GR-288

Comparative Performance Analysis of Hybrid Quantum Machine Learning Algorithm to Assess Post Stroke Rehabilitation Exercises

Abstract

Due to the advancements in technology, data is growing exponentially. With this increased dataset size, the computation to process the generated information is rising sequentially. And the currently available classical computational tools and learning algorithms will not work due to the limitations of Moore's law. To overcome the computational issues, we have to switch to Quantum Computing which works based on the laws of Quantum Mechanics. Quantum Machine Learning (QML), a subset of Quantum Computing, is faster and more capable of doing complex calculations that a classical computer can not. Classical Computers work on bits - 0 or 1, whereas a Quantum Bit (also known as a qubit) works on the superposition principle and can be 0 and 1 at the same time before it is measured. Other properties known as Quantum Entanglement, Quantum Parallelism, etc., also will help in understanding the other qubit state and parallel processing the data. In this paper, we introduce hybrid quantum and convolutional models built using PennyLane on the UI-PRMD dataset for the Kinect sensor. By involving quantum layers in a traditional network, a better performance can be achieved compared with the traditional neural network performance.

Introduction

Therapeutic exercises will be suggested after surgeries and accidents to the patients to correct impairments and restore muscular and skeleton function. Patients can use motion capture systems such as Vicon and Kinect to reduce their dependency on their dearest ones. These sensors can calculate the joint angles, which can help the patients in evaluating the referred exercises. Though these sensors are accurate and inexpensive, they need more versatility, and there is a scope for research to improve the scores of every individual movement model exercise.

Quantum Computing, which will be the next future of computing, has the capacity to identify and learn complex patterns from given data. Superposition of states, Entanglement, and other techniques help Quantum Machines to build a larger and more complex model faster than the traditional computing models. In this project, we propose various simple quantum machine learning models built using PennyLane, which works similarly and better than the existing conventional deep learning models.

Research Question(s)

- How Quantum Machine Learning reacts to Time Series data?
- How is Quantum Machine Learning performing compared to traditional Machine Learning?

Materials and Methods

UI-PRMD dataset contains the data of 10 movements data that were generated using both the Kinect V2 and Vicon Sensors. A total of 10 individuals have performed the correct and incorrect ten movements in front of the sensors. The ten exercises that are covered in the UI-PRMD are deep squat, hurdle step, inline lunge, side lunge, sit to stand, standing active straight leg raise, standing shoulder abduction, standing shoulder extension, standing shoulder internal, external rotation, and standing shoulder scaption. Vicon has 39 joints, and Kinect has 22 joints for exercise movements.

