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Histopathological Pancreatic Cancer Detection

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Abstract

We demonstrate a successful use of quantum machine learning in the medical domain. This study focuses on a classification issue employing quantum transfer learning for the identification of histopathological pancreatic cancer. numerous transfer learning models, including VGG-16, ResNet18, AlexNet, Inception-v3, and numerous highly expressible variational quantum circuits (VQC), are used in this work model instead of a single one. Consequently, we offer a comparative evaluation of the models, highlighting the top-performing transfer learning model for histopathological cancer diagnosis, which has a prediction AUC of around 0.93. Additionally, we noticed that Classical (HQC) and Hybrid Quantum offered a little higher accuracy (0.885) than classical (0.88) for 1000 photos using Resnet18.

Keywords: *Classical Deep neural networks, Quantum Hybrid machine learning, Convolutional auto-encoders, Classifier, Pancreatic Cancer*

1. Introduction

One of the most feared cancers among patients and medical professionals is pancreatic cancer. Due to local invasion and comorbidities, patients have a low survival rate and a reduced quality of life; for clinicians, it presents difficulties in making an early diagnosis and initiating treatment. Forecasts from the American Cancer Society [1] state that in 2023 there would be 600,000 cancer-related deaths and 1.9 million new instances of the disease in the US. Globally, cancer claims the lives of 19 to 20 million people annually, according to recent research [2]. In these situations, it is crucial to find cancer cells as soon as possible to save lives. In order to diagnose and stage pancreatic cancer, histopathological pancreatic cancer detection is essential. It aids in determining the quantity and existence of malignant cells, which influences the prognosis and choices for therapy. Furthermore, histological investigation might offer important details regarding the aggressiveness of the tumor and its possible reaction to particular treatments. It's critical to remember that histopathology analysis is a challenging and specialized discipline requiring knowledge and training. In order to correctly diagnose patients and analyze tissue samples, pathologists must complete rigorous training.

Applications for artificial intelligence (AI) are numerous, particularly in the medical field [3, 4]. Currently, research has successfully examined and demonstrated the effectiveness of several traditional machine learning techniques, such as advanced deep learning, self-supervised learning, and transfer learning, in the detection of various cancer types, such as breast cancer [5, 6], burns [7], and histopathological cancers [8]. This research offers a hybrid quantum machine learning application for the processing of medical images. It focuses on a classification issue of quantum transfer learning for histopathological cancer diagnosis [9]. Several transfer learning models, including ResNet18 [10], VGG-16 [11], Inception v3 [12], AlexNet [13], and other variational quantum circuits (VQC) [14], are used in this work model instead of a single learning model. In light of this, we provide an effective and new way to create classification models in this era of Noisy Intermediate Scale Quantum (NISQ) systems using hybrid classical and quantum computers [15]. With variational quantum circuits, we hope to achieve similar prediction accuracy and excellent expressibility.

2. Data Set

Machine learning models are fundamentally constructed using datasets. They are essential in training, verifying, and assessing these models' efficacy. This work makes use of a series of digital pathology pictures from the PatchCamelyon (PCam) benchmark dataset. The Camelyon16 data served as the source for this extensive patch-level dataset. The slide-level picture, which is composed of all the patches together, may be used to stage cancer and estimate the chance of metastasis. There are 100,000 photos in the entire data collection. But for this work model, we utilized 10,000 photos. The sample of the dataset is shown in the below.

(a) (b)

Figure 1: Sample Dataset (a) non-cancerous pancreatic image (b) cancerous pancreatic image.

3. Materials and Methods

After the features are extracted from the images using convolution neural networks, the fully connected layer with the softmax function receives the extracted features and classifies the images. Using CUDA for parallelization, the PyTorch framework is used to train the model.

Up to 100,000 data make up the enormous data collection that makes up the input unit. There are three subsets of this input data set: training data, testing data, and validation data.ed except for the letters and words that are originally capitalized. Leave one blank lines after the title.

3.1 Transfer Learning Model

A model that has been trained on one job can be repurposed or modified for a different but related task using the machine learning approach known as transfer learning. For transfer learning, a number of well-liked pre-trained models are accessible in a number of fields, such as speech recognition, computer vision, and natural language processing. In our model we use computer vision. The ImageNet dataset has been used to train pre-trained models for image classification tasks, including as VGG, ResNet, Inception, and EfficientNet. For further vision tasks like object identification, segmentation, or even domain-specific classification, these models can be adjusted or utilized as feature extractors. Our final work model incorporates the optimal transfer learning model among the four options, selected based on its compatibility with the quantum neural network (QNN). Prior to being entered into these transfer learning models, the original picture data is scaled. Images are re-sized by selecting a new pixel size depending on the requirements of the input picture for the chosen transfer learning model. Three layers make up these transfer learning models: a fully connected layer, a convolutional layer and a pooling layer.

