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Quantum Perceptron: A Novel Approach to Predicting Unemployment Levels in North Sumatra Province

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Abstract

The application of Quantum Computing to improve the perceptron algorithm in unemployment prediction is a new aspect of this research. This study focuses on unemployment, which is a big challenge for the young generation in Indonesia, especially in the North Sumatra region. This research applies the quantum perceptron method to provide an alternative solution for predicting the unemployment rate. The data used in this analysis comes from the North Sumatra Central Statistics Agency and includes published unemployment rates (TPT) for individuals aged 15 years and over from 2017 to 2023. This research uses seven variables ranging from x1 to x7 to produce accurate data. Quantum perceptron methods offer specific advantages over traditional methods, including higher computing speeds and the ability to handle greater data complexity. This analysis aims to identify unemployment patterns and trends in North Sumatra and provide more accurate predictions by applying the quantum perceptron method. Although the results of this research are still limited to analysis, this research shows promising results and opens up opportunities for further, more in-depth research. This research is limited to predicting unemployment rates in North Sumatra. The use of quantum computing using the quantum perceptron method shows great potential for application to various other socio-economic problems in the future. This research contributes by introducing a new approach that utilizes quantum technology to improve prediction accuracy in economic analysis.

Keywords: *Analysis; quantum perceptron; quantum computing; initial prediction*

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1. Introduction

Quantum Perceptron is a new technology that leverages quantum effects to achieve significant results and, in some cases, exponentially increase the speed of algorithms compared to classical algorithms. The growing importance of machine learning in recent years has led to several studies investigating the potential of quantum computers in machine learning. [1], [2], [3].

One of the main challenges in the economic sphere that has a detrimental impact on societal welfare is unemployment. Unemployment is not only a social problem but also an individual issue with psychological implications for those affected. Data from the Central Bureau of Statistics over the period from 2017 to 2023 shows that the number of unemployed people in North Sumatra has tended to increase over the past seven years. [4], [5], [6].

The Central Bureau of Statistics (BPS) of North Sumatra recorded a workforce of 7.48 million people in the province as of February 2021. This number increased by 129,000 compared to August 2020. Among the working population, there were 449,000 unemployed individuals in February 2021. On a year-on-year basis, the unemployment rate in North Sumatra has started to decline, albeit slowly. The number of unemployed in August 2021 was 475,000, and in August 2022, it was 473,000. However, compared to February 2023, the unemployment rate in North Sumatra saw a significant increase from the previous 413,000 individuals, with the number of unemployed rising by 59,000.

As a developing country, Indonesia faces challenges in addressing unemployment. The unemployment rate is an indicator that affects a country's income and wealth. Therefore, forecasting the number of unemployed and estimating future unemployment figures is essential for

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North Sumatra to prepare appropriate solutions to build a more prosperous society [7], [8], [9].

Prediction is a step to estimate the value of a variable in the future by referring to available information from the past. The information typically used for making predictions is quantitative data. The goal of prediction is not to provide a definitive answer about what will happen but to attempt to estimate the most likely outcome. The term prediction is often interpreted as a forecast or estimate (forecast) [10], [11], [12]. Several previous studies that serve as references for this research include the Neural Network Analysis for Estimating the Open Unemployment Rate in North Sumatra. The dataset used encompasses unemployment data in North Sumatra from 2010 to 2015, using the backpropagation method and comparing five architectural models. Another reference study is the Optimization Analysis of Training Functions for Machine Learning Neural Networks in Poverty Forecasting. This dataset includes poverty data in Indonesia over 12 years (2009 - 2020) covering 34 provinces. The training and testing results showed that the Bayesian Regulation training function was the best option compared to Standard Backpropagation and Step Secant (OSS). Therefore, the Bayesian Regulation training function can be used to address poverty forecasting issues in Indonesia. The Bayesian Regulation training function (trainbr) enables more efficient network training, with faster training epochs/performance, and lower Mean Squared Error (MSE) rates in testing compared to other training functions. However, no research has yet utilized quantum computing in this context.

