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Detection of the Diabetic Retinopathy by Classical - Quantum Transfer Learning

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Abstract
Diabetic Retinopathy (DR), one of the major eye disease which eventually cause blindness if not detected in early phase. The primary cause of DR is due to increase in blood sugar, which blocks the tiny blood vessels eventually causing the hemorrhages in the retina. This paper proposes the hybrid model to detect the DR by addressing the problem in automatic detection of DR. The main concept behind this is embedding of classical CNN and Quantum computing(QC) in which classical CNN extracts the feature and QC is responsible for classification task. Three different pre-trained models ResNet-34, Inception V3 and VGG-19 are used for feature extraction and best performing model is chosen for feature extraction. The dataset used in the experiment is benchmark MESSIDOR-I with two classes, one containing the infected and another the normal one. The performance of hybrid model is compared with the output of classical CNN where, hybrid model with accuracy 86.75% outperformed the classical CNN with accuracy of 82.97%.

Keywords
Diabetic Retinopathy, Quantum computing, CNN, ResNet-34, Entanglement

1. Introduction

Diabetic Retinopathy (DR), one of the most common of eye disease, which can cause blindness eventually. Initially, it is symptomless or shows mild symptoms and gradually its symptoms get more noticeable.Basically, to diagnose DR color fundus images are used. Highly trained domain experts can only manually analyze the DR and is, therefore, expensive in and consumes more time. Due to this reason, computer vision methods are used to automatically analyze the fundus images which will be helpful in assisting the ophthalmologist. Figrue 1 is the healthy retina. As of Figure 2, retinal abnormalities caused by DR may comprise, hamorages, aneurysm, retinal neovascularization [1].It is curable or manageable if it is early diagnosed. Since, the symptoms in early stage is not noticeable, so regular fundus examination of eye is necessary.

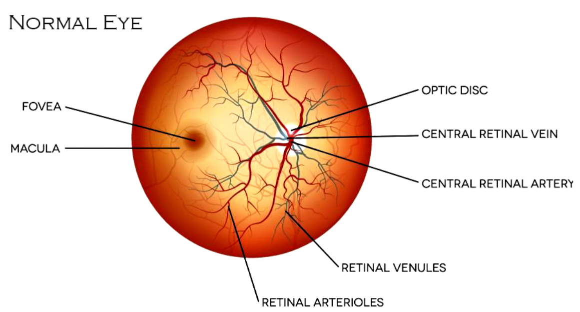


Figure 1: Normal Eye Retina

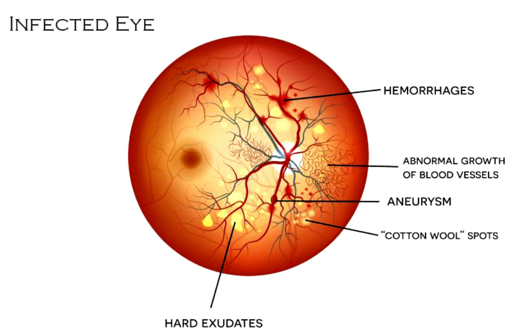


Figure 2: Infected Eye Retina

The paper presents hybrid classical-quantum model for detection of diabetic retinopathy. Previously, image classification task is mostly accomplished by CNNs models. Due to presence of high trainable parameters and hidden layers, model is very complex. Here, classical CNN extracts the feature from the images. Three different pre-trained CNN models ResNet-34, Inception V3 and VGG-19 are experiment and best performing model is chosen for feature extraction. The classification task is carried out by the quantum computing, which reduces the complexity of models in terms less trainable parameters. Variational quantum circuit is trained by using the extracted features, which then classifies the images in two classes No-DR and DR.

The proposed model is compared with the classical pre-trained model in terms of model accuracy.The dataset chosen for experiment is publicly available benchmark MESSIDOR-I dataset containing the 800 fundus images divided into two classes.

The paper comprises literature review in section 2. In section 3 methodology is discussed, section 4 describes the discussion of result and analysis and conclusion follows the section 5.