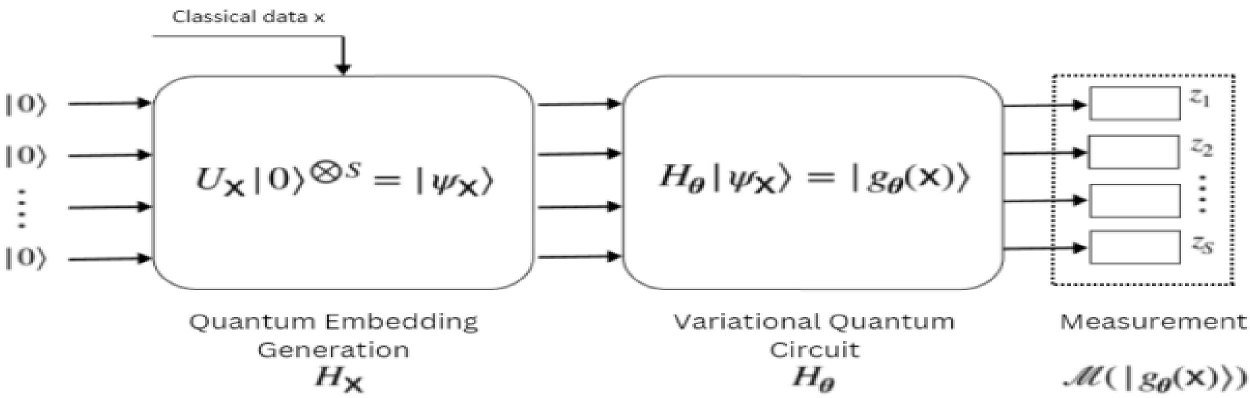

Figure 2: An illustration of QNN based on VQC.

A QNN is used to alter these models' last completely linked layer. Depending on the number of output classes, this QNN is switched between two neuron layers and one output neuron layer. To precisely extract engineered characteristics from pictures, the transfer learning model is used as the first layer in the work model that is being provided. These characteristics may eventually be utilized as an input source for VQC-based QNNs. We are able to adapt our models to the quantum hardware that is now on the market, despite its inability to process large amounts of data at once, thanks to this altered design.

3.2 QNN based on VQC

VQC-based QNN comes before the traditional transfer learning models. This unit consists of repeated VQC layers and input. To construct the QNN, these layers are evaluated for various combinations of two-qubit and single-qubit rotational controlled gates. Several VQCs forward and process the characteristics that are obtained from the traditional CNN. Following feature processing on many VQC, we choose the optimal VQC with the maximum expressibility. Due to its inherent ability to manage errors brought on by quantum hardware, VQCs are utilized for efficient computing on fault-tolerant quantum and NISQ devices. The final stage involves doing the quantum measurements to acquire the QNN's final findings.

