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OPTIMIZING QUANTUM PERCEPTRON ARCHITECTURE USING QUANTUM CIRCUITS FOR DATA CLASSIFICATION

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Abstract. *This research is motivated by previous research with a quantum circuit architecture on the quantum perceptron algorithm that is not yet optimal, characterized by its probability value, which is still 90.7%. The perceptron quantum architecture is built using composed quantum circuits. Researchers conducted training and testing of the proposed perceptron quantum architecture to test the probability value. The result of this research is a model of the quantum circuit architecture on the perceptron quantum algorithm that can solve problems in data classification. This architecture was tested using IBM Quantum Experience. The measurement results of the quantum circuit architecture with four input data show a probability value of 100% with the average training and test error = 0. Based on the test results, the proposed architecture is feasible to classify the data.*

Keywords: Classification, Quantum computing, Quantum perceptron, Architecture, Quantum circuit

1. **Introduction.** At this time, in a new era, new technology is emerging. Quantum computing is a new technology that utilizes quantum concepts in its computational operations. Using quantum computing in the learning algorithm produces an algorithm improvement compared to the previous algorithm [1]. Many researchers from various countries who are researching in the field of machine learning use quantum computing to improve the performance of the proposed algorithm [2].

The superposition of particles in quantum computing, when converted into computations, can be in the form of bits or called qubits [3]. Qubits can be interpreted with the following values $|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ or $\langle 0| = \begin{bmatrix} 1 & 0 \end{bmatrix}$ and $|1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ or $\langle 1| = \begin{bmatrix} 0 & 1 \end{bmatrix}$. In addition, some qubits can form *entanglements*, for example, $|11000110\rangle$ can be represented as $\begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}$. In addition, qubits have a superposition form which is written in the equation $\begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = c_0 \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix} + c_1 \cdot \begin{bmatrix} 0 \\ 1 \end{bmatrix} = c_0|0\rangle + c_1|1\rangle$.

Quantum neural network is an artificial neural network whose operations already use quantum computing. Artificial neural networks using classical computing will increase the speed of the calculation process [4,5]. Quantum perceptron is an artificial neural network method that combines artificial neural networks with quantum computing. Providing a more efficient classical neural network concept is the primary goal of combining these two

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methods. Based on [6], the use of quantum computing has not been comprehensive in the proposed learning algorithm, which causes the learning algorithm to be not optimal. This problem is fundamental in today's quantum learning algorithms.

In [7], the result of this research is an implementation of an artificial neural network using a quantum hopfield algorithm for pattern recognition which results in fast convergence time. In [4], the result of this study is an implementation of an artificial neural network using Widrow-Hoff learning rules and quantum computing which results in a quantum gate and quantum circuit design and linear time complexity. In [8], this research is to show that quantum neural networks, qubits, quantum gates, and quantum circuits can be used for machine learning and can provide exponential acceleration in the simulation of certain neural network models. In [9], this research produces an artificial quantum neural network and Monte-Carlo architecture for handwriting pattern recognition. In [10], this study produces a simulation of a quantum neural network, quantum circuits can recognize patterns well. In [11], this study produces several variations of the quantum neural network, quantum circuit, Gaussian, and no-Gaussian gate models with several comparisons of performance simulation results. In [12], this study produces simulations that show the time coherence of several proposed models, namely quantum neural network and spin coherence. In [13], this research resulted in a comparison of perceptrons with quantum perceptrons. In [14], this study resulted in a simulation of quantum neural network architecture evaluation with good performance results in pattern recognition. In [15], this study resulted in the implementation of the deep neural network method, and quantum annealing quantum fluctuation showed the simulation results of processing several datasets were very good. In existing research [16], this research resulted in a neural network method, quantum codes showing the results of the simulation of the efficiency of the existing dataset classification. In [17], this research resulted in an artificial neural network method, the restricted-Boltzmann-machine (RBM) architecture which resulted in an efficient implementation in the classification of existing datasets. In [18], this research resulted in a method of the neural network, quantum network, quantum autoencoder resulting in a good implementation of the proposed algorithm. In [3], this research resulted in a method of quantum neural networks, PCA algorithm, a quantum computation which resulted in effective and efficient implementation of the proposed algorithm. In [19], this research resulted in a method of quantum artificial neural networks which resulted in effective and efficient implementation of the proposed algorithm. In [20], this research resulted in a quantum neural network method, quantum perceptron which resulted in an efficient implementation in the classification of existing datasets. In [1], this research resulted in a quantum computation method, quantum perceptron which produces effective and efficient simulations for the classification of existing datasets. In [14], this research resulted in a method of the quantum neural network, quantum perceptron, quantum perceptron over a field (QPF), superposition based architecture learning algorithm (SAL) resulting in optimization of learning speed algorithms in the classification of existing datasets. In [5], the result of this research is a method of the quantum privacy-preserving algorithm, perceptron algorithm that produces an efficient implementation in the classification of existing datasets. In [21], the result of this research is a method of quantum neural network, quantum neural circuits, quantum associative memory, quantum perceptron which results in an efficient implementation in the classification of existing datasets. In [22], the result of this research is a quantum perceptron method, and a neural network produces an optimization of the learning speed of the algorithm in the classification of existing datasets. In [23], the result of this research is a method of artificial neural networks, quantum weightless neural network (qWNN) which produces the learning algorithm speed of the proposed algorithm. In their research [24], they proposed a kind of complex fuzzy system or complex neural network. Both systems, namely fuzzy systems, and quantum systems have similarities in these forms. Researchers hope that some parts of the brain and its network functions can be described using complex fuzzy neural network methods or quantum fuzzy processes.

