Quantum transfer learning for image classification

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ABSTRACT

Quantum machine learning, an important element of quantum computing, recently has gained research attention around the world. In this paper, we have proposed a quantum machine learning model to classify images using a quantum classifier. We exhibit the results of a comprehensive quantum classifier with transfer learning applied to image datasets in particular. The work uses hybrid transfer learning technique along with the classical pre-trained network and variational quantum circuits as their final layers on a small scale of dataset. The implementation is carried out in a quantum processor of a chosen set of highly informative functions using PennyLane a cross-platform software package for using quantum computers to evaluate the high-resolution image classifier. The performance of the model proved to be more accurate than its counterpart and outperforms all other existing classical models in terms of time and competence.

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1. INTRODUCTION

Designing learning algorithms has become a focus for machine learning engineers, as they strive to make machine learn like human. In several automations, such as image and speech recognition, the machine learning research has seen tremendous improvement in the past few years using the concept of transfer learning. Transfer learning is a learning model that gains information in a specific context which can be included in another model to reuse the knowledge for related predictions. Transfer learning has been applied to all kinds of unsupervised, supervised and reinforced learning tasks. The integration of transfer learning with quantum computing and machine learning seems to be more promising among all prevailing learning algorithms. Transfer learning model and its importance is explored in the perspective of quantum machine learning in this work. Quantum transfer learning proves to be efficient in classifying traditional images utilizing the quantum state classification. Quantum classification operations could be effectively solved in an optimal duration using quantum algorithms. Transfer learning is the use of the experience learned by performing one task to help solve another, but linked, problem. Information is leveraged from a source task during transfer learning, in order to enhance learning in a new task. It has been a proven scenario to be successful when the model development starts from a pre-trained deep network rather than training a complete network from its initial stages, then optimize any or more of the initial layers for a given function and appropriate datasets. If the transfer process ends up reducing the new task's output it is considered a negative transfer.

A key problem is to maintain successful transfer between related things while preventing negative transfer among less related things when implementing transfer learning.

Modern machine learning and deep learning algorithms have traditionally been designed to work in isolation. These algorithms are qualified for the resolution of complex tasks. If the feature-space distribution shifts, the models must be rebuilt from scratch. Microsoft proposed a deep residual learning architecture to address this issue. Many problems can be handled by employing the residual network, including:

– Although residual network (ResNets) are simple to optimise, “plain” networks (those that merely stack layers) have a larger training error as the depth increases.
– ResNets can readily gain accuracy from more depth, resulting in better results than earlier networks.

It is evident that the ResNet convolutional neural network (CNN) models provide superior object detection and classification accuracies. Considering the higher accuracy and affordable complexity of this CNN paradigm, we employed this model’s transfer learning into the quantum machine learning so as to get a promising performance by the quantum machine learning strategy. Our experimental observations also substantiate that the chosen transfer learning coupled with quantum machine learning provides good classification accuracy.

In this work, we implemented transfer learning-based quantum machine learning method to classify images in order to achieve high performance and the paper focuses on applying the quantum neural network (QNN) by using transfer learning method in order to classify images as ant/bee and potato leaf image datasets. QNN is modelled by using computer quantum simulator circuit which is designed by making use of PennyLane, a cross platform software library, tested in Google Colab. Evaluating the possibility and level of probability to develop a transfer learning model in the perspective of quantum learning serves as the main objective of this work.

2. RELATED WORKS

Quantum machine learning is evolving day by day and this work is to mainly analyze the capability of quantum processors in exploring the transfer learning concept. Both the classical and quantum model has been hybrid to create a neural network that can perform all type of computations. Three new forms of learning transition arise naturally: quantum to classical (QC), classical to quantum (CQ), and quantum to quantum (QQ) [1]. CQ transfer learning is especially appealing nowadays with its noisy intermediate-scale quantum (NISQ) devices as it enables the chance of using some great deep neural network to pre-process large input samples of high-resolution in a traditional way and manipulating few but extremely insightful features successively with a variational quantum circuit. Currently, CNNs are the deep learning models that are most widely used and are most frequently used for image classification. They make supervised use of stochastic gradient descent and back-propagation for training. In addition, learning to pass QC and QQ may be very promising techniques notably once wide quantum computers are accessible. In this case, it might be possible to pre-train fixed quantum circuits as generic quantity extractors, imitating the well-known classical models and use them as pre-trained blocks e.g. ResNet, visual geometry group (VGG)Net, inception, and AlexNet (for image processing), or, transformer, bidirectional encoder representations from transformers (BERT) [2]. The goal is to establish CQ to a specific dataset with the existing resource, and make it precisely suitable to the evolving approaches of hybrid neural networks with variational quantum circuits.

