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Hybrid quantum computing based early detection of skin cancer

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Abstract

As image processing techniques constantly grow in complexity & volume, meeting the required demand for data storage and computational power is a challenge. Using hybrid quantum-mechanical systems to encode and process image information could help overcome such challenges. We propose to implement a hybrid quantum mechanical system with 2 qubits operation for the purpose of classifying between cancerous and non-cancerous pigmented skin-lesions in the HAM10000 dataset. In view of the ever-increasing number of

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skin cancer deaths, such a system could have potential for the early diagnosis of the disease. Until fully scalable quantum hardware becomes available, the hybrid model could be a viable alternative to overcome the limitations of classical computing systems.

Subject Classification: *68U99*

Keywords: *Skin Cancer, Cancer Detection, PennyLane, Quantum Image Processing, Hybrid Quantum*

1. Introduction

In the age of Artificial Intelligence (AI), the analysis of visual information has become a reality that enables machines to process the information contained in images resulting in rapidly expanding applications in widely differing fields such as Surveillance, Transportation and Healthcare (Diagnostics). In particular, the increasing volume of image data as well as increasingly challenging computational tasks have become important driving forces for further need of efficiency in image processing and analysis.

One of the major healthcare applications of AI is cancer diagnostics. In our paper, we focus on the classification of skin cancer. According to the WHO [1], the incidence of skin cancer has been increasing over the past decades with around 2 to 3 million cases of non-melanoma skin cancer and 132,000 cases of melanoma skin cancer occurring globally each year [2, 3]. The most salient feature of skin cancer is that there are very distinct visual markers, which means one can identify if a person has skin cancer or not from a visual examination of the affected area. There have been several successful efforts to generate high quality data and design algorithms that can classify between different types of cancerous and non-cancerous skin lesions using Machine Learning. Deep Learning algorithms such as the Convolutional Neural Network (CNN) have been particularly successful in classification of lesions in a supervised fashion [4]. They have outperformed human experts and are the current state-of-the-art; however one of the problems faced by deep learning algorithms requirement for large amounts of processing power and storage to handle ever increasing computational complexity.

A Quantum Computer takes advantage of properties such as superposition and entanglement to solve certain problems faster and more efficiently than classical computers. The Shor algorithm [5] is one of the best examples of the above statement. If used in the quantum domain, it is powerful enough to break current encryption systems. The nature of a quantum computer is mostly linear, probabilistic and reversible. Hence, algorithms that operate in the quantum domain are designed differently than classical computing algorithms. Image classification problems can be roughly defined as optimization problems where a cost function is minimized in order to learn a representation of a certain image. Poonia et al. [6] discusses strategies on how to map classical bits to quantum bits using software simulation and hardware chips.

There have been a handful of quantum image processing and classification models that have been proposed recently. The various use cases are of quantum machine learning are discussed in Schuld et al. [7]. Some of the most popular quantum image models are the Quantum Fourier Transform [8] and the Quantum Wavelet Transforms [9]. Peter Wittek [10] in his paper gives an extensive overview of different quantum process techniques such as quantum circuits and adiabatic quantum computing. Killoran et al. [11] propose continuous variable quantum neural network architecture and its application in fraud detection. Nguyen et al. [12] and Farhi et al. [13] have proposed quantum classifiers using the adiabatic computing and quantum neural networks respectively. Dendukuri et al [14] surveyed multiple quantum image processing models such as FRQI (Flexible representation of Quantum Images) which stores information in the form of quantum amplitudes [15] and NEQR (Novel Enhanced Quantum Representation) [16] which are used to store images as quantum information.

2. Quantum Machine Learning & Hybrid Computing

A quantum circuit is a quantum counterpart to a classical circuit. Instead of the logic gates we use to build classical circuits, quantum circuits used specialized gates called quantum gates. All such gates are unitary i.e. they are reversible. As it is hard to calculate quantum gradients and perform non-linear optimization procedures, there are no scalable implementations of quantum machine learning algorithms.

