



Analyzing perceptron algorithm for global gold price prediction using quantum computing approach

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Abstract

The price of gold has garnered significant attention in the world of finance and investment due to its role as a safe haven asset and an indicator of global economic stability. An inherent risk of investing in gold is the daily fluctuation in prices, which can rise, fall, or remain stable. Investors are constantly seeking accurate ways to predict gold price movements in order to make informed investment decisions. While classic algorithms like artificial neural networks have been used for gold price prediction, they often struggle with analyzing complex data and identifying the hidden patterns within large datasets. It is widely acknowledged that accurately and consistently predicting the gold price movements, exchange rate, and whether the gold price will rise or fall is very challenging. To address this challenge, this study explored the use of quantum perceptron algorithm for predicting global gold prices. This approach harnesses the principles of quantum computing to improve the efficiency and performance of neural network models. Quantum computers can perform multiple computations simultaneously, enabling the solution of problems that are difficult for classical computers. This study utilized global gold data from January 2018 to December 2022, with 80:20 split of training and testing data; data from January 2018 to December 2021 for training and data from January 2022 to December 2022 for testing. This study aims to offer insights into the potential and application of quantum algorithms in predicting gold prices. The research involved an analysis of global gold price predictions using the quantum perceptron algorithm and quantum computing.

1. Introduction

Gold prices have become a primary focus in the world of finance and investment due to its crucial role as a safe-haven asset and an indicator of global economic stability. Gold is one of the alternative investments that tends to be safe and relatively risk-free [1]. A common risk when investing in gold is the daily fluctuation of prices [2]. Gold prices are considered time series data, as they can fluctuate daily [3],[4]. Market participants are always looking for ways to accurately predict the movements of gold price in order to make profitable investment decisions [5]. While classical algorithms like artificial neural networks have been used for gold price prediction [6]–[8], they often struggle in handling complex data and identifying patterns within large datasets. It is widely acknowledged that accurately and consistently predicting gold price movements, exchange rate, and whether the gold price will rise or fall is very challenging [9]. To mitigate this risk, there is a need for an application that can predict gold prices using the Quantum Perceptron method.

One potential solution for addressing this challenge is through Quantum Neural Network models, which are artificial neural networks inspired by quantum mechanics [10]. The integration of quantum computing and machine learning has become an exciting area of research in the development of machine learning [11]–[16]. This development has emerged in response to the significant challenges of handling increasingly large and complex data [17], [18]. As the number of input parameters and layers in neural networks increases, the computational costs increase significantly [19], [20]. Quantum Neural Network concept utilizes the principles of quantum computing to improve the efficiency and performance of neural network models. Quantum computing enables more efficient parallel computations compared to classical computers [21]–[23] because qubits (quantum bits) can exist in an infinite linear superposition of both states. When transformed into computation, superposition can be seen as a bit where the value is only 0 or 1. However, in quantum computing, the value of a bit can be 0, 1, or a combination of both [24]. By utilizing this quantum mechanical effect, quantum computers can perform multiple computational paths simultaneously, enabling the solution of problems that are challenging for classical computers [25]–[27].

The related research that discusses gold price prediction [28] is "Prediksi Harga Emas Dengan Algoritma Backpropagation". In this study, researchers predicted gold prices using the Backpropagation Algorithm and obtained a Mean Square Error (MSE) of 0.0034849 with a maximum iteration of 3000 epochs. Despite achieving optimal results, this research required 3000 epochs to obtain them.

Research [29] discusses "*Multilayer Perceptron untuk Prediksi Sessions pada Sebuah Website Journal Elektronik*." In this study, researchers aimed to forecast website journal sessions to enhance quality and accreditation score using the multilayer perceptron method. The researchers obtained the best model evaluation results with MSE and RMSE values of 0.015357 and 0.123999 for the training set and 0.018996 and 0.137826 for the testing set. The execution time required for forecasting was 580.0651 seconds or 9.667751 minutes.