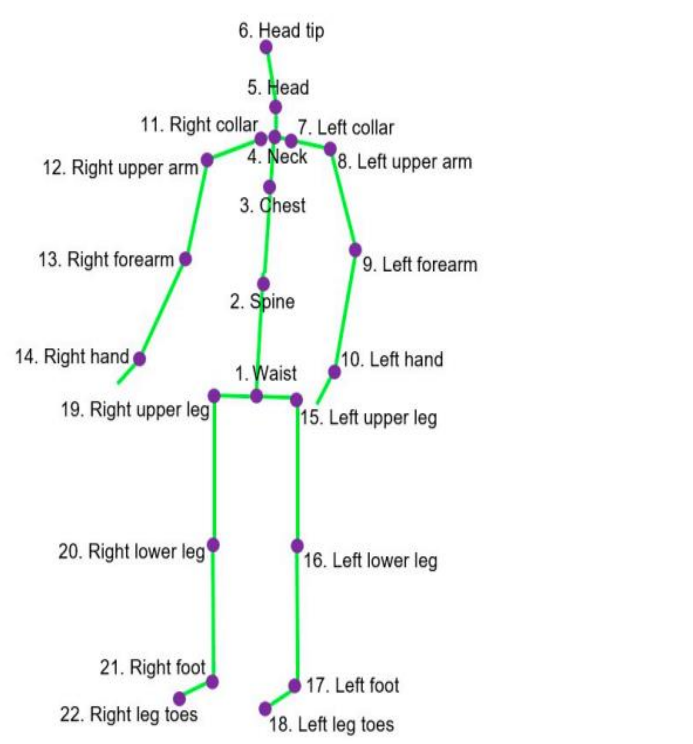

Fig.1 Joints in the skeletal model of Kinect-recorded data

Using PennyLane and TensorFlow, we have designed the 2-qubit hybrid Quantum Machine Learning models. We've built a total of 3 models using 2 different quantum devices.

Our list of models are:

- Hybrid Sequential Model
- Hybrid Non-Sequential Model
- 2-bit Quantum Convolutional Hybrid Model (Q-CNN)

Sequential and Non-Sequential Models:

For creating any Quantum Neural Network, a QNode designed with various parameters is used to communicate with the Keras layers in the network. To construct the QNode for our Sequential and Non-Sequential models, we have used the "default.qubit" simulator and layers such as AngleEmbedding and BasicEntaglerLayers. Angle embedding encodes the features (N) using the specified rotation operation of n qubits, where N ≤ n. BasicEntaglerLayers will perform single-qubit rotation on each qubit and uses CNOT gates to connect the qubit with its neighbor.

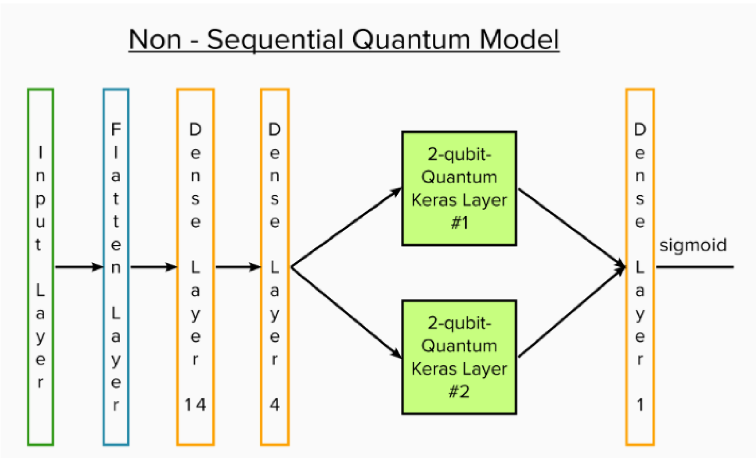

Fig.2 Non-Sequential Model

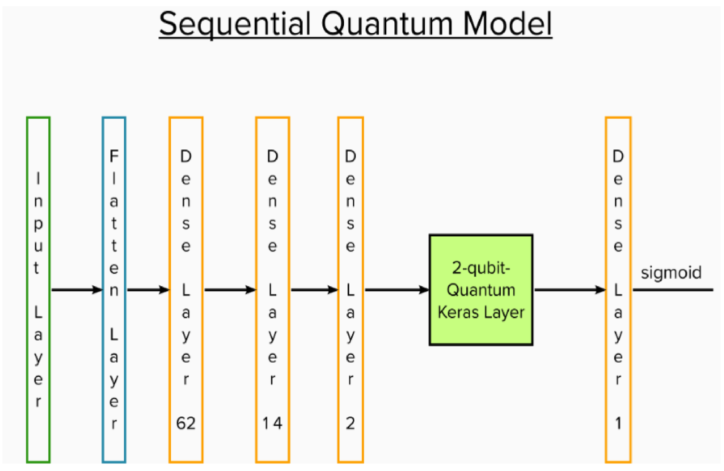

Fig.3 Sequential Model

Quantum-Convolutional NN (Q-CNN):

A general Convolutional NN has multiple Convolutional Layers combined with Pooling Layers followed by fully connected layers and activation functions. Mathematically, this can be represented as L(x)=φ(Wx+b), where W ∈ Rm×n is a matrix, b∈Rm is a vector, and φ is a nonlinear function (also known as the activation function). We bring this traditional convolutional neural network into a quantum realm using the Continuous Variable (CV) architecture. We used the Strawberry Fields Flock library, which supports all continuous-variable (CV) operations and observables, including Gaussian and non-Gaussian operations.