Hybrid models use both classical and quantum computing procedures in order to make training easier and more feasible in the current scenario. A hybrid model uses a quantum circuit for classification. Once it receives an expectation value (prediction), it uses a 'classical optimization technique' such as gradient descent to optimize the parameter space similar to a simple feedforward neural network. The model used in this project is based on the 'Variational Classifier model' mentioned in Schuld and

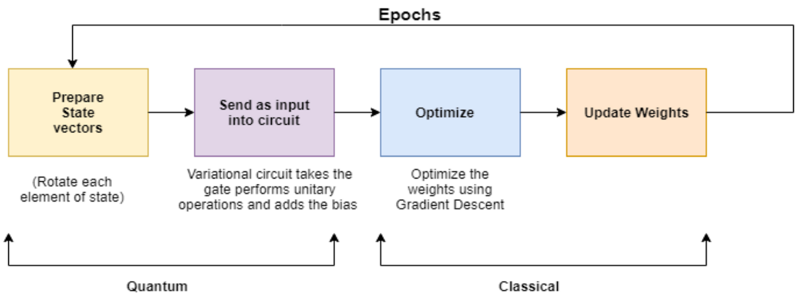

Figure 1

Hybrid Model Training

Petruccione [17]. An illustration of the working of a Variational classifier is shown in Figure 1.

The Variational classifier can be described mathematically using the equation (1). The task of the variational classifier is to interpret the output in the form of an expectation value of an observable O, given the input data x. θ Refers to the parameters that need to be optimized. $f(x; \underline{\theta})$ Represents the variational classifier, $\psi(x; \theta)$ is a mathematical representation of the quantum variational circuit.

$$f(x;\theta) = \left\langle \psi(x;\theta) \middle| O \middle| \psi(x;\theta) \right\rangle \tag{1}$$

The variational circuits are quantum circuits with tunable parameters. It consists of layers and in each layer the input goes through a set of operations. In this case they are unitary operations performed using quantum gates. An illustration of how the variational circuit works is given in Figure 2.

The 'state preparation routine' where the vector is converted into quantum amplitudes, is implemented as mentioned by Möttönen, et al. [18]. We modified the implementation of the Variational Classifier model using the Pennylane framework introduced by Bergholm et al. [19].

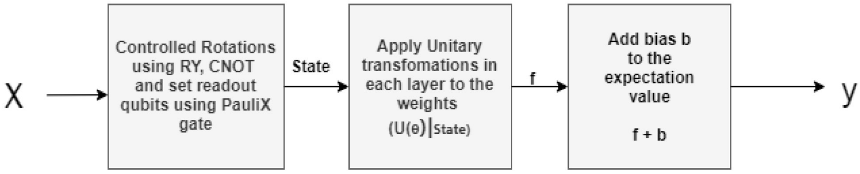

Figure 2

Variational Classifier

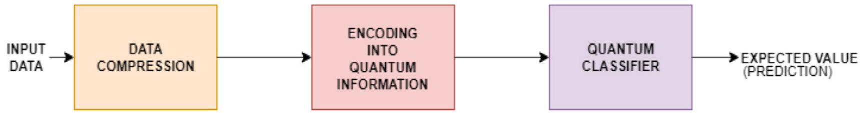

Figure 3

Procedure

3. Setup and Implementation

This section talks about the procedure we used to classify high-resolution biomedical images. These images have a size of 128x128 and 3 (RGB) channels. They cannot be used as input directly due to their high-dimensionality. Hence we use traditional deep learning algorithm known as an Autoencoder in order to perform dimensionality reduction. A rough overview of the procedure is below in Figure 3.

The data used for this project is from the ISIC archive skin lesions dataset [20, 21]. This dataset consists of 10000 dermatoscopic images containing some of the most common pigmented skin lesions including basal cell carcinoma, dermatofibroma, melanoma among others. For our task we used images belonging to two classes from the dataset namely melanoma (mel) and melanocytic nevi (nv). Melanocytic nevi are generally non-cancerous skin pigmentations commonly referred to as birthmarks or moles. The average number of images available per class between 750-1000 with the exception of melanocytic nevi. Hence, to avoid class imbalance we extracted images from both classes in a 1:1 ratio. Sample images from the dataset are shown in Figure 4.