The primary reference of this research is the research of Zheng et al. [25]. The data input to this circuit is 4 data qubits. This circuit was tested using IBM Quantum Experience's quantum computer. This circuit consists of 16 qubits to classify 4 sample data. The 4 sample data consists of 4 points, namely: point x_1, point x_2, point x_3, and point x_4. These points will be separated by two lines, namely the blue line and the red dotted line. From the picture below, the previous researchers classified 4 data marked with point x_1, point x_2, point x_3 and point x_4.

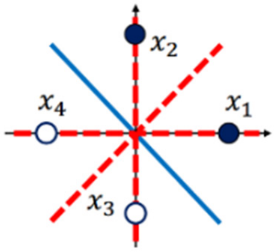

Figure 1. Binary classification with four samples in two-dimensional features [24]

The results showed that only the blue line could classify the sample data correctly. Previous researchers tested the quantum circuit architecture using the IBM Quantum Experience, obtaining a uniform superposition of 16 candidate weight vectors. However, this weight vector represents only nine candidates because zero and minus zero are the same. The highest probability is 90.7%, with vector weight (-1.1).

The testing of the quantum perceptron algorithm is still limited to simulation data. Still, the actual dataset has not been tested, so that a model that matches the real dataset has not been obtained. The researcher will propose an architecture of the optimal perceptron algorithm by testing the data using the actual dataset.

Based on these problems, the researcher intends to develop a quantum circuit architecture built from a quantum gate on a quantum perceptron algorithm to classify data by measuring the proposed learning algorithm. The research parameters that the researcher presents are the architecture, probability, and error values of each model.

The focus of this research is on the problem of applying qubits as key features that are transformed into superpositions. Then the data transformed is used as a dataset into the data processing process, both the training process and the testing process on machine learning using the artificial neural network method with the quantum perceptron algorithm [1].

The probability value of the proposed perceptron quantum architecture will be influenced by qubit formation and superposition as the main features in this study. Therefore, it is necessary to measure the proposed algorithm using IBM Quantum Experience's quantum computer to measure this effect. In addition, the proposed artificial neural network architecture uses a quantum circuit constructed from several quantum gates. This analysis is expected to provide several factors that influence the increase in the probability value at the time of measurement results in the proposed learning algorithm. This article is organized into five parts. At the beginning of the paper, there is an introduction that leads to this research problem. The second part describes the research method explaining the stages in the implementation of the research. The third part is continued by presenting the research results and followed by a discussion explaining the results of the research in the fourth part. The fifth part is the conclusion.

2. **Research Method.** Research stages are presented as the following.

1) Dataset

   This study uses data from the bank's marketing database to determine the eligibility of customers entitled to receive offers to become depositors. The dataset will be divided into two parts: the dataset for learning and the dataset for testing.

2) Quantum Bit Formation and Superposition

   At this stage, data transformation is carried out from the existing dataset into a quantum bit dataset to be processed as a learning base and a test dataset.

3) Training Dataset

   The training dataset is used for the training process using the quantum perceptron algorithm with the proposed quantum circuit architecture. The training dataset is taken from the marketing bank dataset. The amount of training data is 60% of the existing 100 sample data from each model.

