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Quantum Perceptron: A New Approach for Predicting Rice Prices at the Indonesian Wholesale Trade Level

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Abstract

The wholesale rice trade in Indonesia encounters various challenges in forecasting prices. These challenges are influenced by factors such as weather, government policies, global market conditions, and other economic variables. Accurate price predictions are crucial for informing government policy in a timely manner. This research introduces a new approach that utilizes the Quantum Perceptron algorithm to forecast rice prices. The algorithm, an innovative method in quantum computing, is expected to enhance the efficiency and effectiveness of price predictions. Although the research is still in the analytical stage, the use of Quantum Perceptron shows promise in dynamically addressing the complexity of market data and the variability of factors affecting rice prices. The method focuses on developing models that can leverage quantum computing to process information more effectively than classical methods. By harnessing the unique properties of quantum mechanics, such as superposition and entanglement, Quantum Perceptron can identify complex patterns and optimize predictions of future rice prices. The research describes the implementation of quantum algorithms in the context of the Indonesian rice wholesale market, including the technical challenges encountered and future development prospects. The research utilizes quantum computing along with the perceptron algorithm. The researchers focused on analyzing the quantum perceptron algorithm because of the limited availability of quantum computing devices. The findings of this research are confined to analysis. In order to advance this research, the author recommends that future studies employ quantum devices to achieve more accurate predictions.

Keywords: prediction; rice price; artificial neural networks; perceptron; quantum computing

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1. Introduction

Rice serves as a crucial food commodity in Indonesia, playing a central role in the daily diet and the national economy. As a staple food, rice significantly impacts food security and community welfare. Its production involves millions of farmers and contributes significantly to the rural economy and the national GDP. Rice is the most consumed staple food in Indonesia[1]. It is a commodity that significantly affects the poverty line in both urban and rural areas [2]. With Indonesia's growing population, the demand for rice continues to rise. Additionally, rice plays a crucial role in the country's economy, influencing government and social policies. Setting prices for essential goods is a critical aspect that requires the government's attention, and it is their responsibility to ensure price stability for basic commodities (Regulation No. 71 of 2015) [3]. This enables the government to anticipate and regulate future fluctuations in rice prices.

Artificial neural networks (ANN) are a crucial part of artificial intelligence that mimics the way the human brain processes information[4], [5]. Modelled after biological neurons, ANNs consist of numerous simple processing units called neurons, which work together in layers to solve complex problems by learning from data[6]. With deep learning principles, ANNs can model complex non-linear relationships, enabling various applications such as voice and image

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recognition, medical diagnosis, and autonomous vehicles. Despite challenges like overfitting and the need for large data, advances in hardware and algorithms have significantly improved the performance of ANNs, making them powerful tools in data analysis and decision-making in various fields.

In this context, rice price predictions are very important to help economic actors make the right decisions in managing rice supplies and selling prices. However, predicting rice prices is a complex challenge because it is influenced by various factors such as production, consumption, imports, exports, and other external factors. This research proposes the use of Quantum Perceptron to predict rice prices [7]. Quantum Perceptron is a machine learning algorithm that uses the principles of quantum mechanics to increase prediction accuracy [8]. By utilizing Quantum Perceptron's ability to handle complex and unstructured data, it is hoped that it can produce more accurate rice price predictions.
There are several previous studies, such as in research [9], previously a survey was conducted to predict rice prices using the least squares method. This research used 132 data. Which consists of 132 training data and 12 final test data. After carrying out the prediction process, the results of rice price predictions for 12 months in 2021 are obtained. The test results of this prediction are in the form of the smallest error value which is considered very good in terms of accuracy for predicting rice prices using the least squares method, namely 5%.

The research[10] results were obtained using the Fuzzy Time Series Cheng (FST Cheng) method, which provided 5 predictions for the prices of Belida rice in the coming years. In 2023, the predicted price was Rp11614.336. For 2024 and 2025, the price of Belida rice is expected to remain stable at Rp11614,336. In 2026, a significant decline in the price of Belida rice is predicted at Rp11379,502. The prediction for 2027 is the same as the 2026 prediction. The mean absolute percentage error (MAPE) obtained from this method was 3.48%, indicating good performance in predicting rice prices in Pekanbaru City.