Research [30] focuses on "*Prediksi Harga Emas Menggunakan Metode BiLSTM Neural Network*." In this study, the method used for the prediction is Radial Basis Function Neural Network (RBFNN). The research results indicate that the gold price experienced an increase in each month of 2022, with an MSE value of 0.54134, which is higher than 50. This indicates that the model failed to produce accurate predictions, necessitating further evaluation.

Research [31] is about "*Analisis Quantum Perceptron untuk Memprediksi Jumlah Pengunjung Ucokopi Pematangsiantar pada Masa Pandemi Covid-19*." In this study, the researcher conducted a quantum perceptron analysis to predict the number of visitors to Ucokopi Pematangsiantar during the Covid-19 pandemic. The result of this research is limited to the analysis of predicting the number of visitors using the quantum perceptron algorithm with quantum computing to forecast the number of visitors to Ucokopi Pematangsiantar.

Research [28] and [29] suggest that backpropagation and multilayer perceptron models require a significant amount of computational time to achieve optimal results. In research [28], backpropagation took 3000 epochs to achieve optimal results. The quantum perceptron algorithm has the potential to accelerate the computational process by leveraging the advantages of quantum computing, which can perform multiple operations in parallel more efficiently. This can reduce the number of epochs needed for convergence as the quantum approach can speed up the model training process. The quantum perceptron algorithm is better suited to handling complexity and nonlinearity in data compared to conventional methods. This is relevant for studies [29] and [31], where predicting the number of visitors and website sessions can involve complex and nonlinear patterns.

The main reference for this research is a study [32] entitled "*Prediksi Harga Emas dengan Menggunakan Metode Naïve Bayes dalam Investasi untuk Meminimalisasi Resiko*". In this study, researchers utilized Naive Bayes algorithm to forecast gold prices for a 14-day period. The researchers employed Rapidminer application for gold price calculations, using a dataset of 16 entries and achieved an accuracy rate of 75%.

The main reference notes that the accuracy results for making predictions are still suboptimal. As a result, researchers have turned to the quantum perceptron algorithm for making predictions. In this study, a computational approach using a perceptron algorithm was employed to predict the global gold prices. The research contributes to knowledge about the potential for utilizing the perceptron algorithm in predicting global gold prices. The novelty of this research lies in the computational implementation of the perceptron algorithm.

This study is divided into 4 sections: Introduction, Research Methods, Results and Discussion, and Conclusions. In Research Methods, the stages of the research are explained as well as the introduction to the material. Results and Discussion contains the calculations using the perceptron fragmentation algorithm to predict the price of gold. In Conclusion section, the researcher explains the conclusions drawn from the results of the calculations.

This study investigated the potential of quantum perceptron algorithm to predict global gold prices. The steps for implementing the quantum perceptron algorithm were outlined, and the results of this study comprised the analysis of the quantum perceptron model for predicting global gold prices.

2. Research Method

2.1 Research Stages

This research was supposedly conducted in 8 stages. However, only 7 stages were completed because the researcher did not have a quantum device to run the algorithm optimally. This research only produced analysis up to the quantum perceptron training stage of the algorithm to find out whether this algorithm can be used to predict gold data. The stages of this research can be seen in Figure 1:

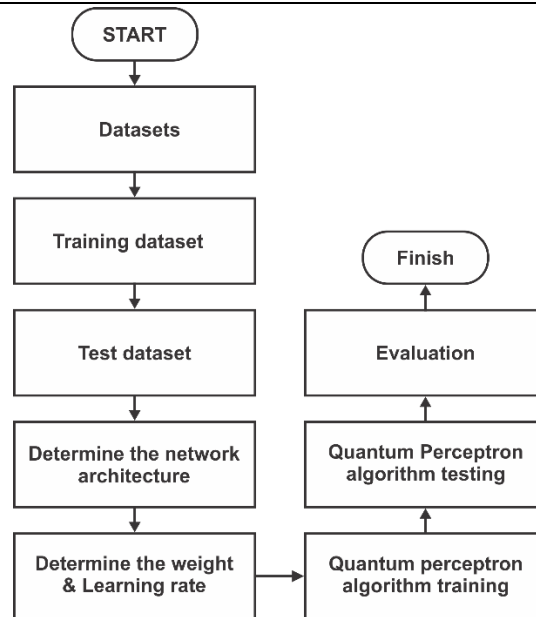


Figure 1. Stages Of Research Carried Out

2.2 Datasets

Researchers used a global gold price dataset from the Kaggle website. The dataset used was the exchange rates of several countries for gold currency. The dataset taken for this research is monthly global gold price data.