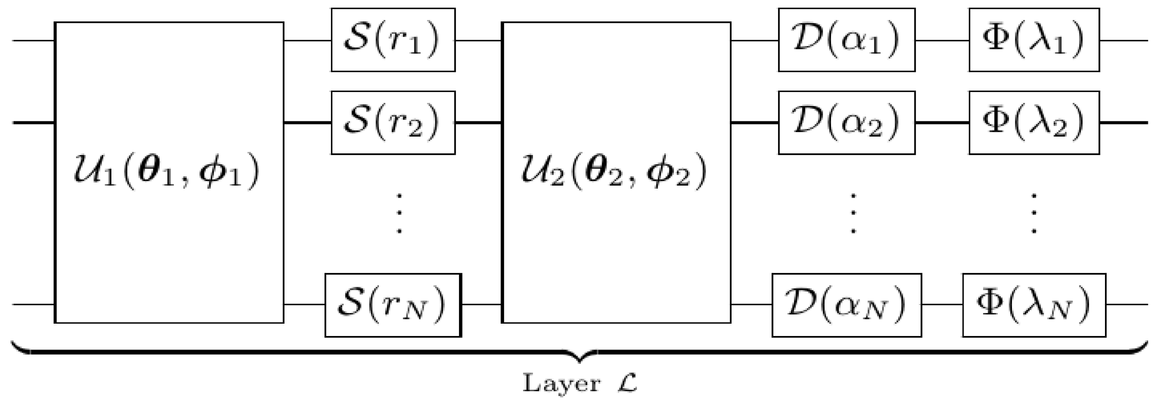

Fig.4 Continuous Variable Architecture

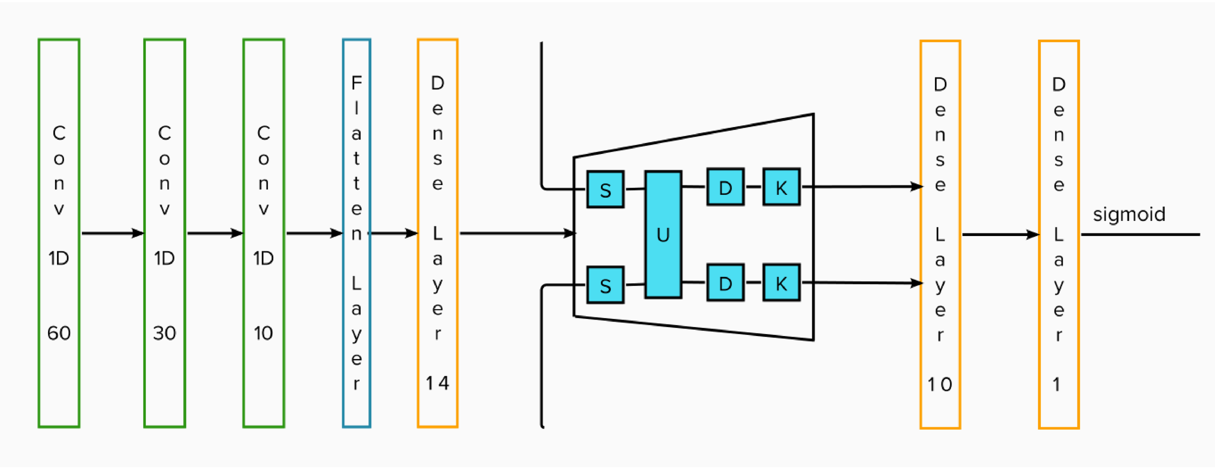

Fig.5 2-qubit Quantum Convolutional NN

Results

To evaluate our model, we have calculated the Mean Absolute Deviation (MAD) scores of every movement. Our experiment shows that with the use of a simple hybrid quantum neural network, we can achieve the nearest performance of a complex network.