The main emphasis of the work carried out stays on the hybrid model development. Hence the paradigm that is conceivable to jointly train quantum variational circuits and classical neural networks to perform difficult data processing are taken up for study. Inherent parallelism in the execution is the great benefit of any quantum models. The speed of execution and most importantly, in comparison to typical classical models, the number of qubits required to encode the information is reduced by an order of magnitude. For example, just 6 qubits are required to encode a 64-dimensional pattern; hence a 32768×32768 binary image may be encoded with just 30 qubits, which is more than a billion-dimensional planar vector [3], [4]. Using superposition states and quantum entanglement only this reduction could be made possible. When compared to bits in conventional systems, the superposition property of quantum states entanglement permits the parallel reconstruction of images from a smaller number of qubits and quantum computation image representation systems to take advantage of this feature and proves to be highly promising for problems with image classification [5]–[7].

3. RESEARCH METHODOLOGY

This section discusses about the different existing hybrid classical and quantum networks available for classification. The section covers the conceptual technical details of classical neural networks, variational quantum networks, and dressed quantum circuits. Also, it discusses the background of transfer learning, classical to classical transfer learning, and transfer learning from classical to quantum.

3.1. Classical neural networks

This is a very common model of comprehensive neural networks for classical machine learning. The elementary deep neural network block is referred as a layer and it converts interface vectors of n_0 real objects to output vectors of n1 real objects [5].

$$E[\psi] = \frac{\langle\psi|H|\psi\rangle}{\langle\psi|\psi\rangle} \geq E_0 \tag{1}$$

Here the notation $n0 = n1$ denotes the number of input and output variables, W is a matrix when $n1 = n0$ and b is a vector which never changes its state and this contributes the purpose of optimization. The nonlinear functio ϕ is random and the inflammatory tangent or the resolute linear component is specified as $ReLU(x) = max(0, x)$. A standard deep neural network is a multilayer connectivity, taking the output of $(n-1)$ layer contributing as the input to the layer n as in (2)

$$C = L_{n_{d-1}\to n_d} o \ldots L_{n_1\to n_2} o \ldots L_{n_0\to n_1} \tag{2}$$

Its depth d (number of layers) and the number of instances (number of variables) for each layer, i.e. the range of integers, are defining hyper-parameters of a deep network is specified for $n0, n1, nd - 1$.

3.2. Variational quantum network

The variational quantum circuit is the one with properties of defining tunable parameters that needs to be iteratively optimized. In artificial neural networks, certain parameters can be used as weights. Due to the absence of quantum error correction and fault-tolerant quantum computing, the parameters can be absorbed during the iterative optimization process by the corresponding deviations leading the variational circuits to become reasonably sensitive to noise [7]. Also, the machine learning algorithms enabled variational quantum circuits to bypass the complex quantum errors that may occur in variety of devices. A variational quantum circuit of depth q is a combination of several quantity layers that corresponds to the sum of several units parameterized by weight variation as (3).

$$Q = \mathcal{L}_q{}^\circ \ldots \ldots .. \mathcal{L}_2{}^\circ \mathcal{L}_1 \tag{3}$$

A given vector x is to be incorporated into a quantum state to inject classical data into a quantum network. A variational x-dependent embedding layer can also do this and can be applied to any relevant state [8] as in (4).

$$\varepsilon: x \to |x\rangle = E(x)|0\rangle \tag{4}$$

It would be challenging to simulate the quantum circuits with large number of qubits via classical computers, which implies that the variational quantum circuits own a better expressive power than the classical function approximations like a neural network. Although it can entail a quantum computation hidden in the quantum circuit, Q is merely a black-box comparable to the classic deep network as viewed from a global point of view. Nonetheless, when working with actual NISQ systems in particular, there are technological drawbacks and physical restrictions that should be taken into account. Traditional feed-forward networks [9] may take any number of characteristics chosen for layers defined in the quantum network as in (4). In general, embedding layers encode each classic aspect of x into some kind of specific framework. This is a constraint for any embedding deep neural network. A quantum network could overcome this common constraint by:

– Adding and discarding/measuring of ancillary subsystems in the center of the circuit.
– Including intricate technologies of embedding and measuring layers.
– Adding the classical layers pre-processing and post-processing.