This research discusses the analysis of the use of the quantum perceptron method to predict the unemployment rate in North Sumatra Province and also to identify unemployment patterns and trends in North Sumatra Province. The data analyzed is the Open Unemployment Rate (OUR) for residents aged 15 and above in North Sumatra Province from 2017 to 2023. Seven variables are used, consisting of six input data and one target data. The results of the quantum perceptron analysis in predicting the unemployment rate in North Sumatra Province can serve as a basis for the next stage of implementation and as a guide for formulating the best solutions to address this issue.

2. Research Methods

In the domain of quantum computing, there is the concept of the quantum bit (qubit), which is the fundamental unit of quantum information. Qubits have two states, represented as $|0\rangle$ and $|1\rangle$, where the notation "$|\rangle$" is known as Dirac's notation. The theory of quantum computing is inspired by phenomena in quantum mechanics, such as superposition, where a particle can exist in two states simultaneously. In classical computing, bits have values of either 0 or 1, but in quantum computing, a bit (qubit) can be 0, 1, or any quantum superposition of these states.

A qubit $|0\rangle$ has a value represented as $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$, and a qubit $|1\rangle$ has a value represented as $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$, Conversely, the bra notation ($\langle 0|$ and $\langle 1|$) represents the conjugate transpose of these states, with $\langle 0|$ and $\langle 1|$ given by $\langle 0| = [1 \;\; 0]$, $\langle 1| = [0 \;\; 1]$. The concept of the qubit is applied to both input and output nodes in the learning process. This allows quantum computing to leverage the superposition principle, enabling qubits to process a vast amount of information simultaneously. By harnessing the properties of qubits, quantum algorithms can perform complex computations more efficiently than classical algorithms, particularly for tasks involving large datasets or complex pattern recognition. [13]. In the context of this study, quantum perceptrons use qubits for input and output values, enhancing the capability to predict unemployment rates by processing information in parallel and identifying patterns with greater speed and accuracy. The quantum perceptron method thus represents a significant advancement in computational techniques for economic forecasting and other applications. [14]. Quantum computing is considered a potential solution for enhancing the performance of computationally expensive machine learning algorithms, especially as classical approaches are increasingly constrained by Moore's law slowing down. [15]. Quantum computing offers exciting new possibilities by being able to bypass the technological and thermodynamic limitations of classical computation through direct utilization of the laws of quantum mechanics. [16], [17], [18].

Artificial Neural Networks are processing systems designed and trained to mimic human abilities in solving complex problems through a learning process by adjusting the weights of their synapses. [19]. These networks simulate the structure of the brain and apply it in innovative software capable of recognizing complex patterns and learning from past experiences. [20]. An information processing system that exhibits properties similar to those of biological neural networks (BNNs). Artificial Neural Networks are created as a general mathematical representation of human understanding (human cognition) [21]. ANN is a computational model consisting of a set of interconnected nodes with weights used for processing large amounts of data [22]. The Artificial Brain Organization employs innovation where PCs are customized to have the option to mimic the operations of the human sensory system. In the human brain, nerves possess various capabilities, one of which is perceiving an object. In the Artificial Brain Organization, PCs are trained to understand designs until they can ultimately comprehend an article [23], [24].

The perceptron is one type of artificial neural network that employs supervised learning with the backpropagation method [25]. It has a three-layer structure, including the input layer, hidden layer, and output layer, where each neuron is connected to all neurons in the next layer. It's often reported that perceptrons perform well in non-linear problems [26]. It's a supervised learning technique in neural networks. When designing a neural network, it's crucial to consider the number of specifications to be identified. The neural network consists of several neurons and corresponding inputs[27] as shown in Figure 1.

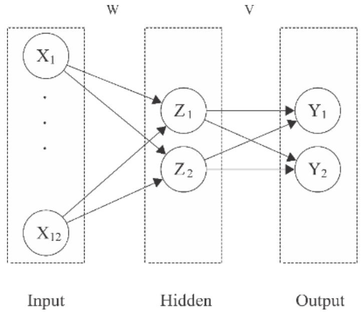

Figure 1. ANN Perceptron Structure Model

A Quantum Perceptron is a variant of artificial neural networks that applies the principles of quantum computing. The quantum perceptron is a mathematical tool capable of processing information with m qubit inputs and producing k qubit outputs[28]. A Quantum Perceptron is a neuron model proposed as an advancement of the classical perceptron. When the weights of the perceptron are in the classical computational basis, it operates like a classical perceptron. However, when these weights are in superposition, the Quantum Perceptron operates according to quantum principles. [29]. The Quantum Perceptron is a key concept in the development of Quantum Neural Networks (QNN) and Quantum Machine Learning (QML) and is analyzed using approaches such as Gardner's program to understand its potential and limitations. [30]. Figure 2 shows an example of a quantum perceptron.