2.3 Training Dataset and Testing Dataset

The training dataset was used for the training process using quantum perceptron algorithm with the proposed quantum circuit architecture. The amount of training data was 80% of the data used. Data from January 2018 to December 2021 was used for training.

2.4 Test Dataset

Test Dataset is useful for evaluating whether the trained model can generalize patterns found in the training data to new, unseen data. The amount of testing data was 20% of the existing data. Data from January 2022 to December 2022 was used for testing.

2.5 Determine the Network Architecture

The network architecture refers to the structure or layout of a neural network. In this research, the artificial neural network architecture used was a 24-2-2 architecture, which consisted of 24 input layers, 2 hidden layers, and 2 output layers. The architecture of the quantum perceptron algorithm can be seen in Figure 2.

2.6 Determine the Weight and Learning rate

Weight is a parameter used to determine the strength of connections between neurons, while the learning rate is an important hyperparameter that determines the step size taken by optimizing algorithm when updating network weights. In this study, the initial weights in the perceptron dimension calculations were created randomly, and the learning rate used was 0.1.

2.7 Quantum Perceptron Algorithm Training

At this stage, researchers used the Quantum Perceptron algorithm to process training data and taught it how to recognize patterns or relationships in the given data.

2.8 Quantum Perceptron Algorithm Testing

At this stage, data was tested using the Quantum Perceptron algorithm to ensure that it could generalize well to previously unseen data.

2.9 Evaluation

This is the evaluation stage of the model. Researchers assessed whether the model can predict global gold data.

2.10 Artificial Neural Networks

Artificial Neural Networks (ANN) are information processing systems with specific characteristics and performance that approximate biological neurons [33]. Artificial neural networks can learn and generate rules or operations from multiple input examples. This enables them to make predictions about likely outputs or store the characteristics of the given input in the neural network [34].

2.11 Quantum Neural Network

The Quantum Neural Network (QNN) is an algorithm that is based on neural networks [35]. QNN is a machine learning model implemented on quantum computers, utilizing quantum effects such as superposition, entanglement, and interference, to perform computations [33]. Quantum algorithms have been developed to improve the computational efficiency of neural networks. They are used to create new computational features for neural networks. The fundamental basis of quantum algorithms is the qubit neuron model, where qubit neurons act as the connection between quantum states and transitions between neurons [35].

2.12 Perceptron Algorithm

A Perceptron is capable of performing calculations by recognizing variables in pattern matching. The output results from the network were then used for decision making [36].

2.13 Quantum Perceptron Algorithm

The Quantum Perceptron combines quantum concepts with the classical perceptron algorithm. This method used quantum bits (qubits), which are the atomic properties in quantum mechanics, for quantum computation. Qubits can exist in different states simultaneously and have different probability values [31]. The steps in implementing the quantum perceptron can be seen below and in Equations 1, Equations 2, Equations 3 and Equations 4:

1. Initialize all inputs, weights, targets, and biases.
Calculate the net using the formula:

$$|Z_i \rangle = \sum |W_{ij} \rangle \cdot |X_i \rangle \quad (1)$$

2. Calculate the output using the formula:

$$|y_i \rangle = \sum |Z_i \rangle \cdot |V_{ij} \rangle \quad (2)$$

3. If $|y\rangle \neq |t\rangle$ then

4.

$$W_{new} = W_{old} + a * (|y \rangle - |t \rangle) * |x_i| \quad (3)$$

If not then

$$W_{new} = W_{old} \quad (4)$$

5. if $y=t$ then stop.