3.3. Dressed quantum circuits

An association of traditional neural networks with quantum variational circuits is to be done to introduce transfer learning to the classical quantum framework. Analyzing the size of the classical and quantum nodes is usually not feasible. The circuit of variation set out and subsystems dependent on nq could be tested. To add some simple input and output data especially pre-processing and post-processing, introducing a classic layer at the middle and end of the quantum network could be termed as a dressed quantum circuit:

$$Q = L_{n_q\to n_{out}}{}^\circ\, Q \circ L_{n_{in}\to n_q} \tag{5}$$

Where in (2) n_0 is defined and Q is the bare quantum circuit connected to it [10]. Here the computation is not shared as the hybrid complex network with the classical and quantum processors. It functions while the quantum circuits conduct the main calculation, where the traditional layers are responsible for supplying the data and fetching data from the model again. Any related hybrid model has been made one of them is helmholtz quantum computer. A dressed quantum circuit is almost identical to a naked one from a hardware standpoint [9]. On the other hand, there are two big advantages of dressed quantum circuit include:
– The two classical layers should be fitted to integrate the input data optimally.
– Amount of variables in input and output is independent of the number of subsystems, making it possible to link flexibly to other networks that could possibly be classical or quantum networks.

Although implementation of the dressed quantum circuits seems to be a simpler application of transfer learning systems, it is also in itself a very powerful paradigm of machine learning and is a non-trivial contribution to this work.

3.4. Transfer learning

Transfer learning is the idea of transferring an attained knowledge rom one network to the other in which either of them could be classical or quantum [11]. As recorded in several surveys, transfer learning has been applied to all kinds of unsupervised, supervised and reinforced learning tasks. Transfer learning has been implemented for various tasks such as reinforcement learning and classification on restricted Boltzmann machines. Ortiz *et al.* [12] applied transfer learning to neural networks and noted it increases both performance and effectiveness. In specific terms, our method uses unlabeled data to acquire a concise, higher-level function representation of the higher-level structure specification of the inputs; the implementation simplifies the role of value classification. Trying to follow the rule that is seen in classical machine learning, all circumstances in which the dataset $D_B 6 = D_A$ is modified and/or the final task $T_B 6 = T_A$ is modified could be described as methods of learning transfer.

$$\#inputs = \#\, subsystems = \#\, outputs \qquad (6)$$

The basic concept behind this approach is that it can always serve as a handy function extractor for another problem, even though A has been developed for a particular problem. This workaround is enhanced by enumerating the final layers of A (step 2), in spite of the fact that the network's final implementations are typically more suited to the particular situation, intermediate elements are more common and thus more appropriate for transfer learning. It includes the definitions of a context and a mission. A field D is a function space X and a conditional probability distribution $P(X)$ over the function space, where $X = X_1 \dots \dots \dots X_n$ ubiquitous X is located. X is the space for all document representations when classifying documents with a bag-of-word representation, x_i is the i^{th} term vector referring to some text and X is a set of training documents [13]. A similar idea is used to inspire generative models: it is assumed that the capacity to generate meaningful images requires an understanding of the underlying image structure, which can be applied to many other activities in turn, while training generative models. This presumption itself is based on the idea that all images are built on a low-dimensional multiplicity, i.e. there is a certain basic picture structure that a model can derive. Recent success with generative adversarial networks in the development of photorealistic images suggests that such a network may theoretically exist [14].

3.5. Classical to classical transfer learning

Until now, modern machine learning and deep learning algorithms have traditionally been designed to work in isolation. These algorithms are qualified for the resolution of complex tasks. If the feature-space distribution shifts, the models must be rebuilt from scratch. Transfer learning is the concept of overcoming the independent learning model by using learned knowledge for one problem in order to solve similar ones [15]. If there are substantially more data available for $T1$ task, it could be utilized for its learning and generalize this information (features, weights) for $T2$ task (which has far less data). It is the first step in the whole method, and the most critical. The aim is to obtain answers to queries related to which part of the information can be moved from source to goal in order to enhance the goal task efficiency.