Research[11] investigated rice price predictions at the Indonesian wholesale level using the Recurrent Neural Network Long Short Term Memory (RNN LSTM) approach. The study utilized average rice price data at the Indonesian wholesale trade level for 2010-2020 obtained from the Indonesian Central Statistics Agency. The evaluation of prediction results from epoch 20 to 1000 yielded the smallest Root Mean Square Error (RMSE) value of 0.43, indicating that the LSTM method is effective for predicting rice prices at the wholesale level in Indonesia.

One of the main challenges in the rice wholesale trade is the complexity of factors that impact rice prices. These factors include weather, government policies, global market conditions, and various other economic variables. Predicting rice prices is essential for obtaining future information to help determine the government's policy direction.
The purpose of this research is to create a more accurate method for predicting rice prices compared to traditional approaches. The goal is to provide valuable insights for rice market participants, the government, and researchers to improve decision-making regarding rice prices in Indonesia.

This study utilizes the Quantum Perceptron algorithm to forecast rice prices in the wholesale market of Indonesia. This method offers the potential to enhance the precision of rice price forecasts by leveraging the capabilities of quantum computing in handling data intricacies. Consequently, this research sets the stage for the creation of more sophisticated and effective price prediction techniques, which could enhance risk management and decision-making in rice trading.
Previous research predominantly utilized classical methods. This study, however, employs quantum computing through Quantum Perceptron for predicting commodity prices, a technique not widely employed in the realm of wholesale rice trading. The utilization of quantum perceptrons not only enhances prediction accuracy but also reduces computing time, potentially rendering it more efficient and effective.
The paper is structured into several main parts. The second part covers materials and methods used, providing a comprehensive overview of datasets, data transformation, quantum computing, and the Quantum Perceptron algorithm. The third part presents the results of applying the Quantum Perceptron model. The fourth section is the Discussion, which evaluates the effectiveness of the model. The fifth section, Conclusion, summarizes the main findings and offers suggestions for implementing the research results in Indonesia's rice trade policy.

2. Material and Methods

2.1 Materials

The research[12] the quantum perceptron method was utilized to predict the number of visitors to Ucokopi Pematangsiantar during the Covid-19 pandemic. This method combines the perceptron algorithm with quantum computing. The analysis used previous visitor data from January 2021 to October 2021 and involved 7 variables denoted as x1 to x7. The outcome is a prediction analysis of the number of visitors to Ucokopi using the quantum perceptron algorithm with quantum computing.

The research[13] compared two machine learning methods, Support Vector Machine (SVM) and Perceptron, along with three optimization methods for finding hyperplanes: Gradient Descent (GD), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The researchers used the Iris Flower dataset from the UCI Machine Learning Repository. They tested the learning rate for the Perceptron and the number of individuals for the optimization algorithms

(GA and PSO). The results indicated that PSO is the most suitable optimization method for both Perceptron and SVM, achieving an accuracy of 93%.

The research[14] aims to introduce a classification analysis model for determining loan status at PNPM Mandiri. The model uses the Perceptron artificial neural network algorithm and is optimized using the Person Correlation (PC) method to measure the accuracy of the variables used. The research dataset is based on historical data from the past 2 years, comprising 67 data samples. The analysis variables include Business Type (X1), Loan Amount (X2), Collateral (X3), Income (X4), and Costs (X5). The results of the analysis indicate that the model offers optimal classification results, with the variable X2 showing no significant relationship. This demonstrates the artificial neural network's capability to provide maximum results in determining loan status. Overall, this research presents an effective analysis model and alternative solutions for determining loan status at PNPM Mandiri.