4) Testing Dataset

   This stage is the stage of determining the test dataset. The test dataset is taken from the marketing bank dataset. The amount of test data is 40% of the existing 100 sample data from each model.

5) *Quantum Gate*

   At this stage, determine the quantum gate used to build a quantum circuit on the quantum perceptron algorithm architecture.

6) *Quantum Circuit*

   This stage is to build a quantum circuit of several quantum gates.

7) Learning Algorithm Design

   This stage is the learning algorithm design stage, which is the stage where the researcher designs a new architecture using quantum circuits to get a new model on the prospective data classification of bank customers to get credit facilities.

   a) Initial Weight Determination

      At this stage, the initial weight value is determined randomly with the value $|0\rangle$ or $|1\rangle$ from the proposed learning algorithm generated from computer memory.

   b) Final Weight

      The final weight value of the proposed learning algorithm.

8) Evaluation

   This stage is the evaluation stage of the model carried out. The researcher evaluates whether the proposed model can provide better learning optimization than the previous model in classifying data.

The dataset used in this study is a bank marketing dataset to determine the eligibility of customers entitled to an offer to become a depositor. The binary code transformation process, in this case, is a form of a superposition of several existing attributes.

The data transformation rule is on the age attribute: if the age is 0 to 21 years, then the weight is 0; if the age is above 21 years, then the weight is 1. Job attribute: if the income is low or there is no income or it does not know, then the weight is 0; if the income is high or moderate, the weight is 1. Attribute status: if the status is divorced or unknown, then the weight is 0; if the status is single or married, the weight is 1. Education attribute: if primary education is unknown, then the weight is 0; if secondary or tertiary education, the weight is 1. House credit attribute: if you have mortgage debt or yes, then the weight is 0; if you do not have mortgage debt, the weight is 1. Attributes of bank loan: if you have bank loans, the weight is 0; if you do not have bank loans, the weight is 1.

Quantum circuit architecture uses four input data qubits, while the data used in this study uses six attributes. Therefore, before training and testing the data, we combine the age and job attributes and the status and education attributes using logic.

The research dataset is a bank marketing dataset to determine the eligibility of customers entitled to an offer to become depositors consisting of 45,211 data. The training dataset is taken from the bank's marketing dataset as much as 60% of the 100 data samples, while the test dataset is taken from the bank's marketing dataset as much as 40% of the 100 data samples.

3. **Result.** The result of this research is a quantum perceptron architecture that is built using a quantum circuit. This quantum perceptron architecture develops from previous researchers [14]. This quantum perceptron architecture consists of the quantum multiplier, quantum adder, uncomplementary and uncomplementary quantum. The architectural design of the quantum perceptron can be seen in Figure 2.