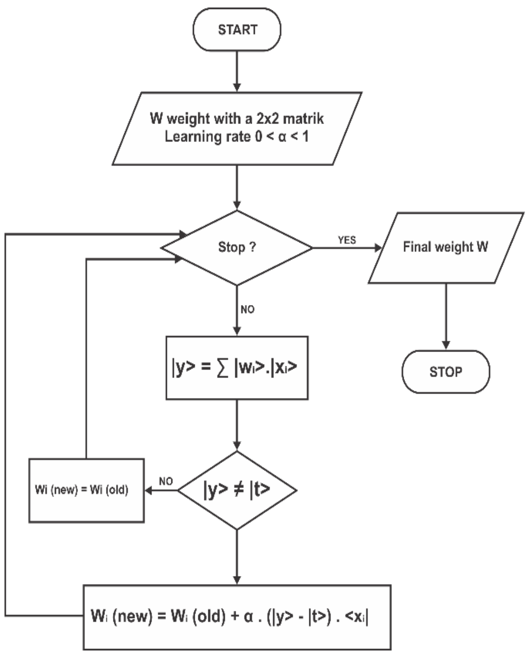

Figure 2. Quantum Perceptron Algorithm[31]

The quantum perceptron can also perform quantum-enhanced feature extraction to improve model accuracy, which is important for natural language processing, drug discovery, and classification.[32]. In this study, researchers implemented a quantum perceptron that uses the sigmoid activation function as a method to efficiently operate on several objects and reverse the process.

Attention to advancements in the fields of deep learning and quantum computing has significantly increased in recent years[33]. The interaction between these rapidly developing areas has led to a new research field called quantum machine learning[34]. By leveraging quantum mechanical phenomena such as superposition and entanglement, the quantum perceptron approach has the potential to offer advantages over its classical counterpart. In recent years, there have been exciting advancements in this interdisciplinary direction. For example, rigorous quantum speedups have been demonstrated in classification models and generative models with complexity theory guarantees[35]. A comparison of the performance of the quantum perceptron model with the classical approach can be seen in Table 1.

Table 1. A comparison of the performance of the quantum perceptron model with the classical approach

Aspect	Quantum Peceptron Model	Classical Perceptron Model
Speed and Computational Complexity	Utilizes superposition and interference for faster parallel processing in certain complex problems.	Sequential and parallel processing on conventional hardware tends to be slower for large-scale and complex problems.
Capacity and Generalization Ability	Leverages the larger Hilbert space, allowing for better generalization and the ability to handle complex data.	Capacity depends on the network architecture, number of neurons, and layers, with good generalization ability in deeper models.
Energy Efficiency	Potentially more energy-efficient as it requires fewer computational steps for certain problems.	Requires more energy, especially for intensive computations.
Robustness and Noise Tolerance	Highly sensitive to noise and external disturbances, with error correction technology still developing.	More resistant to noise and disturbances, with mature hardware and robust algorithms.
Implementation and Accessibility	Still in the research and development phase, with limited and expensive hardware access, requiring specialized knowledge.	Well-established, can be implemented on various conventional hardware with many available software and tools.
Applications and Usefulness	Potential for optimization, molecular	Widely used in industries for image recognition,

Aspect	Quantum Peceptron Model	Classical Perceptron Model
	simulation, and highly complex information processing, but practical applications are still limited.	natural language processing, recommendation systems, and more.