3. Results and Discussion

3.1 Dataset

The dataset used in this study was sourced from the Kaggle and consisted of monthly gold prices in Rupiahs. The researcher analyzed data from January 2018 to December 2021, covering a total of 48 months. For prediction purposes, 12 variables were used: January (x1), February (x2), March (x3), April (x4), May (x5), June (x6), July (x7), August (x8), September (x9), October (x10), November (x11), and December (x12). The input data included January to November, while December was the target data.

3.2 Transformasi Qubit Dan Superposisi

The data used by the researcher was the gold price data from 2018 to 2021, as shown in Table 1:

Table 1. 2018-2021 Global Gold Price Dataset

Year	2018	2019	2020	2021
Jan	18008199.3	18489110.6	21632250.3	26149114.7
Feb	18118458.7	18557141.3	23097324.3	24818185.4
Mar	18226102.9	18446494.6	26241973.7	24562502.0
Apr	18269894.3	18272772.2	25328406.3	25533702.8
May	18137836.2	18490734.6	25256306.3	27131285.3
Month Jun	17918947.8	19905647.5	25257309.9	25565673.6
Jul	17606098.3	20009965.6	28687538.6	26404909.4
Aug	17712087.8	21680352.6	28503910.8	25884299.5
Sep	17691805.9	21083830.7	28077070.6	24943825.7
Oct	18470276.6	21209204.5	27522057.7	25064431.2
Nov	17414006.1	20595414.4	24887206.7	25843517.6
Dec	18392020.0	21028516.9	26520781.4	25737878.5

To facilitate the formation of criteria and data calculations, the obtained data is converted into percentage form using the Equation 5:

$$\frac{(\text{Old Data} - \text{New Data})}{\text{Old Data}} * 100 \quad (5)$$

The results of Equation 5 can be seen in Table 3. The Gold Price data is transformed into binary form, specifically 0 and 1, according to the rules outlined in Table 2.

Table 2. Criteria Table for Transformation Biner

No	Criteria	Weight
1	Percentage <0	0,0
2	Percentage >= 0 and <= 2	0,1
3	Percentage >2 and <= 7	1,0
4	Percentage >7	1,1

The Global Gold Price data spans from January 2018 to December 2021, comprising 48 months, with each year consisting of 12 months. The gold price data has been calculated using Equation 5.

Table 3. Global Gold Data After Transformation to Percent

Year	2018	2019	2020	2021
Jan	2.81%	0.53%	2.87%	-1.40%
Feb	0.61%	0.37%	6.77%	-5.09%
Mar	0.59%	-0.60%	13.61%	-1.03%
Apr	0.24%	-0.94%	-3.48%	3.95%
May	-0.72%	1.19%	-0.28%	6.26%
Month Jun	-1.21%	7.65%	0.00%	-5.77%
Jul	-1.75%	0.52%	13.58%	3.28%
Aug	0.60%	8.35%	-0.64%	-1.97%
Sep	-0.11%	-2.75%	-1.50%	-3.63%
Oct	4.40%	0.59%	-1.98%	0.48%
Nov	-5.72%	-2.89%	-9.57%	3.11%
Dec	5.62%	2.10%	6.56%	-0.41%

The binary transformation of the Global Gold Price data is illustrated in Table 4, following the rules outlined in Table 2.

Table 4. Transformation Data to Biner

Year	2018	2019	2020	2021
Jan	1,0	0,1	1,0	0,0
Feb	0,1	0,1	1,0	0,0
Mar	0,1	0,0	1,1	0,0
Apr	0,1	0,0	0,0	1,0
May	0,0	0,1	0,0	1,0
Jun	0,0	1,1	0,1	0,0
Jul	0,0	0,1	1,1	1,0
Aug	0,1	1,1	0,0	0,0
Sep	0,0	0,0	0,0	0,0
Oct	1,0	0,1	0,0	0,1
Nov	0,0	0,0	0,0	1,0
Dec	1,0	1,0	1,0	0,0

In this Quantum Perceptron calculation, the researcher used a 24-2-2 architecture to analyze the Global Gold Price dataset which can be seen in Figure 2.