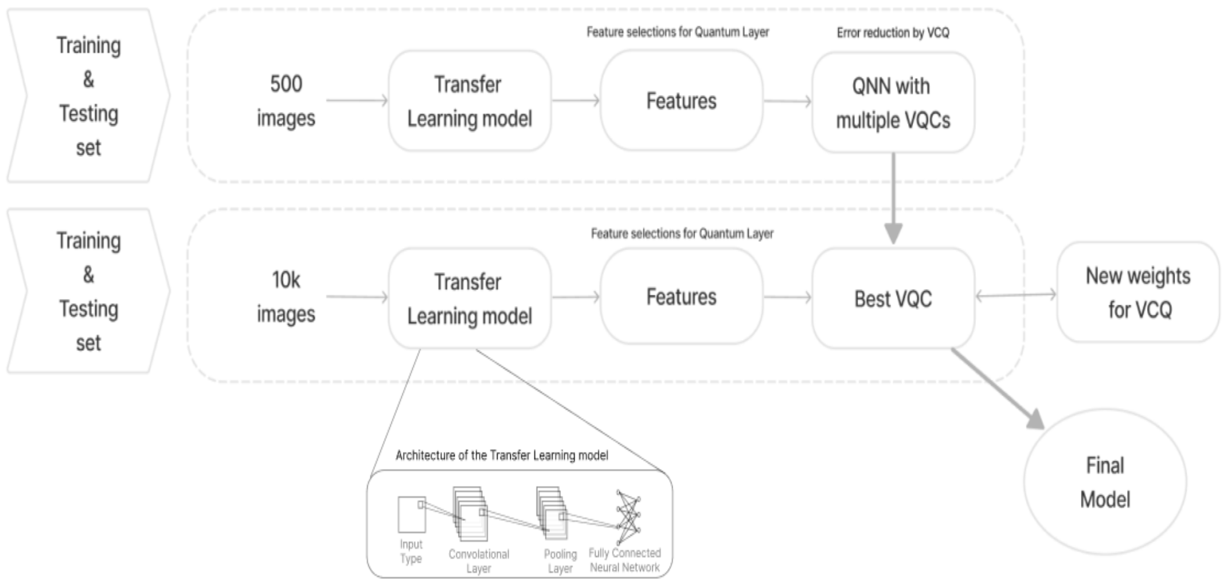

Figure 3: Framework of the model

3.3 Artificial Neural Network

An ANN may be trained to learn and generalize the complex and non-linear properties of the input data. In the architecture that is being given, a fully linked neural network is the final unit. With a softmax activation function, the output of the quantum unit that is a VQC based QNN is mapped onto this unit's final output layer.

The universal approximation theorem establishes that the multi-layer perceptron is a universal function approximator. Regarding the necessary number of neurons, the network architecture, the weights, and the learning parameters, the evidence is not constructive. The softmax activation function is given below.

$$y_i = \frac{e^{x_i}}{\sum_{j=1}^{c} e^{x_j}}$$

This shows how ANNs can analyze and understand complicated visual data in an efficient manner, paving the way for improvements in a variety of industries, from automated surveillance to medical imaging.

3.4 ResNet-18 Model

ResNet offers a novel "skip connections" solution to the vanishing gradient issue. Multiple identity mappings, or inactive convolutional layers, are stacked by ResNet, which then bypasses those levels and repurposes the activations from the preceding layer. By condensing the network into fewer layers, skipping accelerates the initial training process. An essential component of the ResNet design are residual blocks. Convolutional layers are layered with batch normalization and nonlinear activation layers, like ReLu, in earlier systems like VGG16. This technique only requires a modest number of convolutional layers; for VGG models, the maximum is about 19. Later studies, however, found that CNN performance could be greatly enhanced by adding more layers. The phrase output = F(x) + x, where x is an input for residual block and an output from the preceding layer, and F(x) is a component of a CNN made up of several convolutional blocks, may be used to describe this in Python code. To prevent from loss of gradient, Residual Network uses skip connection in the layers to allow some input data to the layer to incorporate flow of information. By this method it also helps in suppressing noise to balance generalization and precision.

The accuracy of ResNet on a large training dataset:

$$H(x) = F(x) + x$$

Where,

x is the input of building block,

F(x) is the output of the layer within the building block of the ResNet.

4. Result

The outcomes of the numerous tests conducted on hybrid quantum computing and traditional computing are displayed in TABLE I.

The several hybrid and classical models that are employed in this framework are shown in Column I. Column II displays the number of photos utilized in each model. The accuracy percentage attained by each transfer learning model is shown in Column III. We determined which VQC was optimal by evaluating each model's performance for a range of VQC. Column V shows that VQC was applied. Columns VI and VII display the expressibility[11] and qubit count for VQC in column V, respectively.

Table 1: Model performance and metric parameters

model	**images**	**acc**	**auc**	**vqc**	**exp**	**qbits**
Classical CNN	5000	76.10	0.82	N/A	N/A	N/A
Classical CNN2	10000	79.10	0.88	N/A	N/A	N/A
Classical ResNet18	1000	88.00	0.95	N/A	N/A	N/A
Hybrid CNN	10000	59.85	0.96	6	0.011	4
Hybrid Res Net 18	10000	88.50	N/A	1	1.431	4
Hybrid VGG 16	1000	55.00	0.73	2	1.078	5
Hybrid Inception v3	5000	79.50	N/A	3	1.007	5
Hybrid Alex Net	1000	63.01	0.67	4	0.201	7
HQC Res Net 18	10000	84.30	0.90	6	0.011	4

A total of twelve distinct major models were examined. We selected four models for classical transfer learning based on the quantum transfer learning algorithm described in, which has different data sizes[9]. We assessed eight models with various quantum circuits for the hybrid classical and quantum computing models based on VQC, the quantity of qubits[12] in the quantum transfer learning algorithm.

The figure 4 displays the reliability curve produced for a total of 1000 pictures using Classical ResNet18 (solid red) and Hybrid CQ ResNet18 (solid blue). Model reliability curves shed light on the calibration process of the model. Model calibration is necessary in the case of binary classification to ensure that the model outputs are neither over- or under-estimating. A completely calibrated model is depicted in Fig. 4 by the central dotted line.