Out of the 1000 images per class, 750 images have been used as training data and remaining 250 as validation data. Each image was resized to 128x128x3, as this dimensionality found to be producing the least amount of training noise in the Autoencoder. Since these images are

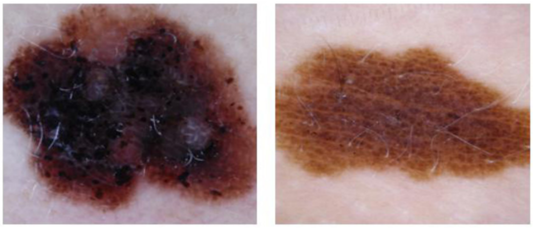

Figure 4

Melanoma & Melanocytic Nevi

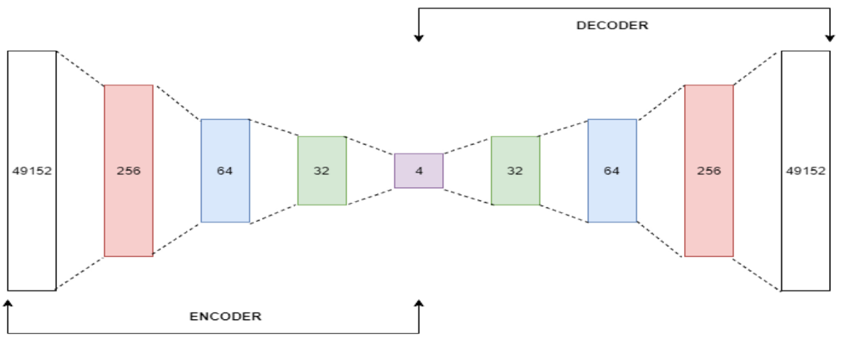

Figure 5

Autoencoder

too big to be fit into the quantum circuit, they need to be encoded into a lower-dimensional space. This is a part of the data compression step, where an autoencoder has been used to achieve this and is illustrated in Figure 5.

The encoder downscales the images to a certain number of dimensions. The decoder then tries to reconstruct the encoded images. As the Autoencoder trains the dataset, the encoder learns to extract the most useful information from the data, whereas the decoder learns to reconstruct realistic images. This architecture is useful for reducing dimensionality of images. The Autoencoder has been coded in PyTorch, a popular deep learning framework to encode images. The images were downscaled from 128x128x3 into a vector of 4 components. These vectors were then encoded into quantum amplitudes and then sent into the quantum circuit as input data.

5. Results and Discussion

The classification model used the '2-qubit simulator' provided by pennylane as quantum backend. The 'Adam optimizer' was used with a learning rate of 0.005. The model was trained for 60 epochs with a batch size of 32, weights and biases sampled at random from a normal distribution. The average training accuracy of the model is around 52% and the validation accuracy reaches a maximum of 60%. The cost function used was a simple square loss function, which exhibits converging behaviour. The model was trained on a 16GB RAM CPU system. Illustrations of the loss function, training and validation accuracy are given in Figure 6, 7 and 8.

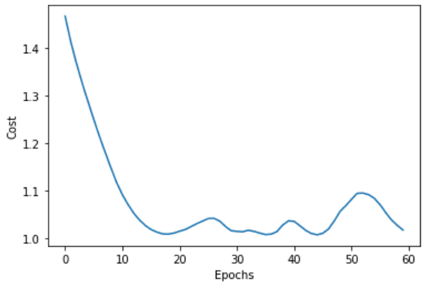

Figure 6

Converging Loss

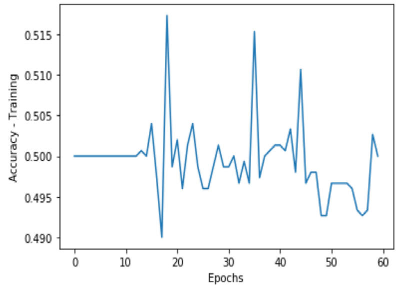

Figure 7

Average Training Accuracy

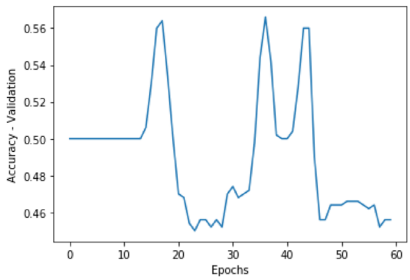

Figure 8

Average Validation Accuracy

6. Conclusion

In this paper, we implemented a '2-qubit hybrid quantum model' for classifying images. However, the nature of the work is exploratory and in order to make such application, deployable needs some enhancements. The image needs to maintain its spatial configuration, unlike other numerical datasets. We can possibly achieve more accuracy with better quantum compression techniques, simulating more qubits or designing a quantum convolutional network capable of dealing with such image data. We are also currently working on implementing multiclass classification problem, that deals with larger datasets and design a pipeline for quantum image classification which can be used to solve real-world problems efficiently.

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