2. Literature Review

Numerous frameworks were proposed within the literature for the discovery and conclusion of DR using various machine learning techniques (MLTs). These frameworks are either based on conventional MLTs, which depend on hand-crafted highlights extraction, or deep learning where the highlights are extricated naturally within the training.There were different methods proposed to detect the abnormality of blood vessels like intersection of vessels, width of vessels by vessel tracking algorithm [2]. To detect the micro aneurysms several algorithm were proposed, basically by using MA-tracker to count microaneurysms. With the development of transfer learning concept, a model was proposed for detection and classification of diabetic retinopathy by using pre-trained CNN models: VGG-16 and VGG-19 along with classical CNN model[3].

Some interesting research was carried out by Gangwar et al [4] in Messidor-1 diabetic retinopathy dataset and APTOS 2019 blindness detection (Kaggle dataset). The model was build incorporating the pretrained Inception-Resnet-V2 and some custom block of CNN layers were added on top. The filter size used in inception block was 3×3, 5×5, 7×7, and 9×9 with input image size of 229x229. The model also performed better on APTOS 2019 data set with accuracy of 82.18.

With emerging charm in quantum computing, some models were developed in medical data-set with outstanding result. These models try to overcome the limitations from classical CNN model. A hybrid classical-quantum model was proposed by T. Shahwar et al [5] for the detection of Alzheimer's using 6400 labeled MRI scans with two classes which optimally preprocesses high dimensional data. Informative feature vector is processed by quantum processor which was embedded by strong classical processor. To extract the feature pre-trained classical model ResNet 34 was used and feed a 512-feature vector to quantum variational circuit (QVC) to produce a four-feature vector for exact choice boundaries. The learning rate is set to 10-4 for and optimized quantum depth of six layers, coming about in a preparing precision of 99.1.

Similarly in a year 2022, in a field of ophthalmology a model developed by using classical-quantum transfer learning [1] results a significant uplift. APTOS 2019 Blindness Detection dataset from Kaggle was used in the research and feature extraction was done by using Inception V3 pre-trained CNN model. Model was trained on Penny Lane default device, IBM Qiskit BasicAer device and Google Cirq Simulator device and Variational Quantum classifier for stratification. Model was built on pytorch libraries giving the accuracies of 93-96%.

There has been some outstanding research on properties of variational quantum circuit. Sim et. al 2019[6] focuses on determining the power and capablities of some quantum circuit. They use discriptors and tries to quantifies the expressibility and entanglement capacity of parami- tized quantum circuits. In their theoritical approach, the quantification is generally done by comparing the true distribuition of fidelities corresponding to PQC, to the distribution of fidelities from the ensamble of Haar random space. The circuits mentioned by sim et al is further experimented and analyzed by Hubregtsen et al[7]. in 2020. They correlated the classification accuracy with expressiveness and entanglement capacity of circuit using the less complex dataset with 1500 data points. They found strong correlation between the expressiveness of circuit in hilbert space with the classification accuracy. Similarly, for the entanglement capacity there was weak correlation observed. This experiments made significant impact on the designing the quantum circuit and which circuit is best for classification tasks. In this particular experiment, the dataset used is simple and less complex. The quantification parameter like expressiveness and entanglement capacity are derived from dataset having less dimensions. So, the proposed model used the hybrid methodology by using pre-trained model for the extraction of features from the complex dataset and classification task is carried out from Variational Quantum circuit.

3. Methodology

Basically, while classifying image two major steps plays an important role in developing a model and they are feature extraction and classification. Here, Figure 2 denotes the block diagram of system and describes the work flow and how it performs the classification.