3. Research Methods

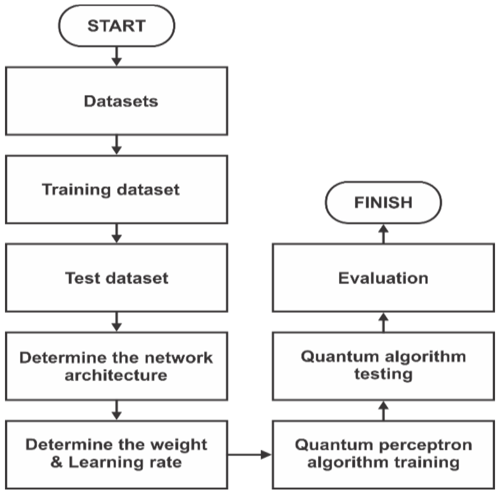

Figure 3. Research Stages

Figure 3 shows the stages of this research. In this study, researchers utilized data on open unemployment rates in North Sumatra Province from 2017 to 2023. This dataset includes the entire North Sumatra Province and its 33 regencies/cities. The data is classified into two sets: a training set and a testing set. Seven variables were used as the basis for projecting unemployment numbers in North Sumatra Province, encompassing the years 2017 (x1), 2018 (x2), 2019 (x3), 2020 (x4), 2021 (x5), 2022 (x6), and 2023 (x7). The period from 2017 to 2022 is considered input data, while the 2023 data is used as the target.

3.1 Qubit Transformations and Superposition

The number of unemployed in North Sumatra Province was converted into a binary format, represented as 0 and 1. This transformation process follows the guidelines described in Table 2.

The data on the number of unemployed individuals in the North Sumatra province according to Regency/City is available for the period from 2017 to 2023. This data encompasses the North Sumatra province and 33 Regencies/Cities within the province, with each Regency/City having data for seven years. The data on the number of unemployed individuals in the North Sumatra province and graphs can be seen in Table 3 and Figure 4.

The graph in Figure 4 shows the change in the unemployment ratio from 2017 to 2023 in North Sumatra province, namely: In 2017, the unemployment ratio was 5.60%; In 2018, the unemployment ratio decreased slightly to 5.56%; In 2019, the unemployment ratio continued to decline to 5.41%; In 2020, the unemployment ratio increased sharply to 6.91%, most likely due to the impact of the COVID-19 pandemic; In 2021, the unemployment ratio will decrease again to 6.33%; In 2022, the unemployment ratio will again decrease to 6.16%; In 2023 the unemployment ratio will continue to decline to 5.89%.

Table 2. Benchmark Data

No	Criteria	Information	Weight
1	2017	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
2	2018	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
3	2019	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
4	2020	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
5	2021	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
6	2022	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11
7	2023	Total <=2% Total >2% and Total <=4% Total >4% and Total <=6% Total >6%	00 01 10 11

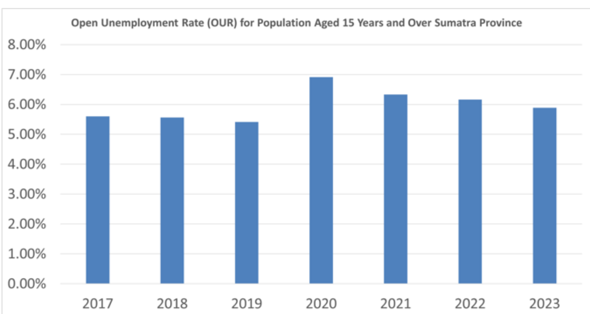

Figure 4. Graph of the unemployment ratio in North Sumatra Province from 2017 to 2023.

The data regarding unemployment in North Sumatra Province was transformed into a binary format according to the guidelines listed in Table 2. The output of this data transformation process is documented in Table 4.