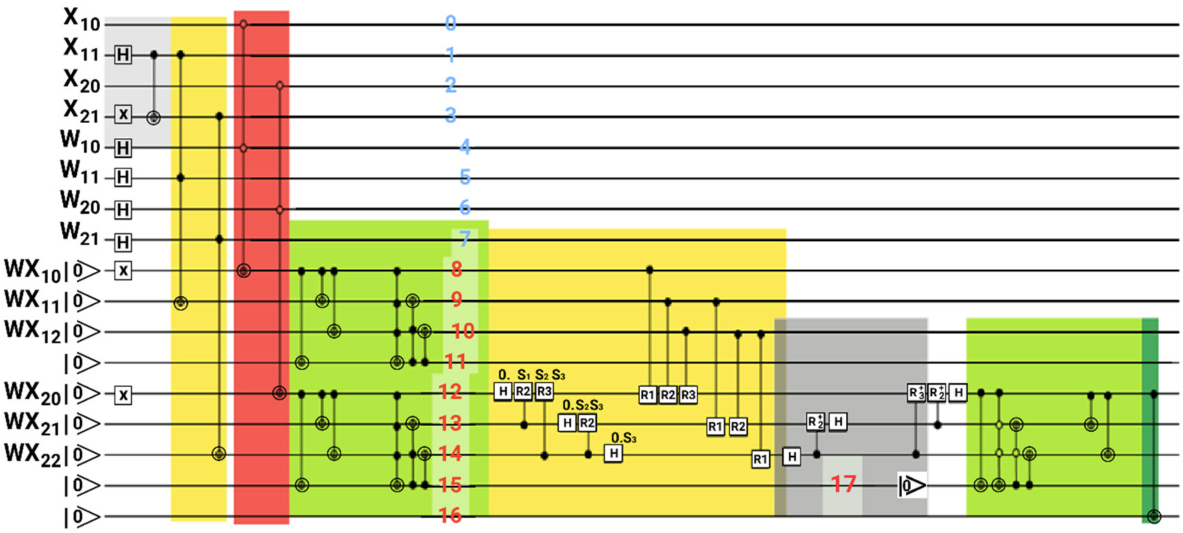

FIGURE 2. Model design

The result of the measurement of the quantum circuit model that the researcher designed is that there is one output binary, namely 10001000000000000 binaries with 100% probability. As expected, the amplitude of each state that is not $|10001000000000000\rangle$ is 0. This means we have a 100% chance of measuring $|10001000000000000\rangle$. The measurement results using a quantum computer belonging to the IBM Quantum Experience can be seen in Figure 3.

After measuring, then proceed with the process of training and testing. For this model, the input data is four qubits. The training and testing process uses four attributes: status,

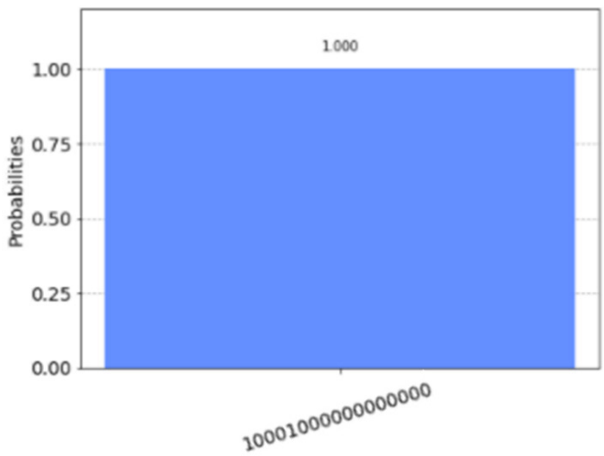

FIGURE 3. Measurement results

education, house credit, and bank loan. The data used are 100 data samples from the marketing bank dataset. The data is divided into two, namely 60% training data and 40% test data. The test results of this model show error = 0 because there is no difference between the target probability and the output probability at the time of testing after measuring, training, and testing the data.

4. **Discussion.** This model was developed in the quantum circuit architecture by improving the complementary circuit and the uncomplementary circuit. The complementary circuit changes to a positive number because the quantum adder circuit cannot perform calculation operations other than positive numbers. In the complementary circuit that is changed is the gate Toffoli 4 by reversing the shape of the gate Toffoli 4 with a row arrangement of qubits, q_{11}, q_{10}, q_9, and q_8 into a row arrangement of qubits, q_8, q_9, q_{10}, and q_{11} and gate Toffoli 4 with the array of qubit rows, q_{15}, q_{14}, q_{13}, and q_{12} being the qubit row arrangement of qubits, q_{12}, q_{13}, q_{14}, and q_{15}. Gate Toffoli 4 operates on four qubits performing a note operation on the fourth qubit if the 1st, 2nd, and 3rd qubits are $|1\rangle$. In addition to changing the shape of the complementary circuit, the researchers also changed the shape of the uncomplementary circuit, namely by changing the gate Toffoli four by reversing the shape of the gate Toffoli 4 with a row arrangement of qubits, q_{15}, q_{14}, q_{13}, and q_{12} into a row arrangement of qubits, q_{12}, q_{13}, q_{14}, and q_{15} which are located after the quantum multiplier sequence. After making changes to the complementary and uncomplementary circuits in the quantum circuit architecture that the researcher designed, it showed significant results when measuring with five measurements from the previous architecture, namely increasing the probability value from 90.7% probability to 100% probability.

The first quantum circuit is the initialization of the input data and the weight data. There are four qubits of input data, namely x_1, x_2, x_3, x_4, and four qubits of weight data, namely w_1, w_2, w_3, w_4. This circuit consists of Hadamard Gate, X-Gate, and CNOT. Hadamard Gate allows us to move away from the poles of the Bloch sphere by the formula $H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$. Hadamard Gate can do transformation $H|0\rangle = |+\rangle$ and $H|1\rangle = |-\rangle$. X-Gate serves to change the amplitude of the states $|0\rangle$ and $|1\rangle$ with formula $X|0\rangle = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = |1\rangle$. We can see the circuit in Figure 4.

