Quantum Neural Network model for Token allocation for Course Bidding

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***Abstract*— Quantum computer has shown the advantage over the classical computer to solve some problems using the laws of quantum mechanics. With a combination of knowledge of machine learning and quantum computing, Quantum neural networks adapted the concept from classical neural networks and apply parameterized quantum gates as neural network weights. In this paper, we present an application of quantum neural networks with real-world data to predict token price used in a course bidding system. The experiments were carried out on the Qiskit quantum simulator. The result shows that quantum neural networks can achieve a good prediction result compared to the classical neural network. The best model configuration has the lowest RMSE 6.38%. This approach opens an opportunity to explore the benefit of quantum machine learning in many research fields in the future.**

Keywords—Quantum Computing, Quantum Neural Network, Neural Networks, Course Bidding, Bid allocation

I. INTRODUCTION

Machine learning and Quantum computing are two research areas that have attracted considerable attention in recent years and have evolved into a new field known as Quantum machine learning [1]. Many research papers include [2, 3, 4, 5, 6] show the potential advantages such as speed up in training a model and in [7] has shown the power of using quantum neural networks to train machine learning model. One promising way to implement Quantum algorithms in the Noisy Intermediate Scale Quantum (NISQ) [8, 9] is using a technique call variational quantum circuits or trainable quantum circuits as a machine learning model [10, 11, 12, 13, 14].

Quantum Neural Networks take advantage of a quantum computer using quantum mechanics such as superposition, entanglement, on quantum bits to perform the calculation [15]. The motivation behind this research is to present the application of Quantum Neural networks with real-world data and practical challenges that are yet to be solved by using the new method on near-term quantum devices.

In this paper, we propose a quantum computing method to predict the token price to suggest and provide information to users in a course bidding system.

II. QUANTUM NEURAL NETWORK

A Quantum neural network is an algorithm designed for execution on a NISQ device by combining quantum computers with classical computers. It is a subclass of variational quantum algorithms using trainable quantum circuits as a machine learning model. Quantum computers will be used as hardware accelerators co-working with a classical computer.

A. Variational quantum algorithms (VQAs)

In the NISQ era, VQAs are algorithms that allow near-term quantum advantage, comprised of an iterative quantum-classical optimization loop between a classical computer and a quantum computer. In each iteration the classical computer sends the set of quantum logic gate parameters θ to the quantum circuit then the circuit was executed on the quantum device. The estimated expectation value is sent back to the classical computer where the classical optimizer is running and suggests a new set of parameters for the subsequent iteration to minimized or maximized the cost function. The well-known algorithm using the concept of variational quantum algorithms is Quantum Approximate Optimization Algorithm (QAOA) [16, 17].

B. Quantum neural network model

QNN is inspired by a classical neural network that tries to mimic the structure of a classical neural network and use the parameterized quantum gates as the weights within a neural network. The training data are encoded into a quantum state via the feature map circuit. The number of qubits used depends on the training data attributes, one attribute per qubit. The feedforward and hidden layer are in the form of the variational quantum circuit. The backpropagation part measures all qubit output and calculates through loss function minimization. The goal is to optimize over a parameterized circuit, then set optimized parameters back to the variational quantum circuit.

III. TOKEN ALLOCATION FOR COURSE BIDDING

In paper [18] presents previous work about the Machine learning model used to predict the token price for allocation to course through a course bidding system. Three machine learning models are compared: Decision Tree, Random Forest, and Artificial Neuron Network (ANN) . The dataset is from a course bidding system and was pre-processed into eight input variables with the highest correlation score and one output variable. ANN is the best performing method to predict token price, with two hidden layers and one output layer, in each hidden layer has eight neurons fully connected.

The result of the experiment shows that ANN is the best method with the lowest RMSE 3.98% over Decision Tree with RMSE 4.18% and Random Forest with RMSE 4.13%. This result inspired us to implement ANN in a new proposed quantum machine learning method to demonstrate the ability to use QNN with the real-world data set.

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IV. METHOD

In this paper, we focus on implementing the QNN model by using a quantum simulator from Qiskit [19]. The quantum computer is very difficult to simulate classically and the resource required to grow exponentially with the number of qubits or the depth of the circuit. From this limitation, we limit the number of the qubit to only four qubits. This means the input for this model needs to be select from the most important by highest correlation score, four attributes shown in Table 1 were selected and data point was filtered by course interesting in which values more than two are used.