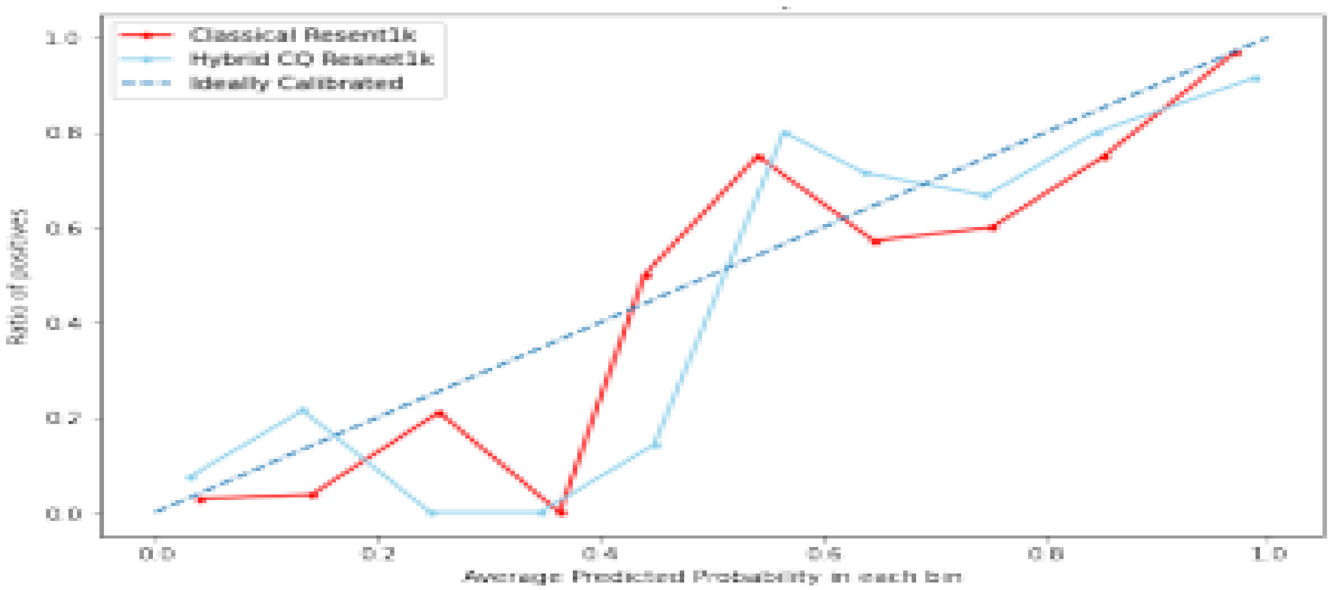

Figure 4: Reliability curve produced for a total of 1000 pictures using Classical ResNet18 (solid red) and Hybrid CQ ResNet18 (solid blue). The blue line with dots represents the optimal dependability curve for the comparison.

The False Positive Rate (FPR) vs. True Positive Rate (TPR) at various categorization levels are displayed as ROC curves in Figure 5. It demonstrates the model's capacity to discern between positive and negative classes.