The research[15] utilized statistical data from BPS Bandung City spanning from 2016 to 2021 to examine the variations in solar radiation levels. The aim was to maximize the utilization of sunlight and forecast extreme fluctuations by implementing a prediction system based on the Multi-Layer Perceptron model (JST-MLP). The study findings demonstrate that this model can accurately predict changes in solar radiation, as indicated by a Mean Squared Error (MSE) of 0.086182 on the training data and 0.10921 on the testing data after 1000 iterations. Internally, this implies the enhancement of a more precise ANN-MLP model, while externally, it can be implemented across various sectors such as agriculture, healthcare, and solar energy to enhance efficiency and optimize solar energy usage.

The research[16] is to improve the efficiency of assessing student knowledge at SD Negeri 1 Ternate City by implementing Artificial Neural Networks (JST) using the Perceptron algorithm. The development method used is a prototype, and testing is carried out using the white box method. The assessment data used includes Daily Assessment Results (HPH), Mid-Semester (HPTS), and End of Semester (HAS). The research results show that the system with the Perceptron algorithm achieves an accuracy of up to 96%, indicating that ANN can be implemented for student assessment according to the 2013 curriculum.

The research[17] addresses the issue of Indonesian people's negative online news reading habits by creating an automatic classification system using Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) algorithms. By employing the Term Frequency-Inverse Document Frequency method for feature selection, the research achieved 74% accuracy with SVM and 78% accuracy with MLP. The precision and recall values were 76% and 74% for SVM, and 79% and 78% for MLP, respectively.

The research[18] is to assist potential students in selecting the most suitable study program to develop their skills and minimize the likelihood of academic underachievement or dropout. The data utilized includes personal information, average grades, majors, and test scores of potential students at the Faculty of Computer Science. The study employs the perceptron, a basic artificial neural network (ANN) training method. The results of the simulation analysis conducted using Matlab demonstrate that the perceptron method is capable of identifying the target output and actual output with an accuracy of 54.28%.

The research[19] the global issue of waste is discussed, and image classification is used to categorize waste according to its type. The study compares the performance of CNN (Convolutional Neural Network) and MLP (Multi-Layer Perceptron) algorithms in terms of classification. The research findings indicate that CNN outperforms MLP, achieving precision, recall, f1-score, and accuracy of 0.98 each. This demonstrates that CNN is more effective than MLP in classifying waste based on its type.

The research[20] aims to categorize the quality of hospitals in DKI Jakarta based on their facilities and service capabilities. The research analyzed data from 338 hospitals, considering 112 different attributes. Two algorithms, C4.5 and Multilayer Perceptron (MLP), were utilized to assess hospital grades. The results revealed that MLP achieved an accuracy of 92.64%, surpassing the 83.82% accuracy of the C4.5 algorithm. Therefore, MLP is considered more effective in determining hospital grades.

This research[21] utilizes a perceptron algorithm in artificial intelligence (AI) to address disturbances in the distribution of electrical energy. The researchers created a simulation model to forecast distribution line damage and categorize load consumption. By implementing machine learning, the perceptron algorithm effectively minimized interference by allocating the maximum load proportion based on the designated network architecture.

The research[22] the aim is to identify the selection pattern of Nagari Wali candidates at the Village Head level using the Perceptron Artificial Neural Network (ANN) algorithm. The selection of candidates is conducted based on the provisions of the General Election Commission (KPU) and is carried out by the Voting Organizing Group (KPPS). One common problem in this process is that many candidates and their supporters doubt the performance of KPPS, leading to a crisis of confidence. The Perceptron algorithm is utilized to identify patterns, rules, and conditions with specified variables, and applies fuzzy logic to provide accurate values based on existing data. The test results demonstrate that the ANN with the Perceptron algorithm is capable of producing precise and accurate output, making it suitable as a selection pattern for Wali Nagari candidates and the basis of a knowledge-based system. Additionally, it can aid in improving KPPS performance during elections.