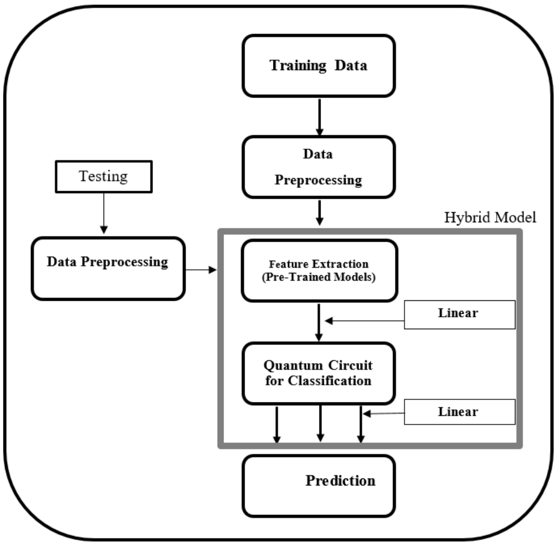


Figure 3: System Block Diagram

3.1 Feature Extraction: Pre-trained CNN

A classical deep neural network grants crude information to be gotten as the input to the network, naturally finding all fundamental connections for performing classification. It is conceivable to construct a various leveled structure of diverse hubs that can learn and calculate nonlinear mapping on their claim, called Deep Neural Network (DNN). A deep neural network includes a grouping of progressively organized hubs. The complete classical layer is complete concatenation of layers.

In this paper, 3 different pre-trained models is chosen to extract the features from dataset. The best performing model is selected to detect the DR.

3.1.1 Inception V3

Inception-v3, a pre-trained convolutional neural network model that's 48 layers profound that's utilized to reduce image to 2048-dimensional feature vector. Firstly, it was module for Google Net and it is the third edition of google Inception CNN. During the imagenet recognition challenge it was first introduced as v3 and was envisioned to allow deeper network. The input dimension of image for this model is 299*299.

3.1.2 VGG-19

It is a convolutional neural network that is 19 layers deep. The network will be loaded that has trained more than millions of images. This network has the capacity to classify the uploaded images into more than 1000 categories of objects like animals, mouse, keyboard, pencils, etc. This means, from the large number of different type of images, the network has learned many features. The image input size of the network is 224*224. The features that are extracted are passed in the connected layer.

3.1.3 ResNET 34

It is also one of the pre-trained CNN model which is 34 layer deep. It consists of convolution, batch normalization, ReLU, and max pooling operations trailed by four layers: layer 1, layer 2, layer 3, and layer 4. It reduces the image dimension to 512 feature vectors by using 224*244 input images. It has been trained on 100,000+ Imagenet dataset with 200 different classes.

3.2 Classification:Variational Quantum Circuit

The entire quantum variational circuit, including the embedding layer, variational layer, and final measurement layer, can be expressed as:

$$Q = |x> \rightarrow y = <x|\hat{y}|x> (Ld...L1)Ex/0 \quad (1)$$

Where, ¡x— ŷ —x¿ is a measurement layer which maps the quantum vector to classical vector, L denotes the quantum circuit, depth of variational circuit is given by d,

E is the notation of embedding layer that rely on x and ground truth. Embedding layer is responsible for mapping the classical vector to the Hilbert space vector.

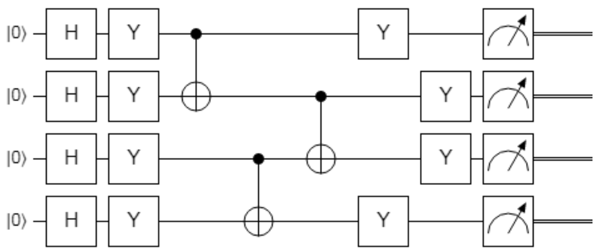


Figure 4: VQC used in experiment

Quantum layer classifies the data according to the features contains in the data. Figure 3 is the diagram of variational quantum circuit used in this experiment. There are mainly three layers which comprises entire quantum layer.

Data Embedding Layer

In this layer, classical data are embedded into quantum states by combining one or more single qubit quantum gates like Hadamard gate, Rotational Y, Rotational X, Rotational Z, etc.