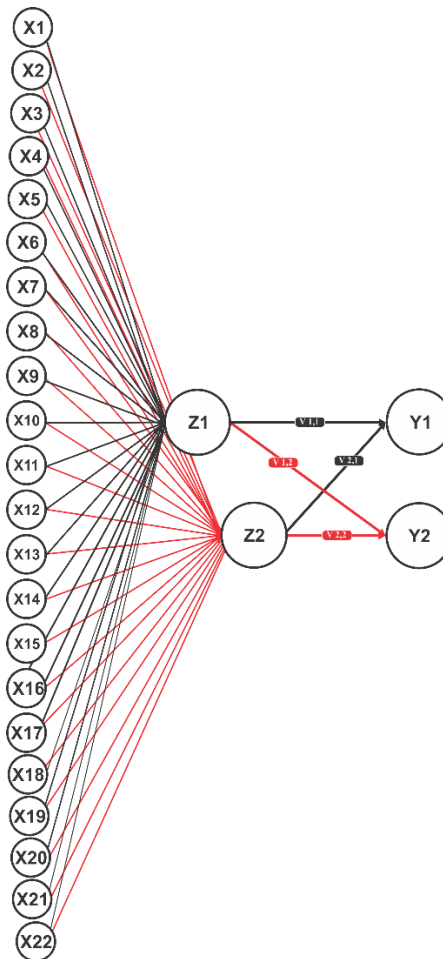


Figure 2. 24-2-2 Architecture

then the researchers randomly determined the initial weights for the quantum perceptron calculation as (1,0):

$$W_{1,1} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, W_{2,1} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}, W_{3,1} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, W_{4,1} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, W_{5,1} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, W_{6,1} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, W_{7,1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, W_{8,1} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, W_{9,1} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, W_{10,1} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, W_{11,1} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}, W_{12,1} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, W_{13,1} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, W_{14,1} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}, W_{15,1} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix},$$

$$4) Y_2 = V_{1,2} * |Z_1\rangle + V_{2,2} * |2\rangle \\ = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} * \begin{bmatrix} 13 \\ 14 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} 13 \\ 14 \end{bmatrix} = \begin{bmatrix} 27 \\ 27 \end{bmatrix} + \begin{bmatrix} 13 \\ 0 \end{bmatrix} = \begin{bmatrix} 40 \\ 27 \end{bmatrix}$$

The interim outputs Y_1 and Y_2 were then compared with the expected output. $T_1 = |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ and $T_2 = |0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ where $\begin{bmatrix} 0 \\ 1 \end{bmatrix} \neq \begin{bmatrix} 27 \\ 45 \end{bmatrix}$ and $\begin{bmatrix} 1 \\ 0 \end{bmatrix} \neq \begin{bmatrix} 40 \\ 27 \end{bmatrix}$. Thus, adjustments were made to each weight. W_{ij} V_{ij} dari $|X_1\rangle$ until $|X_{22}\rangle$ and the calculation of error value. First, the weights were adjusted for $W_{1,1}$ until $W_{24,1}$, $V_{1,1}$, $V_{2,1}$ on $Y_1 \neq T_1$:

$$1) W_{1,1 New} = W_{1,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_2| \\ = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 0 & 27 \\ 0 & 44 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 2,7 \\ 0 & 4,4 \end{bmatrix} = \begin{bmatrix} 0 & 3,7 \\ 0 & 4,4 \end{bmatrix}$$

$$2) W_{2,1 New} = W_{2,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_1| \\ = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 2,7 & 1 \\ 5,4 & 1 \end{bmatrix}$$

$$3) W_{3,1 New} = W_{3,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_3| \\ = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 3,7 & 1 \\ 5,4 & 0 \end{bmatrix}$$

$$4) W_{4,1 New} = W_{4,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_4| \\ = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 0 & 27 \\ 0 & 44 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 2,7 \\ 0 & 4,4 \end{bmatrix} = \begin{bmatrix} 1 & 2,7 \\ 0 & 5,4 \end{bmatrix}$$