TABLE I. INPUT AND OUTPUT VARIABLE

input	output
course interesting all_mean enrolled_min enrolled_mean	Token price

A. Data Encoding

The first step is to translate classical data into the quantum state. We use a Second-order Pauli-Z evolution circuit (ZZFeatureMap) developed in [20] with four qubits and two repeated circuits. Hadamard gate applies on each qubit, followed by a layer of RZ-gates used to encode data and CNOT-gates on every pair of a qubit. With full entanglement, each qubit is entangled with all the others. The output of the feature map circuit is quantum state and will be used as input of the quantum neural network. ZZFeatureMap circuit is shown in Fig. 1

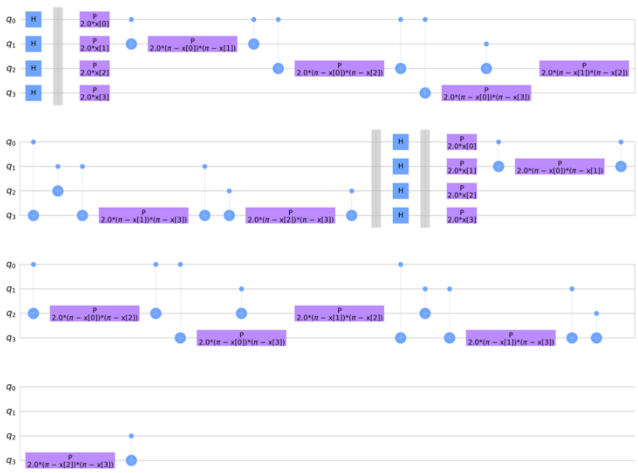

Fig. 1. Second-order Pauli-Z evolution circuit (ZZFeatureMap) with two repeated circuits, Hadamard gate applies on each qubit, followed by a layer of RZ-gates and CNOT-gates on every pair of a qubit.

B. QNN Model

For QNN, we used RealAmplitudes variational circuit shown in Fig 2, The circuit consists of 4 qubits with Full entanglement. The layer of parameterized RY-gates is applied to each qubit and used as neural network weights. Increasing the depth of the variational circuit means we have more trainable parameters in the model. The number of weight or trainable parameters can be calculated as $d = (D+1)S$, where S is an input size or the number of qubits and D is the depth of the circuit (the number of the repeated circuit).

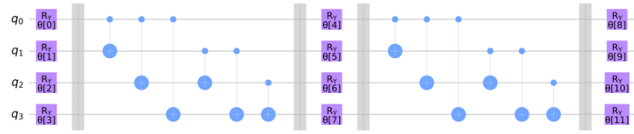

Fig. 2. RealAmplitudes circuit with two repeated circuits, Layer of RY-gates followed by CNOT-gates is applied on every pair of a qubit. The circuit has a total of 12 trainable parameters.

C. Model Training

In this paper, we experiment on the number of repeated circuits to find the best model structure. We trained the model for 500 iterations on circuit depth range from 2-5, ADAM [21] optimizer with learning rate 0.001 and 100 iterations on circuit depth range from 4-7. ADAM optimizer with learning rate 0.1 is used to shorten the training time. Both use the same MSE loss function. The overview of the training process is shown in Fig. 3 and the training loss values are plot in Fig.4-5

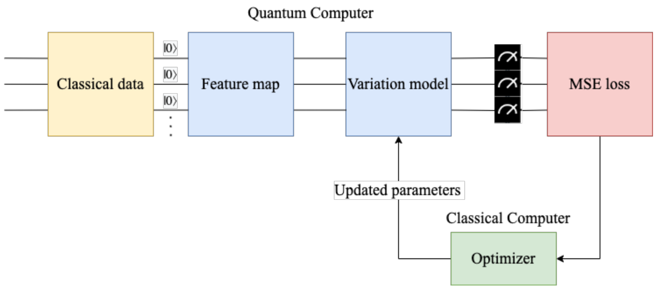

Fig. 3. Overview of the quantum neural network training process. Feature map and Variation model are executed on quantum computer and optimization is on a classical computer.