Variational Circuit Layer

In this layer, two qubit gates such as controlled NOT gate, Controlled Z gate, Controlled Rx and Ry gates etc. with single qubit parameterized gate like Rotational Y gate, U1, U2 etc. are used to design a parameterized circuit. It is one type of quantum circuits with tunable parameters which are optimized in an iterative manner by a classical computer. These parameters can be seen as the weights in artificial neural networks. The variational quantum circuit approach has been shown to be flexible in circuit depth and somewhat resistant to noise.

Measurement Layer

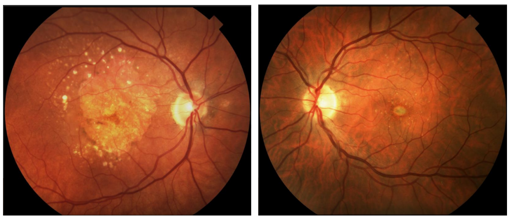
Quantum measurement component is used to read the current state of the qubit. The results from the quantum layer are transferred to the next layer as classical data. Pauli's Z gate is used for measurement in this experiment. Pauli z matrix is given below:

$$\sigma_z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \tag{2}$$

3.3 Dataset

A benchmark data- set MESSIDOR-1[] database is used to perform the experiment. These 800 eye fundus color images of the posterior pole are collected from three ophthalmologic departments, from color video 3CCD camera (on a Topcon TRC NW6 non-mydriatic retinograph over a 45 degree field of view). The related images were captured via 8 bits per color plane at, respectively, 1440*960, 2240*1488 or 2304*1536 pixels.

Figure 5 is all about the dataset of both infected and normal class.



(a) Retina With DR **(b)** Normal Retina

Figure 5: Retina with DR and NoDR

3.4 Data Pre-Processing

The collected images have different dimensions. To feed images into CNN the size of images should be same. So, the first thing done on the data set was resizing. To perform resizing first bounding box was designed and with the help of it the extra boundary portion was removed by center cropping. The output was square image and after that resize of image was performed to desired dimension. To get better result image smoothing was carried out by applying Gaussian filter of radius 1.Also, data augmentation was performed in this experiment inorder to balance the data set. Here, horizontal flip, vertical flip, rotation about 45, 80,135 180, 270 degrees were performed.

Table 1: Standard Data-Set Details

	Before Augment.	After Augment.
DR	254	1530
No-DR	546	1632

3.5 Linear Embedding

On using pytorch the reduction of features is generally executed by torch.nn.linear module. This module comprises the linear layer in this proposed model which converts the feature vector obtained from classical CNN into desired dimension. The logic behind this task is affine transformation. Let us consider the equation 3 below which is responsible for the transformation of dimension:

$$Y = XA^T + b \tag{3}$$

Where, X: input feature, A: Weight of features, b: Bias

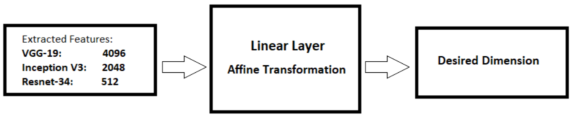


Figure 6: Block Diagram of Linear Layer

3.6 Design of Quantum Classifier

1. Firstly no of qubit will be chosen according to the need of model in this case 4 qubit is chosen. The qubit are initializing to —0¿ state and then Hadamard (H) gate is applied to make the qubit in zero and one state.

2. Additional transformation on classical data by using 4-dimensional feature vector as a parameter in circuit obtained from linear layer is applied to encode in unitary circuit consisting rotational y gate, Ry(fi) followed rotational x gate Rx(fi).