Quantum vs Traditional:

Movement #	2-bit Q-CNN	Sequential	Non-Sequential	Simple CNN - Author's Code	Spatio Temporal – Author's	Difference (Min Model – QCNN)
m01	0.045752379	0.055823443	0.042140216	0.121071536	**0.035003428**	0.01074895
m02	0.005345709	0.045327298	0.018167625	0.008027657	**0.004275854**	0.00106986
m03	0.012509944	0.020710756	0.01456681	0.013969985	**0.008640952**	0.00386899
m04	0.010740411	0.014790532	0.023069624	0.018876064	**0.009701565**	0.00103885
m05	0.022011064	0.033181933	0.021832711	0.045177572	**0.017011522**	0.00499954
m06	0.010007636	0.022561662	0.032152194	0.012825705	**0.007907281**	0.00210036
m07	0.02353986	**0.019346541**	0.021208186	0.036551722	0.020459395	N/A – Quantum is minimum
m08	0.010464189	0.051006839	0.034358629	0.013694164	**0.008275765**	0.00218842
m09	**0.013665695**	0.030806917	0.021377844	0.029906616	0.014819997	N/A – Quantum is minimum
m10	0.023603624	0.030430689	0.020693744	0.027815605	**0.015934979**	0.00766864

Individual Quantum Results:

Movement #	2-bit Q-CNN	Sequential	Non-Sequential	Conclusion
m01	0.045752379	0.055823443	**0.042140216**	Non-Sequential
m02	**0.005345709**	0.045327298	0.018167625	2-bit Q-CNN
m03	**0.012509944**	0.020710756	0.01456681	2-bit Q-CNN
m04	**0.010740411**	0.014790532	0.023069624	2-bit Q-CNN
m05	0.022011064	0.033181933	**0.021832711**	Non-Sequential
m06	**0.010007636**	0.022561662	0.032152194	2-bit Q-CNN
m07	0.02353986	**0.019346541**	0.021208186	sSequential
m08	**0.010464189**	0.051006839	0.034358629	2-bit Q-CNN
m09	**0.013665695**	0.030806917	0.021377844	2-bit Q-CNN
m10	0.023603624	0.030430689	**0.020693744**	Non-Sequential

Out of all the quantum models, 2-bit Q-CNN works better for most of the models. For the models where the non-sequential network is working better than the 2-bit Q-CNN, the error difference is significantly less and can be neglected.

Conclusions

Our project concludes that quantum models will benefit us with better performance and prediction. Because of the quantum properties such as entanglement, parallelism, etc., one can achieve the complex traditional neural network performance with a simple quantum layer and conventional neural networks. One can even outperform traditional neural networks' performance by designing complex quantum layers.

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References

[1] Y. Liao, A. Vakanski, and M. Xian, "A deep learning framework for assessing physical rehabilitation exercises," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 2, pp. 468–477, Feb. 2020.

[2] S. Deb, M. F. Islam, S. Rahman and S. Rahman, "Graph Convolutional Networks for Assessment of Physical Rehabilitation Exercises," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 30, pp. 410-419, 2022

[3] T. Hamaguchi et al., "Support vector machine-based classifier for the assessment of finger movement of stroke patients undergoing rehabilitation," J. Med. Biol. Eng., vol. 40, no. 1, pp. 91–100, Feb. 2020.

[4] Y.-J. Choi, Y.-W. Lee, and B.-G. Kim, "Residual-based graph convolutional network for emotion recognition in conversation for smart Internet of Things," Big Data, vol. 9, no. 4, pp. 279–288, Aug. 2021.

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