The research[23]compared the performance of the Multilayer Perceptron (MLP) and K-Nearest Neighbor (KNN) algorithms in classifying migraine types based on symptoms to assist in diagnosis and treatment. The researchers used a dataset from Kaggle.com with 24 attributes and 400 rows of data. The results of the study revealed that MLP achieved an accuracy of 91%, while KNN achieved an accuracy of 72%. These findings indicate that MLP outperforms KNN in the classification of migraine types.

This research[24] examines the use of traditional machine learning techniques to predict the frequency of forest fires, which have negative environmental and economic impacts. The methods analyzed include Random Forest, Decision Tree, Logistic Regression, Naive Bayes, and Multilayer Perceptron (MLP), implemented in the Python programming language. Test results demonstrate that MLP performs the best with an accuracy of 93.35% and an F1 Score of 93.69%, using a hidden layer size of 64. Compared to other methods, MLP yields significant results, improving the accuracy of forest fire prediction.

The research process consists of a series of systematic steps in scientific inquiry aimed at answering research questions or testing hypotheses. These steps include identifying the problem, reviewing existing literature, formulating a hypothesis, designing research methods, collecting and analyzing data, and interpreting the results.

2.2 Research Stages

This research was carried out in eight stages. Because researchers do not yet have a quantum device to run the algorithm optimally, this research will only analyze the quantum perceptron training stage of the algorithm to find out whether it can be used to predict rice price data at the Indonesian wholesale trade level. Figure 1 shows the results of this study.

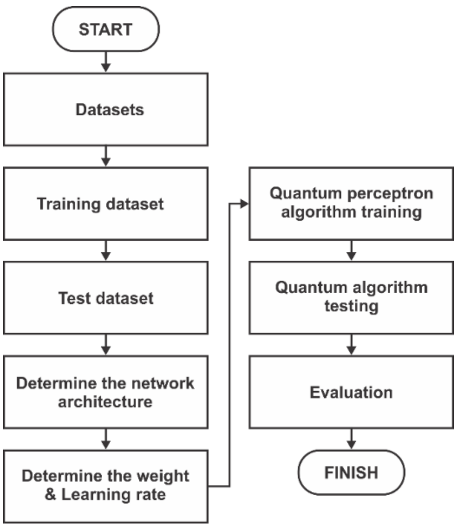

Figure 1. Research Stages

Researchers utilized a dataset of rice prices from the Indonesian wholesale trade level, obtained from the Central Statistics Agency (BPS). The dataset used in this study comprises monthly rice price data. The training process is conducted with the training data set and the quantum perceptron algorithm, which was designed using the proposed quantum circuit architecture. The ratio of training data to data used is 80:20. The training data is derived from a period spanning January 2020 to December 2023. Test data sets are a valuable tool for assessing whether a trained model can apply patterns from the training data to new, unseen data. Twenty per cent of the current data is designated for testing purposes. Data from January 2024 to December 2024 will be used for testing.

Figure 2 illustrates the architecture of the quantum perceptron algorithm. The neural network structure utilized in this study is a 12-2-2 architecture, comprising 12 input layers, 2 hidden layers, and 2 output layers. The strength of connections between neurons is measured by the weight parameter. The learning rate, which determines the step size taken by the optimization algorithm when updating the neural network, is a crucial parameter. In the study, the perceptron dimensions are initially calculated randomly, and the learning rate is set at 0.1.