3. The variational quantum layer is repeated in sequence and no of repetition is given by quantum depth d. These variational quantum layer Q consists of entanglement layer K(combination of C-RX gates) and a data encoding circuit.

$$Q = L_1.L_2.L_3.L_4.L_5.L_6 \tag{4}$$

$$L(w): |x\rangle \rightarrow |y\rangle = k \otimes_{k=4}^{4} (R_y(wk)|x\rangle)(R_x(wk)|x\rangle) \tag{5}$$

Where L(w) is the variational layer.

$$K = (CRX \otimes ||3,4)(||_{1,2} \otimes CRX)(||_2 \otimes CRX \otimes ||_3) \tag{6}$$

4. At the end measure of each qubit will be carried out to get expected output along with z vector.

$$M(|y\rangle) = y = \begin{pmatrix} \langle y|Z \otimes || \otimes || \otimes |||y\rangle \\ \langle y|||\otimes Z \otimes || \otimes |||y\rangle \\ \langle y|| \otimes || \otimes Z \otimes |||y\rangle \\ \langle y|Z \otimes || \otimes || \otimes Z|y\rangle \end{pmatrix} \tag{7}$$

3.7 Algorithm of Proposed Model

1. Stage 1: Pre-processing of data-set is performed as described in 3.4 section.

2. Stage 2: After pre-processing, the preprocessed images is feed to classical CNN model for feature extraction.

3. Stage 3: Model with best accuracy is chosen as base model for feature extraction.

4. Stage 4: Embedding of classical and quantum layer is done in Dressed Quantum Circuit by linear Transformation described in 3.5.

5. Stage 5: The feature vector mapped is passed to tanh activation function to prepare final feature vector and passed to quantum layer for classification and design of Quantum Classifier is discussed in 3.6.

6. Stage 6:Next step is State preparation of qubit in embedding layer with a balanced superposition of $|0\rangle$ and $|1\rangle$ qubit by using Hadamard gate.

7. Stage 7: According to the feature vector feed to Ry and Rx gate, it rotates the qubit to train the quantum circuit. Entanglement of the qubits is obtained in entanglement layer by using C-Rx gate.

8. Stage 8: The output of Variational quantum circuit is measured in measurement layer giving a classical output.

9. Stage 9: Linear prediction layer predicts the output.

10. Stage 10: The transferred model is trained with train data set.

11. Stage 11: Sample image is predicted with final model.

3.8 Performance Analysis

Confusion Matrix 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. Usually, columns are the actual class and rows are observed class. Performance Evaluation

Table 2: Confusion Matrix

	DR	**NODR**
DR	True Positive	False Positive
NODR	False Negative	True Negative

from Confusion Matrix

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{9}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{10}$$

$$F-Measure = \frac{2*(Precision*Recall)}{(Precision+Recall)} \tag{11}$$

3.9 Experimental Setup

The model is developed on python programming on Jupyter Notebook. Various libraries like Pytorch, Keras, Numpy, Pandas, Matplotlib, Seaborn etc. are used according to need of experiment.

Since, it was not feasible to use quantum physical computer for quantum computing. So, Penny Lane quantum computing simulator is be used for the classification task. IBM quantum experience is also used to model a variational quantum circuit.

After, development of model the model is tested on the PC with configuration as of Table 3.

Table 3: System Configuration

CPU:	Intel i5-6300HQ CPU @ 2.30GHz
RAM:	16 GB
GPU:	NVIDIA GEFORCE GTX
GPU SIZE:	4 GB DEDICATED
OS:	WINDOWS 10

Some Experiments are performed on Google Colab.