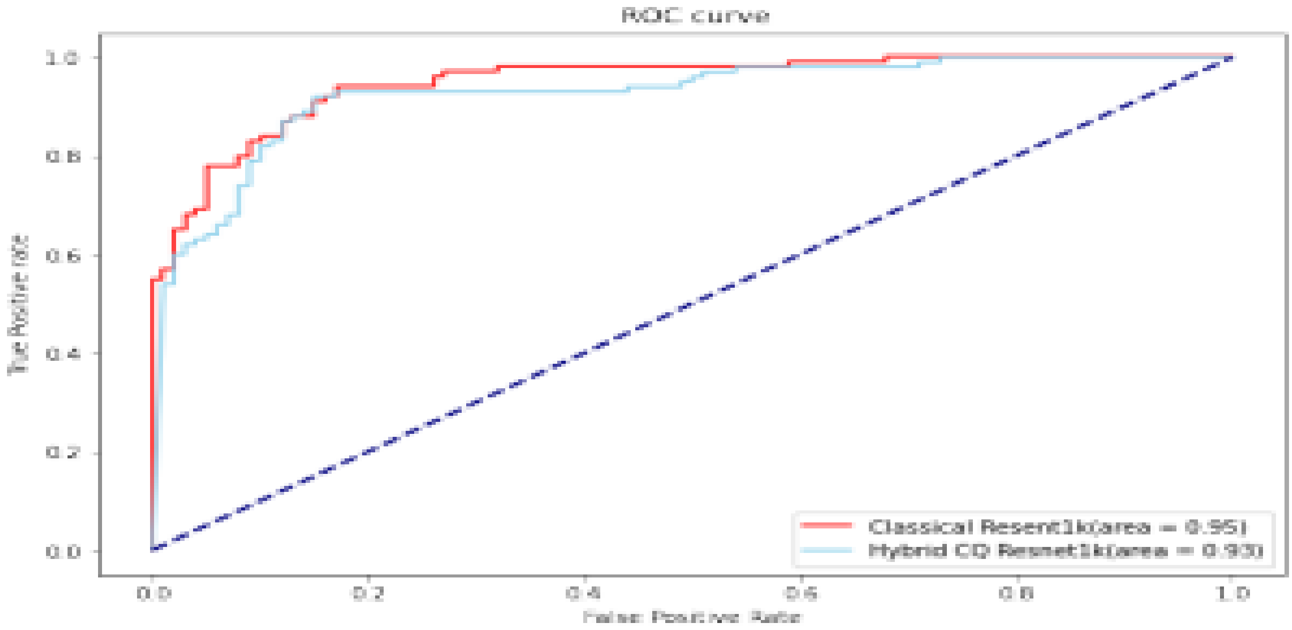

Figure 5: ROC curve produced by the hybrid CQ ResNet18 (solid blue) and classical ResNet18 (solid red). The comparison's dotted purple line represents the optimal ROC curve.

A larger area under the ROC shows that more positive classes are classified as positive by the model, and more negative classes as negative [21]. The middle-dashed line indicates that a model is unable to discriminate between positive and negative classes.

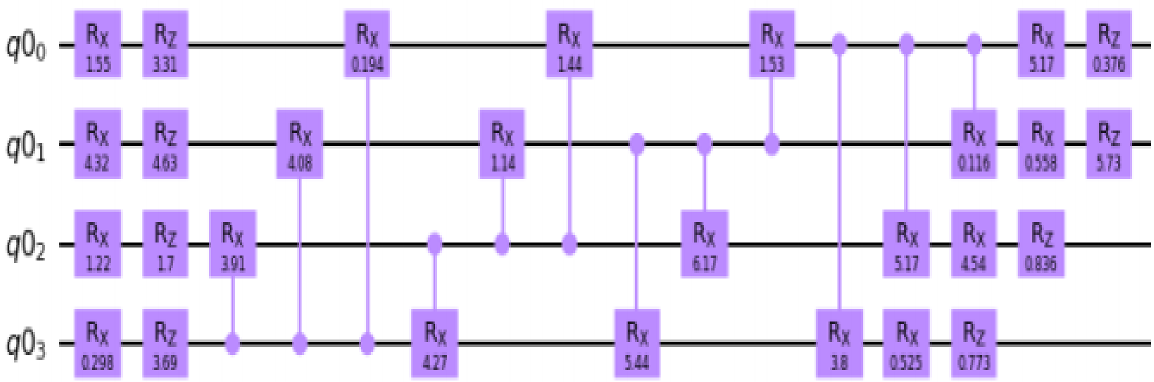

Figure 6: Using rotating quantum gates and four quantum registers (q00, q01, q02, and q03), VQC is employed in the model that has the highest expressibility.

5. Conclusion and future work

As part of our present study, we have evaluated several variational quantum circuit combinations using our selected transfer learning models (ResNet-18, VGG-16, Inception-V3, and AlexNet). The performance accuracy of the ResNet-18-based transfer learning model in the VQC circuit depicted in Figure 4 is 85%, which is equivalent to the 90% performance of the traditional ResNet-18 model with a similar architecture. This is an initial investigation into the potential advantages of using variational quantum circuits for quantum machine-learning problems related to medical image processing.

As of right now, Pennylane's quantum simulators have been utilized. The PennyLane-Cirq plugin combines the quantum machine learning capabilities of PennyLane with the Cirq quantum computing platform. A cross-platform Python package called PennyLane is used for hybrid quantum-classical computing optimization, automated differentiation, and quantum machine learning. We want to test our trained quantum circuit on real quantum hardware as a following step. Additionally, we want to assess how resilient these models are to different cyberattacks, including adversarial assaults. The advantages of the quantum system in computing, the ability of quantum entanglement to reveal a range of counterintuitive patterns, and the benefits of VQCs in the already existing Noisy intermediate-scale quantum (NISQ) system all contributed to the conception of the unique notion given here. We firmly think that this framework can provide trustworthy machine-learning models for assessing medical pictures, and that as quantum technology advances alongside classical computers, so too will the performance of these models.

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