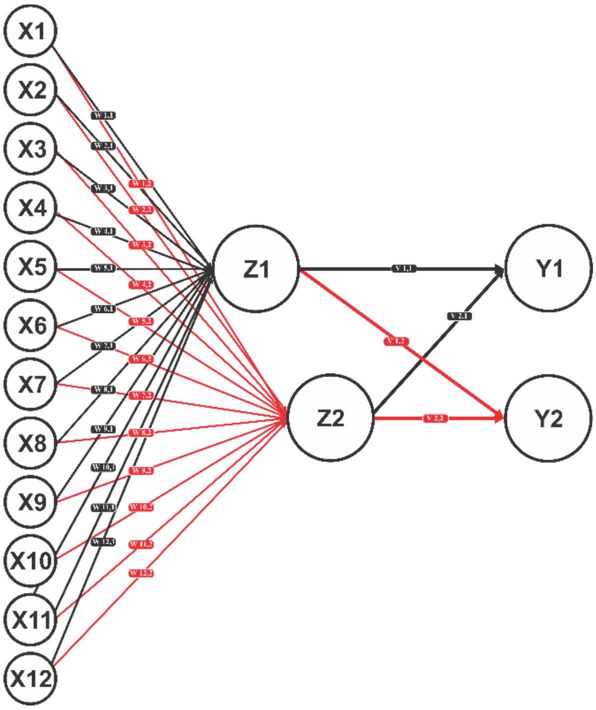

Figure 2. 12-2-2 Quantum Perceptron Structure Model

At this Quantum Perceptron Algorithm Training stage, researchers utilize the Quantum Perceptron algorithm to process training data, leveraging the advantages of quantum computing to recognize patterns or relationships in given data. At the Quantum Perceptron Algorithm Testing stage, the data is tested using a quantum perceptron algorithm to ensure that it can be well generalized to previously unseen data. At the

Evaluation stage, the researchers evaluated the model's ability to forecast rice prices on a large scale in trading.

The dataset utilized in this study is the Indonesian wholesale rice price dataset (Rp/Kg) for the period of 2020-2023 sourced from the Central Statistics Agency (BPS). The dataset is split into training and test data. Data from 2020-2022 (x1-x3) is employed as input data, while data from 2023 (x4) is used as target data, as presented in Table 1.

Table 1. Rice Price Dataset

Rice Price (Month)	X1 2020	X2 2021	X3 2022	X4 2023
January	12342,74	10474	10496	11647,91
February	12355,15	10479	10471	11990,12
March	12368	10424	10463	12041,64
April	12382,1	10356	10455	12092,38
May	12293,03	10385	10448	12102,7
June	12223,98	10384	10448	12115,81
July	12212,63	10361	10449	12141,72
August	12212,07	10352	10551	12265,68
September	12188,86	10351	10772	13036,96
October	12186,97	10367	10947	13315,29
November	12178,62	10375	11012	13380,4
December	12184,52	10429	11363	13458,06

The dataset used in this research is first converted into binary form, specifically 0s and 1s according to predefined rules. The specific conditions for this conversion are outlined in Table 2.

Table 2.Data Transformation Rules

No	Year	Provision	Weight
1	2020	Total <10400	00
		Total >= 10400 and Total <= 11500	01
		Total >= 11501and Total <= 13000	10
		Total > 13000	11
2	2021	Total <10400	00
		Total >= 10400 and Total <= 11500	01
		Total >= 11501and Total <= 13000	10
		Total > 13000	11
3	2022	Total <10400	00
		Total >= 10400 and Total <= 11500	01
		Total >= 11501and Total <= 13000	10
		Total > 13000	11
4	2023	Total <10400	00
		Total >= 10400 and Total <= 11500	01
		Total >= 11501and Total <= 13000	10
		Total > 13000	11

Table 3 presents the binary results of data transformation, converting data into 0 and 1, based on the specifications outlined in Table 2.

Quantum computing is a groundbreaking field that applies the principles of quantum mechanics to conduct calculations. Unlike classical computers, which work with only 0s and 1s, quantum computers use qubits. Qubits can exist in a superposition *of 0* and 1 simultaneously. This unique capability, combined with other quantum phenomena like interference and entanglement, enables quantum computers to solve certain problems that are impossible for classical computers, including the most advanced supercomputers.

Table 3. Data Transformation Rules

Rice Price (Month)	X1	X2	X3	X4
January	10	01	01	10
February	10	01	01	10
March	10	01	01	10
April	10	00	01	10
May	10	00	01	10
June	10	00	01	10
July	10	00	01	10
August	10	00	01	10
September	10	00	01	11
October	10	00	01	11
November	10	00	01	11
December	10	01	01	11

The Perceptron algorithm is fundamental to machine learning, particularly in artificial neural networks (ANN), where it is used for binary classification to separate data into two distinct classes. The perceptron operates by taking a vector input, multiplying its elements by specific weights, and then applying an activation function to produce an output. The learning process of the perceptron involves adjusting weights based on training data so that it can correctly classify the data. While this algorithm is effective for linearly separable data, it has limitations in handling non-linearly separable problems and is not well-suited for complex problems. To address this, more sophisticated neural network models such as the multilayer perceptron (MLP) have been developed.