$$5) W_{5,1 New} = W_{5,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_5| \\ = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 3,7 & 1 \\ 5,4 & 1 \end{bmatrix}$$

$$6) W_{6,1 New} = W_{6,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_6| \\ = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 0 & 27 \\ 0 & 44 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 2,7 \\ 0 & 4,4 \end{bmatrix} = \begin{bmatrix} 1 & 2,7 \\ 1 & 4,4 \end{bmatrix}$$

$$7) W_{7,1 New} = W_{7,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_7| \\ = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 3,7 & 1 \\ 4,4 & 1 \end{bmatrix}$$

$$8) W_{8,1 New} = W_{8,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_8| \\ = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 0 & 27 \\ 0 & 44 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 2,7 \\ 0 & 4,4 \end{bmatrix} = \begin{bmatrix} 1 & 3,7 \\ 0 & 4,4 \end{bmatrix}$$

$$9) W_{9,1 New} = W_{9,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_9| \\ = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 3,7 & 1 \\ 5,4 & 1 \end{bmatrix}$$

$$10) W_{10,1 New} = W_{10,1 Old} + \alpha * (|Y_1\rangle - |T_1\rangle) * \langle X_{10}| \\ = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 & 0 \\ 44 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 2,7 & 0 \\ 4,4 & 0 \end{bmatrix} = \begin{bmatrix} 3,7 & 0 \\ 5,4 & 0 \end{bmatrix}$$

$$\begin{aligned}
 23) \quad & V_{1,1} \text{ New} = V_{1,1} \text{ Old} + \alpha * (|Y_1 > -|T_1 >|) * < Z_1 | \\
 & = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * [13 \quad 14] = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * [13 \quad 14] = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 351 & 378 \\ 572 & 616 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} + \\
 & \begin{bmatrix} 35,1 & 37,8 \\ 57,2 & 61,6 \end{bmatrix} = \begin{bmatrix} 36,1 & 38,8 \\ 57,2 & 62,6 \end{bmatrix} \\
 24) \quad & V_{2,1} \text{ New} = V_{2,1} \text{ Old} + \alpha * (|Y_1 > -|T_1 >|) * < Z_2 | \\
 & = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} + 0,1 * \left(\begin{bmatrix} 27 \\ 45 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) * [17 \quad 14] = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 27 \\ 44 \end{bmatrix} * [17 \quad 14] = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} + 0,1 * \begin{bmatrix} 459 & 378 \\ 748 & 616 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} + \\
 & \begin{bmatrix} 45,9 & 37,8 \\ 74,8 & 61,6 \end{bmatrix} = \begin{bmatrix} 45,9 & 38,8 \\ 75,8 & 62,6 \end{bmatrix}
 \end{aligned}$$

Afterwards, the weights $W_{1,2}$ to $W_{2,2}$ and $V_{1,1}$ to $V_{2,2}$ were adjusted. When the weight adjustments for W and V were completed, the learning process continued for the second set of data. This algorithm will continuously modify the weights until the expected output value (T) matches the interim output value (Y) or until the error value reaches 0. Weight adjustments will continue until the goal is achieved. It is evident that the quantum perceptron algorithm can be manually calculated during the first epoch. The manual calculation of epoch 1 demonstrates that the weight changes for the subsequent epoch calculation can be computed. This enables the calculation to be continuously performed with a quantum computing device.

4. Conclusion

This study suggests that the Quantum Perceptron algorithm can be utilized for predicting global gold prices. While manual calculations can derive new weights, advanced calculations can be performed using quantum devices. Due to the limitations in computing resources, this research was limited to analysis only. The study was analytical and utilized the quantum perceptron algorithm using quantum computation. Further research is needed to test its applications. In order to predict the global gold price, it is necessary to proceed to the implementation stage. The method used for predicting the global gold price is the Quantum Perceptron Artificial Neural Network using quantum computation.

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