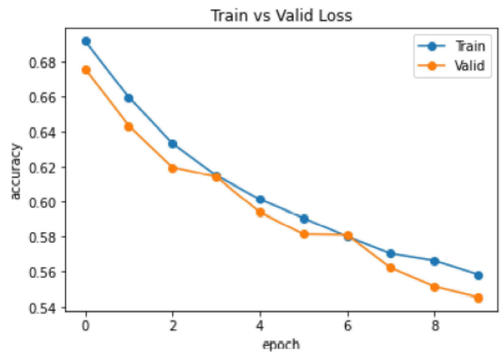
4. Results and Discussion

4.1 Experiment 1: Data Set Refinement

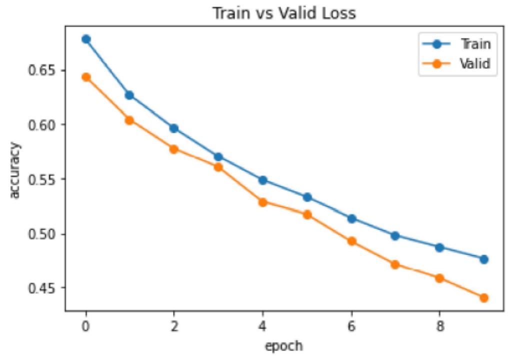
This Experiment was carried out in order to check the performance of model with normal and smooth data set. The standard data set was smoothed by using Gaussian filter of radius 1 to remove granular noise. The Table 4 gives the clear picture about the performance of model in various condition of dataset. The feature extraction was done by Resnet 34. The

Table 4: Comparison normal vs smoothened Dataset

	Normal	Smoothen
Sensitivity	0.8324	0.8389
Specificity	0.8611	0.9051
Precision	0.8780	0.9207
F1-Score	0.8546	0.8789
Accuracy	84.54	86.75



(a) Classical CNN



(b) Hybrid Model

Figure 7: Train Vs Val. loss Comparison of normal and smoothened dataset

figures 7 gives clear sketch about the loss of the model during training and validation. The loss of experiment when smoothened dataset was use is found to be around 0.45 and with normal dataset is about 0.54, which also validates the use of Gaussian filer improves the result.

4.2 Experiment 2: Determination base feature extractor

This experiment was carried out on standard dataset with three per-trained CNN architecture as a feature extractor. Table 5 signifies the result:

Table 5: Comparison of Pre-Trained Architecture

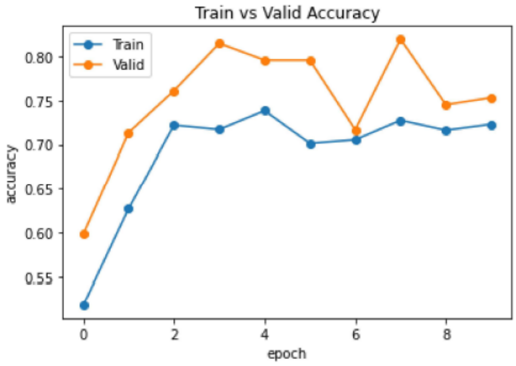
	Inception V3	VGG-19	Resnet-34
Sensitivity	0.7391	0.7978	0.8324
Specificity	0.9	0.8417	0.8611
Precision	0.9329	0.8659	0.8780
F1-Score	0.8248	0.8304	0.8546
Accuracy	79.49	81.70	84.54

From this experiment 2 model with Resnet 34 outperformed other two model in every aspect except in specificity with inception v3. This may be because of output features from Resnet 34 are of small dimension compared to other two. So, base model for the rest of the experiment was done with resnet 34. Figure 8 is Train vs Validation graph of Experiment 2.

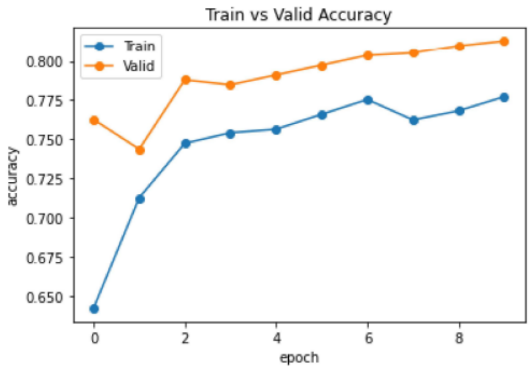
The convergence of model was found better in ResNet 34. The experiment was carried out with parameters mentioned in Table 6:

Table 6: Hyper-Parameters used in Experiment-2

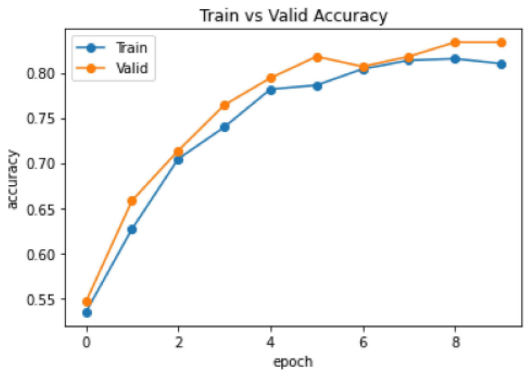
No of Epoch	10
Batch Size	8
No of qubit	4
Learning Rate	0.0001
Quantum depth	6



(a) Inception V3



(b) VGG-19



(c) ResNet 34

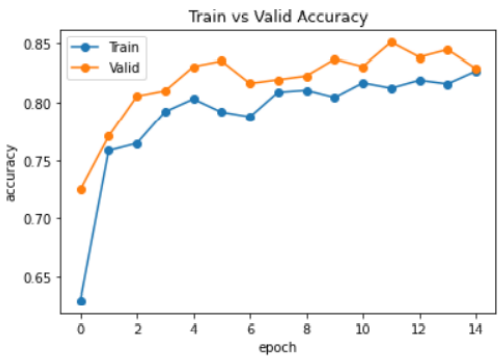
Figure 8: Train Vs Val. Accuracy

4.3 Experiment 3: Comparison with Classical computing

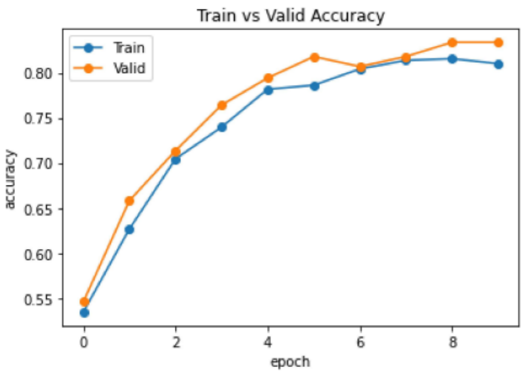
Complete classification task was carried out with classical CNN model. Softmax was used as classifier in the final layer and pre-trained model Resnet 34 was used to develop the model. The primary objective of this experiment is to analyze the performance of hybrid model and classical CNN model. Hybrid model with resnet 34 as feature extractor outperformed the classical CNN model. The experiment was performed on standard smoothed dataset. Experimental details is mentioned in 7 makes more clear findings: In every aspects, Hybrid classical-quantum model outperformed the classical CNN model. The addition of quantum layer makes a significant differences in model performance. Reduction of dimensionality by quantum layer reduces the complexity than classical CNN in increasing the accuracy of model. The hyper-parameter used for the classical and hybrid model are exact in batch size, learning rate, epoch, and optimizer. The graphs of Figure 9 suggests us the convergence of model is better in case of hybrid model than classical CNN model. Hybrid model possess the smooth graph than classical model.

Table 7: Comparison of Classical Vs Hybrid Model

	Classical	Hybrid Model
Sensitivity	0.8274	0.8389
Specificity	0.8322	0.9051
Precision	0.8474	0.9207
F1-Score	0.8373	0.8789
Accuracy	82.97	86.75



(a) Classical CNN



(b) Hybrid Model

Figure 9: Train Vs Val. Accuracy Comparison of Classical and Hybrid Model

5. Conclusion

This developed hybrid classical-quantum model involves in detecting the diabetic retinopathy in the images. The dataset was smoothed by applying the Gaussian filter to remove the noise and sharp edges.This helped in improving the feature extraction resulting in better performance of model. ResNet-34 performed better than VGG-19 and Inception V3 due to less output features.Due to this factor learn-able parameter of model was reduced. The introduction of quantum computing reduced the complexity of model resulting in significant output. From figure 8, it can be observed that the hybrid model over all learning was smooth than classical CNN model. Still there are lots of area to improve the performance of model like varying the quantum depth and qubit.Hyper-parameter tuning can be done to improve the performance of model. The behavior of model can also be experimented with different fundus dataset to test the data dependency of model.

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