Table 3. Unemployment Data for North Sumatra Province

	OUR by Regency/City (Percent%)						
Regency/City	2017	2018	2019	2020	2021	2022	2023
Sumatera Utara	5.60	5.56	5.41	6.91	6.33	6.16	5.89
Nias	1.19	1.62	1.09	3.49	3.12	2.81	2.31
Mandailing Natal	5.75	4.43	6.37	6.50	6.12	7.64	7.45
Tapanuli Selatan	5.80	5.28	4.17	4.42	4.00	3.65	3.49
Tapanuli Tengah	7.39	6.38	7.26	7.54	7.24	7.97	7.81
Tapanuli Utara	1.89	1.42	1.33	2.94	1.54	1.07	1.03
Toba	2.18	2.15	1.26	2.50	0.83	1.39	1.30
Labuhan Batu	7.09	6.98	5.70	6.05	5.66	6.90	5.99
Asahan	5.95	5.26	6.86	7.24	6.39	6.26	6.12
Simalungun	5.62	5.10	4.39	4.58	4.17	5.51	5.35
Dairi	1.42	1.69	1.58	1.75	1.49	0.88	1.23
Karo	1.34	1.50	1.09	1.83	1.95	2.71	2.63
Deli Serdang	6.16	7.06	5.74	9.50	9.13	.79	8.62
Langkat	3.57	4.67	5.30	7.02	5.12	6.88	6.33
Nias Selatan	1.28	3.77	2.25	4.15	3.91	3.69	3.48
Humbang Hasundutan	0.31	0.34	0.33	0.84	1.94	0.42	0.84
Pakpak Bharat	0.49	0.43	0.19	1.93	1.36	0.26	0.45
Samosir	1.28	1.35	1.25	1.20	0.70	1.16	1.03
Serdang Bedagai	5.98	5.10	4.37	5.54	3.93	4.98	4.97
Batu Bara	5.00	5.39	6.69	6.48	6.62	6.21	5.88
Padang Lawas Utara	3.21	3.15	3.21	3.11	3.19	4.31	4.42
Padang Lawas	4.24	4.10	4.24	4.11	4.07	5.90	5.75
LabuhanBatu Selatan	5.68	4.79	4.80	4.90	4.71	3.15	3.43
LabuhanBatu Utara	6.35	5.67	5.84	6.82	5.71	3.75	4.84
Nias Utara	2.67	2.40	3.07	4.54	3.00	2.59	2.57
Nias Barat	1.23	1.23	1.63	1.71	0.74	0.53	0.80
Sibolga	9.29	8.61	7.40	8.00	8.72	7.05	6.79
Tanjung Balai	5.50	5.58	6.82	6.97	6.59	4.62	4.47
Pematang Siantar	8.80	12.14	11.09	11.50	11.00	9.36	8.62
Tebing Tinggi	9.73	7.23	8.60	9.98	8.37	6.39	6.24
Medan	9.46	8.25	8.53	10.74	10.81	8.89	8.67
Binjai	5.95	7.40	6.14	8.67	7.86	6.36	6.10
Padang Sidimpuan	3.78	5.18	4.34	7.45	7.18	7.76	7.57
Gunung Sitoli	6.00	5.92	5.59	5.94	4.80	3.65	3.67

Table 4. Transformation Result Data

Regency/City	OUR by Regency/City (Percent%)						
	2017	2018	2019	2020	2021	2022	2023
Sumatera Utara	10	10	10	11	11	11	10
Nias	00	00	00	01	01	01	01
Mandailing Natal	10	10	11	11	11	11	11
Tapanuli Selatan	10	10	10	10	01	01	01
Tapanuli Tengah	11	11	11	11	11	11	11
Tapanuli Utara	00	00	00	01	00	00	00
Toba	01	01	00	01	00	00	00
Labuhan Batu	11	11	10	11	10	11	10
Asahan	10	10	11	11	11	11	11
Simalungun	10	10	10	10	10	10	10
Dairi	00	00	00	00	00	00	00
Karo	00	00	00	00	00	01	01
Deli Serdang	11	11	10	11	11	11	11
Langkat	01	10	10	11	10	11	11
Nias Selatan	00	01	01	10	01	01	01
Humbang Hasundutan	00	00	00	00	00	00	00
Pakpak Bharat	00	00	00	00	00	00	00
Samosir	00	00	00	00	00	00	00
Serdang Bedagai	10	10	10	10	01	10	10
Batu Bara	10	10	11	11	11	11	10
PadangLawas Utara	01	01	01	01	01	10	10
Padang Lawas	10	10	10	10	10	10	10
Labuhan Batu Selatan	10	10	10	10	10	01	01
Labuhan Batu Utara	11	10	10	11	10	01	10
Nias Utara	01	01	01	10	01	01	01
Nias Barat	00	00	00	00	00	00	00
Sibolga	11	11	11	11	11	11	11
Tanjung Balai	10	10	11	11	11	10	10

Pematang Siantar	11	11	11	11	11	11	11
Tebing Tinggi	11	11	11	11	11	11	11
Medan	11	11	11	11	11	11	11
Binjai	10	11	11	11	11	11	11
Padang Sidimpuan	01	10	10	11	11	11	11
Gunung Sitoli	10	10	10	10	10	01	01

3. Results and Discussions

The quantum perceptron learning phase employs a 12-2-2 structure and utilizes a dataset of unemployment numbers in the North Sumatra region. Initially, the weights \(w \) and \(v \) are assigned random values {0,1} as shown in Figure 5.