The second quantum circuit is a quantum multiplier circuit that functions to multiply the input data with the weight data with the formula $|y\rangle = |w_1\rangle \cdot |x_1\rangle$. The *Quantum Multiplier* consists of *Hadamard Gate*, $\boldsymbol{R\phi}$ *Gate*. *Hadamard Gate* transforming $H|0\rangle = |+\rangle$ and $H|1\rangle = |-\rangle$ with formula $H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$. $\boldsymbol{R\phi}$ *Gate* rotates ϕ around the axis direction Z and is sometimes known as Rz-gate, which has matrix $\boldsymbol{R\phi} = \begin{bmatrix} 1 & 0 \\ 0 & e^{\phi} \end{bmatrix}$. We can see the circuit in Figures 4 and 5.

The third quantum circuit is a quantum adder that adds up all the multiplication results between the input and weight data with the formula $|y\rangle = \sum |w_1\rangle \cdot |x_1\rangle$. The quantum adder circuit consists of CCNOT gates that implement Pauli-X if the first two bits are in the $|1\rangle$ state on the third bit; otherwise it does nothing.

The fourth quantum circuit is a complementary quantum circuit that changes to positive numbers because the quantum adder can only handle positive numbers. The complementary circuit consists of CNOT Gate and CCNOT Gate. CNOT Gate works by applying Pauli-X if the first two bits are in the $|1\rangle$ state. Otherwise, it does nothing.

The fifth quantum circuit model is an uncomplementary quantum circuit that functions to change back to its original number form. Just like complementary quantum circuits, uncomplementary circuits consist of a CNOT Gate and a CCNOT Gate.

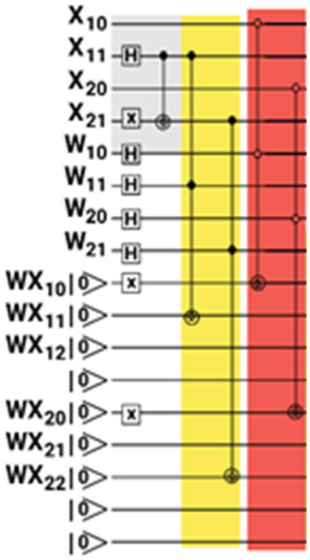

FIGURE 4. Initialization circuit

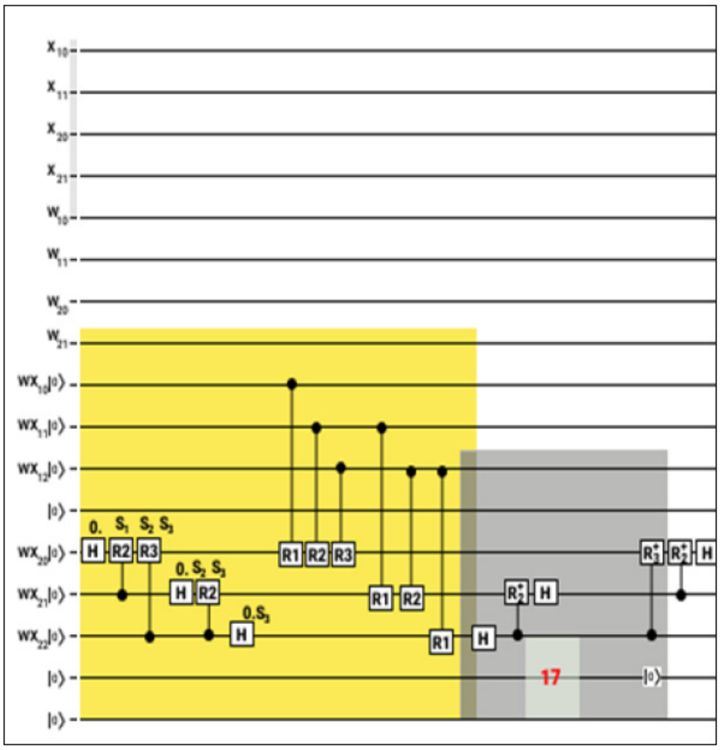

FIGURE 5. Quantum multiplier circuit

5. **Conclusions.** From the results of this study, the authors succeeded in making a model of the quantum circuit architecture on the perceptron quantum algorithm. After measuring the quantum circuit architecture model using a quantum computer belonging to the IBM Quantum Experience, it shows an increase in the probability value of 100% from the previous probability value of 90.7% with one binary data output. It is hoped that further researchers will develop this quantum circuit architecture by adding several variables so that the classification process is even better.

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