In attempting to address this question, we seek to classify the source-specific portion of information and what's common between the source and the target. Given source and target domains D_s and D_t where $D = \{X, P(X)\}$ are source and target tasks T_s and T_s where $T = \{\mathrm{Y}, \mathrm{P(Y|X)}\}$. Source and target requirements will differ in four ways – i) the source and target domain featues spaces are distinct from each other; ii) the relative confidence intervals of the input and the output domain are different; iii) two different scenario spaces have two different label spaces; and iv) source and target conditional probability distributions are different; all these aspects could be explained as an example of classification:

1) $X_s \neq X_t$ Referred to as, the source and target domain feature spaces are distinct, e.g. there are two different languages in which the documents are written. This is typically adaptation in the sense of natural language processing-cross-lingual.
2) $P(X) \neq P(X)$ The relative confidence intervals of the input and the output domain are different, e.g., the papers cover various subjects. This circumstance is commonly known as domain adaptation.
3) $Y_r \neq Y_r$ This situation typically happens for scenarios because it is exceptionally unusual for two different tasks to have different label spaces, but the same conditional probability distributions. The label spaces between the two tasks are different, e.g. documents need to be allocated different labels in the target task.
4) $P(Y_s\,|X_s) \neq P(Y_t \mid X_t)$ Source and target tasks' conditional probability distributions are different, e.g. source and target documents are unbalanced with respect to their classes. In practice and methods such as over-sampling, under-sampling, this scenario is very prevalent.

In several simulation data, the proposed algorithm is applied to the task of image processing and also the model is tested with a sample dataset of ants and bees [16]. It can be understood on the image processing domain, for every sample in each class, the model trains itself adhering to the aforementioned source-target specifications. For the complete learning of the solution space, the source and the target spaces are mapped optimally only because of the source-target requirements. The quantum learning algorithm learns this mapping and attempts to produce the optimal classification results.

3.6. Classical to quantum transfer learning

The transformation from classical to quantum transfer learning in the modern technological era using the implementation of NISQ devices is perhaps the most promising one [17]. Also, now, the conditions exist that machines exist with intermediate quantum computers hit the plateau of quantum domination and simultaneously, classical deep learning approaches could be applied that are very successful and well-tested. The existing algorithms are commonly accepted as the best performing in machine learning, particularly for the processing of images and texts using transfer learning. The CQ conversion research comprises of using such classic pre-trained models specifically as information extractors and then post-processing this information on a quantum computer. This hybrid method helps in manipulating high-resolution images because a quantum computer is implemented in this setup only to a comparatively small number of abstract elements, which is far more practical than embedding millions of individual pixels in a quantum device [18]. The alternate solutions are also to be analyzed to handle large image datasets. And it is also being tested with the quantum simulator provided by the PennyLane platform as in Figure 1.

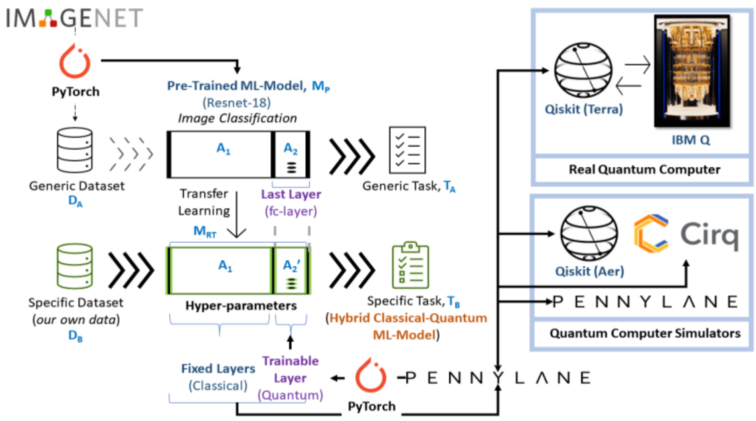

Figure 1. Hybrid quantum transfer learning model

3.7. Proposed algorithm

The steps and procedures discussed above are summarised as a single algorithm. The logical aspets for each step summarized, has been explained in the previous sections. The algorithm outline for the implemented hybrid transfer learning model is given [19], [20]:
1) A pre-trained CNN model is loaded with a large dataset.
2) The weights of hyper parameters in model's lower convolutional layers are frozen.
3) Replace the upper layers of the network with a custom quantum classifier and the number of outputs must be set equal to the number of classes.
4) After the custom quantum classifier with required layers of trainable parameters are added to the model, the layers to freeze are adjusted depending on similarity of new task to original dataset.