Perceptrons and more complex artificial neural networks are utilized in various applications such as pattern recognition, image classification, and natural language processing, with the basic concepts remaining essential in machine learning. This phase involves a learning process for the perceptron algorithm to predict wholesale rice prices in Indonesia using a quantum computing approach. Equations 1, 2, 3, and 4 demonstrate the process of implementing the quantum perceptron.

Initialize all inputs, weights, targets, and biases.

Calculate the net using Equation 1.

$$|Z_i> = \sum |W_{ij}>.|X_i> \tag{1}$$

Calculate the output using Equation 2.

$$|y_i> = \sum |Z_i>.|V_{ij}> \tag{2}$$

If $|y> \neq |t>$ then

$$W_{new} = W_{old} + a*(|y> -|t>)*<xi| \tag{3}$$

If not then

$$W_{new} = W_{old} \tag{4}$$

if y=t then stop.

This stage is the evaluation stage for the development of the perceptron algorithm. Researchers evaluated by testing a quantum computing approach using the perceptron algorithm. The quantum computing approach processes data using an algorithm that employs qubits, which means utilizing the values 0 or 1, or 0 and 1 simultaneously. The notation used is Dirac notation, specifically bra and ket.

3. Results and Discussions

In this study, the researchers utilized a 12-2-2 architecture with a learning rate value of 0.1. The research involved the use of the Quantum Perceptron algorithm with a network structure comprising X1-X12 as the input layer, Z1-Z2 as the hidden layer, and Y1-Y2 as the output layer.

The Quantum Perceptron leverages quantum principles to process input through hidden layers Z1-Z2 and generate predictions or outputs through Y1-Y2 based on the learned data. The first step involves randomly assigning weight values of {0,1} to w and v.

$W_{1,1}= \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix}$, $W_{1,2} = \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}$, $W_{2,1}= \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}$, $W_{2,2} = \begin{bmatrix}0 & 0\\1 & 0\end{bmatrix}$, $W_{3,1}= \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix}$, $W_{3,2} = \begin{bmatrix}1 & 0\\1 & 1\end{bmatrix}$, $W_{4,1}= \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix}$, $W_{4,2} = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}$, $W_{5,1}= \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix}$, $W_{5,2} = \begin{bmatrix}0 & 1\\0 & 1\end{bmatrix}$, $W_{6,1}= \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix}$, $W_{6,2} = \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}$,
$V_{1,1}= \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}$, $V_{1,2}= \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}$, $V_{2,1}= \begin{bmatrix}0 & 0\\1 & 0\end{bmatrix}$, $V_{2,2} = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix}$.

Then the testing starts with data number 1, using 011001011010 as input and 01 as output. The next step is to determine the output values at Z1 and Z2.

$Z_1 = W_{1,1}.|X_1\rangle + W_{2,1}.|X_2\rangle + W_{3,1}.|X_3\rangle + W_{4,1}.|X_4\rangle + W_{5,1}.|X_5\rangle + W_{6,1}.|X_6\rangle = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix}.|1\rangle + \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}.|0\rangle + \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix}.|0\rangle + \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix}.|1\rangle + \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix}.|0\rangle + \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix}.|1\rangle = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0 & 1\\0 & 0\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} = \begin{bmatrix}5\\1\end{bmatrix}$