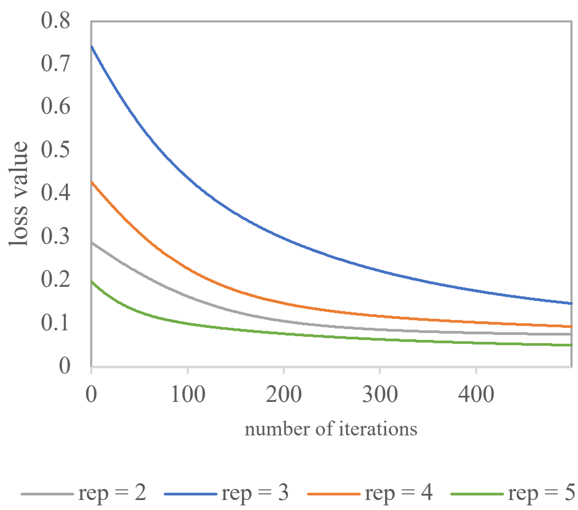

Fig. 4. ADAM optimizer with learning rate 0.001, Mean squared error loss as a function of training. The number of repeated circuit range from 2-5. We find that five repeated circuits have the lowest loss value.

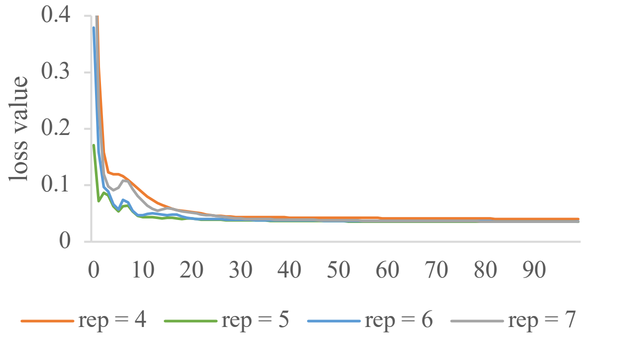

Fig. 5. ADAM optimizer with learning rate 0.1, Mean squared error loss as a function of training. The number of repeated circuit range from 4-7. We find that five repeated circuits still have the lowest loss value.

V. Result

The result of the QNN model prediction is shown in Table 2. We measure model performance by using RMSE on the testing data. Testing data was selected randomly for 30% of the samples.

Increasing the number of repeated circuits from 2-5, the model can perform better and RMSE values are decreasing dramatically. Increasing the number of repeated circuits to more than five, the model seems to be overfitting. RMSE values from testing data of repeated circuits 6-7 are very close to 5.

The best model configuration is five repeated circuits with 24 trainable gates, with a learning rate of 0.001 has the lowest RMSE at 7.8%, learning rate of 0.1 has RMSE at 6.38%. RMSE values from 500 iterations are plotted in Fig. 6

TABLE II. Experiment Result

Number of repeated circuits	**Number of trainable gates**	**RMSE**	
		lr = 0.001	***lr = 0.1***
2	12	0.0952	-
3	16	0.1198	-
4	20	0.1097	0.0691
5	24	0.0780	0.0638
6	28		0.0632
7	32		0.0633

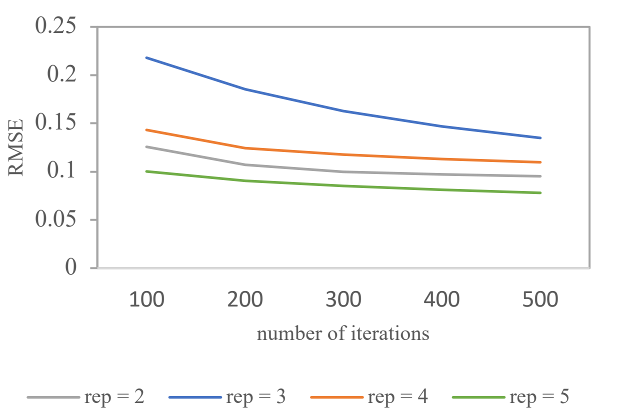

Fig. 6. ADAM optimizer with learning rate 0.001, RMSE on four different model. QNN Model with five repeated circuit has shown the lowest error.

VI. Conclusion

In this paper, The result has shown that the Quantum Neural Network model can be trained and can perform regression tasks on real-world data set with a good result compared to the classical neural network. Our Quantum Neural network model with a limited input size of 4 and 24 weight parameters has the lowest RMSE 6.38% compared to the ANN model in paper [18] with 8 inputs and 153 weight parameters has the lowest RMSE 3.98%. The variational algorithms only employ shallow depth quantum circuits and can be implemented on noisy intermediate-scale quantum (NISQ) devices. It has shown the potential of using Quantum computers in Machine learning.

In addition, increasing repeated circuit or RY-gate is similar to increasing the number of nodes in a classical neural not only increases the capacity of a model network but also helps reduce training loss value and reduce the error of the predicted result.

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