5) The classifier layers on training data available for task is trained.
6) Train only the custom quantum classifier layers for the task thereby optimizing the model for the given dataset.
7) Hyper parameters are fine-tuned to give optimal accuracy and more layers are unfrozen if required.

We concentrate on the classical quantum transfer learning algorithm and provide a specific example to illustrate the training process.

– We employ ResNet18, a deep residual neural network that has been pre-trained on the ImageNet dataset, as our pre-trained network named 'A'.
– We acquire a pre-processing block, named 'A', after eliminating its final layer, which translates any input high-resolution image into 512 abstract features.
– A 4-qubit "dressed quantum circuit" –'B', which is a variational quantum circuit sandwiched between two classical layers, is used to classify such features.
– The hybrid model is trained on a subclass of ImageNet comprising images of ants and bees, while maintaining A' constant'

The model is experimented to get trained for classification of ants and bees as in Figure 2 and also to classify potato leaf diseases as in Figure 3. We have about 800 training images and 400 testing images for ants and bees. The potato leaf disease dataset consists of 1500 image files of 3 different classes, namely early blight, late blight, and healthy. Usually, this is a very small dataset to generalize upon, if trained from scratch. Since we are using transfer learning, we should be able to generalize reasonably well. The dataset used is same for both the classical and classical to quantum transfer learning.

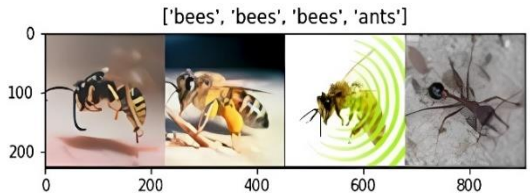

Figure 2. Ants and bee's dataset

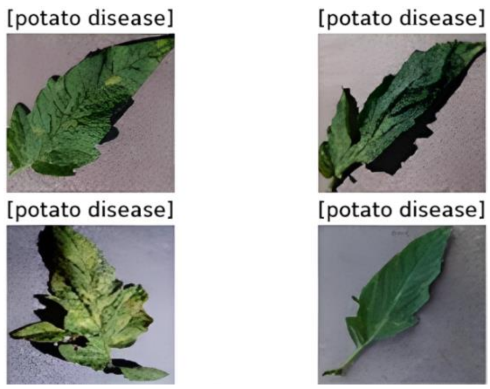

Figure 3. Potato leaf dataset

In classical transfer learning the image classification in done by using RestNet 50 pre-trained model. First CNN in applied for bees and ant's classification using Keras API. Then the data is trained form the retained model, now transfer learning is applied, CNN is trained with ImageDataGenerator. Same process is applied for leaf diseases dataset. On imagenet image recognition tasks such as VGG, genesis, and ResNet, Keras provides easy access to many high performing templates [21]. The aim is to find maximal values for each of these filter matrices, so that when the image is propagated through the network, output crypto keys can be used correctly. The method used to identify these values. Classical to quantum transfer learning is implemented with the same Dataset consists of ant and bees. It is first trained numerically and the model is tested on the open source platform of quantum computing PennyLane with the help of PennyLane libraries [22]. PennyLane provides two quantum simulators for running quantum codes. So, this example has also been run into PennyLane default simulator strawberryfields.fock.

– dev = qml.device ('strawberryfields.fock', wires = 1, cutoff_dim = 10)
– This model is divided into different phases; it has a public dataset with 1000 images which is provided by image net, a pre-trained residual neural network RestNet 18 which is created by microsoft in early 2016. RestNet 18 removing the fully connected final layer, receiving a 512-function pre-trained extractor. And images of two different classes: ant and bees separated into two different sets one for training that is of 800 images and second set is of 400 images for testing.
– $B = Q = L_{4-2} \circ Q \circ L_{512-4}$: i.e., a 4-qubit dressed quantum circuit (9) with 512 input features and 2 real outputs.
– T_B = classification (2 labels).

