantum depth two in which two layer of random initialized weights are embedded on each qubits using RY gate followed by controlled not gate operations for entanglement.The hyper-parameter on each experiment of hybrid model was similar to the hyper-parameter defined in Table 1.At first hybrid classical quantum model using quantum depth-one was run and obtained 0.9738 as model accuracy.

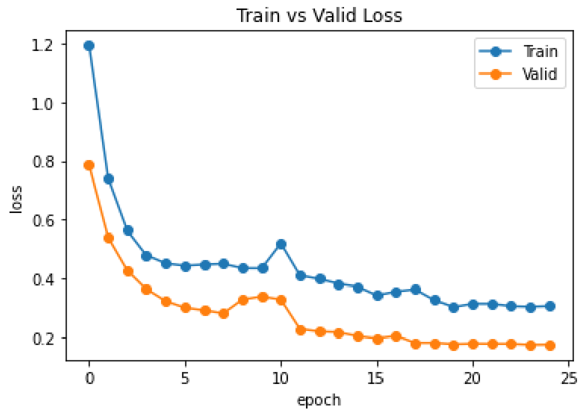

Figure 6: Training loss vs Validation loss

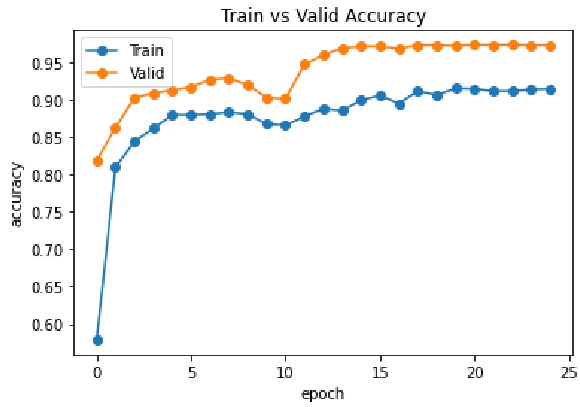

Figure 7: Training accuracy vs Validation accuracy

The model performance of hybrid classical quantum neural network with quantum depth one enhance the performance of pre-trained model of CNN architecture.From the training and valditation accuracy of quantum depth-one, training and validation accuracy converge into 0.9143 and 0.9721 starting from 0.5794 and 0.8185 respectively.To smoothen the validation and training curve of their respective loss and accuracy, quantum depth is increaesed and the hybrid model with quantum depth is run and found better result and smmoth curve of training and validation curve of their respective accuracy and loss.

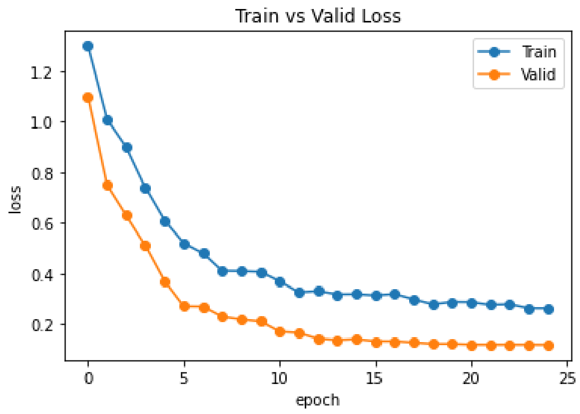

Figure 8: Training loss vs Validation loss

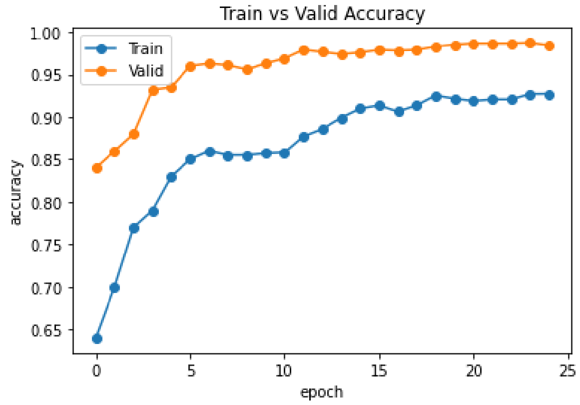

Figure 9: Training accuracy vs Validation accuracy

The hybrid classical quantum model was run increasing the number of depth by one and model accuracy of 0.9922 was obtained.From the training and valditation accuracy of quantum depth-two represent in Figure 8, training and validation accuracy converge into 0.9273 and 0.9845 starting from 0.6412 and 0.8445 respectively. The quantum depth in hybrid model behaves like the hidden layer in CNN. When increasing the quantum depth, the model performance also increased. From the above result, we found that the performance of pre-trained model is enhanced after embedding the quantum layer.

Models Comparison in terms of Learning Parameters:

The number of trainable parameter of CNN was from the second layer of fully connected layer of pre-trained vgg16 model was found 16797696 as a training parameter. The number of trainable parameter of hybrid classical quantum model was derived as:
Trainable parameter=4096*number of qubits+ number of qubits*number of depth +output size

Table 2: Number of learnable training parameters

	CNN	Hybrid model-depth-1	Hybrid model -depth-2
Trainable parameters	16797696	20490	20495

From the table 2,it was found that the learnable training parameters of hybrid model was less than classical CNN architecture.With less number of training parameters,the perfomance of hybrid classical-quantum neural network was better than classical CNN architecture.With the use of quantum circuit in pre-trained model, the complexity and dimension of pre-trained model was reduced.

Comparison of performance of models:

A confusion matrix is an N*N matrix which is used for the evaluation of performance of the model. It is a table that represents both the class distribution in the data and classifiers predicted class distribution with the breakdown of error types.

Performance Evaluation from Confusion Matrix

- $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- $Precision = \frac{TP}{TP+FP}$
- $Recall = \frac{TP}{TP+FN}$
- $F-Measure = \frac{2*(Precision*Recall)}{Precision*Recall}$

where,

True Positive (TP): Correct items are correctly identified as correct.

True Negative (TN): Correct items are correctly identified as incorrect.

False Positive (FP): Incorrect items are incorrectly identified as correct.

False Negative (FN): Incorrect items are incorrectly identified as incorrect.

The performance of models are derived from confusion matrix which are given in table below:

Table 3: Performance evaluation of models

	accuracy	precision	recall	F measure
CNN	0.93	0.89	0.93	0.90
depth 1	0.97	0.97	0.96	0.96
depth 2	0.99	0.99	0.99	0.99

From the table 3 ,it was found that the overall perfomance of hybrid model 0f quantum depth two was enhanced after embedding the quantum circuit in classical CNN architecture.

5. Conclusion

In this study, we provide a novel classification scheme and representation for interstitial lung diseases.The hybrid model i.e. embedding quantum circuit in the pretrained model enhanced the performance of pretrained model with less number of trainable parameters.Our experiment shows that the performance of hybrid classical quantum model is better than classical CNN architecture and also reduced the dimension and complex algorithm of pre-trained model. In this study, input feature was embedded using angle encoding method in quantum circuit so single batch operation was performed in quantum circuit.Due to the single batch operation in quantum layer, the computational speed was slower.In future ,other encoding technique of input feature like amplitude encoding method will be considered to improve the computational speed of hybrid classical-quantum neural network.

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