$Z_2 = W_{1,2}.|X_1\rangle + W_{2,2}.|X_2\rangle + W_{3,2}.|X_3\rangle + W_{4,2}.|X_4\rangle + W_{5,2}.|X_5\rangle + W_{6,2}.|X_6\rangle = \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}.|1\rangle + \begin{bmatrix}0 & 0\\1 & 0\end{bmatrix}.|0\rangle + \begin{bmatrix}1 & 0\\1 & 1\end{bmatrix}.|0\rangle + \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}.|1\rangle + \begin{bmatrix}0 & 1\\0 & 1\end{bmatrix}.|0\rangle + \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}.|1\rangle = \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0 & 0\\1 & 0\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1 & 0\\1 & 1\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0 & 1\\0 & 1\end{bmatrix} . \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix} . \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}1\\5\end{bmatrix}$

$Y_1 = V_{1,1}.|Z_1\rangle + V_{2,1}.|Z_2\rangle = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}.\begin{bmatrix}5\\1\end{bmatrix} + \begin{bmatrix}0 & 0\\1 & 0\end{bmatrix}.\begin{bmatrix}1\\5\end{bmatrix} = \begin{bmatrix}5\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}5\\2\end{bmatrix}$

$Y_2 = V_{1,2}.|Z_1\rangle + V_{2,2}.|Z_2\rangle = \begin{bmatrix}0 & 0\\1 & 1\end{bmatrix}.\begin{bmatrix}5\\1\end{bmatrix} + \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix}.\begin{bmatrix}1\\5\end{bmatrix} = \begin{bmatrix}0\\6\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} = \begin{bmatrix}1\\6\end{bmatrix}$

We can see that the temporary outputs Y1 and Y2 are then compared with the target output $Y1=|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$ and $Y_2 = |1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$ if $\begin{bmatrix}1\\0\end{bmatrix} \neq \begin{bmatrix}5\\2\end{bmatrix}$ and $\begin{bmatrix}0\\1\end{bmatrix} \neq \begin{bmatrix}1\\6\end{bmatrix}$ then the weights w and v are changed from |X1> to |X6>. The weight changes from W1, to W6,1, V1,1, V2,1 are as follows.

$W_{1,1}\text{ new} = W_{1,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_1| = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 1| = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [0 \quad 1] = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}0{,}5 & 1\\1{,}1 & 0\end{bmatrix}$

$W_{2,1}\text{ new} = W_{2,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_2| = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 0| = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [1 \quad 0] = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}1{,}5 & 0\\0{,}1 & 1\end{bmatrix}$

$W_{3,1}\text{ new} = W_{3,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_3| = \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 0| = \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [1 \quad 0] = \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}0{,}5 & 0\\0{,}1 & 1\end{bmatrix}$

$W_{4,1}\text{ new} = W_{4,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_4| = \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 1| = \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [0 \quad 1] = \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}0{,}5 & 1\\1{,}1 & 1\end{bmatrix}$

$W_{5,1}\text{ new} = W_{5,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_5| = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 0| = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [1 \quad 0] = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}1 & 0\\0 & 0\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}1{,}5 & 0\\0{,}1 & 0\end{bmatrix}$

$W_{6,1}\text{ new} = W_{6,1}\text{old} + \alpha . (|Y_1\rangle - |T_1\rangle) . \langle X_6| = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - 1\right) . \langle 1| = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \left(\begin{bmatrix}5\\2\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . [0 \quad 1] = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5\\1\end{bmatrix} . [1 \quad 0] = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + 0{,}1 \ . \begin{bmatrix}5 & 0\\1 & 0\end{bmatrix} = \begin{bmatrix}0 & 1\\1 & 0\end{bmatrix} + \begin{bmatrix}0{,}5 & 0\\0{,}1 & 0\end{bmatrix} = \begin{bmatrix}0{,}5 & 1\\1{,}1 & 0\end{bmatrix}$

5. Conclusions

The research utilizes quantum computing along with the perceptron algorithm. The researchers focused on analyzing the quantum perceptron algorithm because of the limited availability of quantum computing devices. The findings of this research are confined to analysis. To advance this research, the author recommends that future studies employ quantum devices to achieve more accurate predictions.

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