The Figure 4 gives the details of the full data processing pipeline of classical to quantum transfer learning.

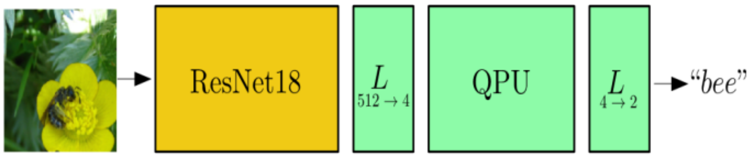

Figure 4. Full data processing pipeline of quantum transfer learning

4. Results and accuracy

The proposed method is evaluated using the following performance metrics and the results are compated with the existing deep learning models. The result states that the dressed quantum circuit is very useful in quantum machine learning, this will help to classify highly non-linear dataset. The variational parameters which are used in this quantum program is 4 qubits with learning rate of 0.0004, the batch size for testing is 4. Number of training epochs is 50 and the main quantum depth is 6. After each epoch the quantum model will be validated by the test dataset. The hybrid model's performance is measured with metrics such as accuracy, precision, recall, F1-score and specificity. True positive (TP) gives the number of correctly estimated positive cases and is provided in Table 1, false positive (FP) gives the number of falsely predicted cases, true negative (TN) gives the number of negative samples correctly estimated and false negative (FN) is the number of samples that are falsely predicted. The accuracy rate indicates the details of correctly classified test data. Recall and precision are two important metrics where the percentage of correctly classified is defined as the recall and there is a trade-off between them. F1 score seek a balance between recall and precision. Specificity discuss about the correctly predicted. The performance of the proposed system is comapared against the other deep learning systems and is provided in Table 2.

Cross entropy is used as a loss function and reduced using the Adam optimizer. The classical entities were conventional recombination and mutation operators are also used. In the case of numerical variables, there are several variance operators present in the literature [22], [23]. The statistical evidence that a quantum network truncation does not necessarily decrease the efficiency of the calculated attributes are expressed by close inspection that is beneficial to increase the classical depth but even after two layers it saturates the precision. In the other side, it is evident that the quantum depth has an entropy value of approximately q = 15, although the accuracy is goes down for larger values.

Figure 5 gives the number of training iterations happened with respect to the evolution of the loss function. This is a representation of total 6 quantum depths trained from the scratch. According to the quantum existence, the qubit state generated by the truncated variational circuit will be interconnected and/or not associated with the principle of estimation. But may in reality be a handy transfer learning technique, is a noteworthy finding. For the classical part, validation is done by the help of validation generator and the losses are binary cross entropy. Figure 6 and Figure 7 depicts the details of training and validation accuracy and loss of the developed hybrid model for the given datasets.

The network built from scratch produces the same or better performance in favour of the network with a set initial layer over a reasonably long training time. Comparing quantum accuracy to classical accuracy there is a phenomenal difference. It can be expressed that the classical to quantum learning model for this example which is being trained from the scratch is a more powerful construction to the classical model because it has extra more variational quantum depth parameters. However, the resources are limited for this scenario though they work properly. In this kind of practical situation quantum models could be used as a convenient transfer learning strategy [24], [25].

Table 1. Result Matrix Formulae

Method	Formula
Sensitivity	$TPR = TP/(TP + FN)$
Specificity	$TNR = TN/(FP + TN)$
Precision	$PPV = TP/(TP + FP)$
Negative predictive value	$NP = TN/(TN + FN)$
False positive rate	$FPR = FP/(FP + TN)$
False discovery rate	$FDR = FP/(FP + TP)$
False negative rate	$FNR = FN/(FN + TP)$
Accuracy	$ACC = (TP + TN)/(P + N)$
F1 score	$F1 = 2TP/(2TP + FP + FN)$

*TP–true positive; TN–true negative; FP–false positive; FN–false negative.

Table 2. Confusion matrix details of hybrid model for both datasets

Method	Performance metrics	Ants/bee's dataset	Potato leaf dataset
ResNet18	Sensitivity	0.94	0.92
	Specificity	0.92	0.92
	Precision	0.92	0.93
	Negative predictive value	0.95	0.92
	False positive rate	0.07	0.07
	False discovery rate	0.08	0.07
	False negative rate	0.05	0.07
	Accuracy	0.935	.925
	F1 score	0.93	0.925
AlexNet	Sensitivity	0.90	0.92
	Specificity	0.90	0.92
	Precision	0.9	0.92
	Negative predictive value	0.91	0.93
	False positive rate	0.099	0.079
	False discovery rate	0.090	0.070
	False negative rate	0.1	0.08
	Accuracy	0.905	0.925
	F1 score	0.90	0.92
VGG16	Sensitivity	0.89	0.90
	Specificity	0.88	0.89
	Precision	0.88	0.89
	Negative predictive value	0.9	0.91
	False positive rate	0.78	0.10
	False discovery rate	0.11	0.091
	False negative rate	0.10	0.11
	Accuracy	0.89	0.90
	F1 score	0.88	0.89
Quantum deep learning	Sensitivity	0.94	0.95
	Specificity	0.94	0.96
	Precision	0.94	0.97
	Negative predictive value	0.95	0.95
	False positive rate	0.059	0.03
	False discovery rate	0.050	0.049
	False negative rate	0.06	0.03
	Accuracy	0.945	0.96
	F1 score	0.944	0.96

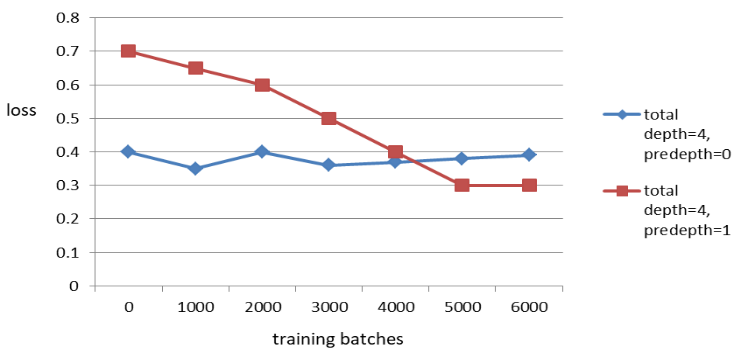

Figure 5. Training with respect to loss function evolution

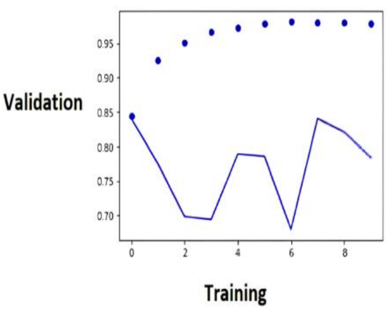

Figure 6. Traning and validation accuracy

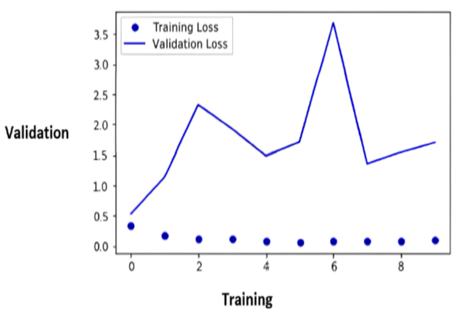

Figure 7. Traning and validation loss

5. CONCLUSION

Researchers started to pay attention to the convergence and implementation of those two disciplines with the accelerated growth of machine learning and quantum computing. Image classification is the key in the pattern recognition. The study of the quantum critical exponents, which describe the action of the order parameters close to the phase transitions, is a natural extension of this work. The theoretical implications could be explored further and algebraic construction of quantum neural networks. The key attribute of quantum models is their exponential acceleration over their classical equivalents. The work is proved by giving two examples of different size of dataset. Considering the accuracy for classical and quantum models it could be confined that the quantum hybrid models are more successful in comparison of classical model. From the experimental and theoretical study, it is inferred that transfer learning is a successful technique which, in the sense of near-term quantum devices, can be a very promising model for classification.

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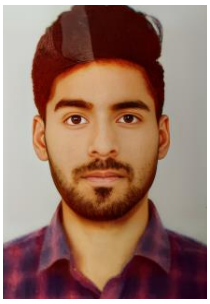

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