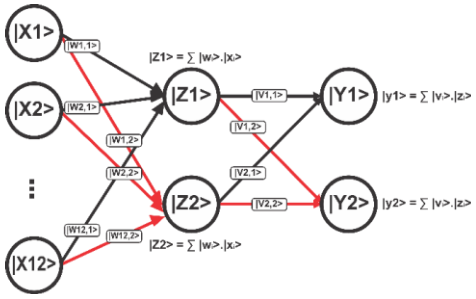

Figure 5. 12-2-2 ANN Quantum Perceptron Structure Model

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

The tested learning rate value is 0,1. The learning process begins with the first data entry from dataset number 1, which consists of the sequence 101010111111 as input and the target output 10. The next step is to find the output in the hidden layers Z_1 and Z_2.

Output $Z_1 = W_{1,1}.|X_1> + W_{2,1}.|X_2> + W_{3,1}.|X_3> + W_{4,1}.|X_4> + W_{5,1}.|X_5> + W_{6,1}.|X_6> + W_{7,1}.|X_7> + W_{8,1}.|X_8> + W_{9,1}.|X_9> + W_{10,1}.|X_{10}> + W_{11,1}.|X_{11}> + W_{12,1}.|X_{12}>$

$$= \begin{bmatrix}0&1\\1&0\end{bmatrix}.|1> + \begin{bmatrix}1&0\\0&1\end{bmatrix}.|0> + \begin{bmatrix}0&0\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&1\\1&1\end{bmatrix}.|0> + \begin{bmatrix}1&0\\0&0\end{bmatrix}.|1> + \begin{bmatrix}0&1\\1&0\end{bmatrix}.|0> + \begin{bmatrix}1&0\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&0\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&1\\1&1\end{bmatrix}.|1> + \begin{bmatrix}1&0\\0&0\end{bmatrix}.|1> + \begin{bmatrix}0&1\\1&0\end{bmatrix}.|1> + \begin{bmatrix}1&0\\0&1\end{bmatrix}.|1>$$

$$= \begin{bmatrix}0&1\\1&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&1\\1&1\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1&0\\0&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&1\\1&0\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&1\\1&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&1\\1&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix}$$

$$= \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}4\\7\end{bmatrix}$$

Output $Z_2 = W_{1,2}.|X_1> + W_{2,2}.|X_2> + W_{3,2}.|X_3> + W_{4,2}.|X_4> + W_{5,2}. |X_5> + W_{6,2}.|X_6> + W_{7,2}.|X_7> + W_{8,2}.|X_8> + W_{9,2}.|X_9> + W_{10,2}. |X_{10}> + W_{11,2}. |X_{11}> + W_{12,2}. |X_{12}>$

$$= \begin{bmatrix}0&0\\1&1\end{bmatrix}.|1> + \begin{bmatrix}0&0\\1&0\end{bmatrix}.|0> + \begin{bmatrix}1&0\\1&1\end{bmatrix}.|1> + \begin{bmatrix}1&0\\0&1\end{bmatrix}.|0> + \begin{bmatrix}0&1\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&0\\1&1\end{bmatrix}.|0> + \begin{bmatrix}0&0\\1&0\end{bmatrix}.|1> + \begin{bmatrix}1&0\\1&1\end{bmatrix}.|1> + \begin{bmatrix}1&0\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&1\\0&1\end{bmatrix}.|1> + \begin{bmatrix}0&0\\1&1\end{bmatrix}.|1> + \begin{bmatrix}0&0\\1&0\end{bmatrix}.|1>$$

$$\begin{bmatrix}0&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0&1\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0&0\\1&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&1\\0&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0&0\\1&0\end{bmatrix} \cdot \begin{bmatrix}0\\1\end{bmatrix}$$

$$= \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1\\0\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}1\\1\end{bmatrix} + \begin{bmatrix}0\\1\end{bmatrix} + \begin{bmatrix}0\\0\end{bmatrix} = \begin{bmatrix}4\\8\end{bmatrix}$$

Output $Y_1 = V_{1,1}.|Z_1> + V_{2,1}.|Z_2>$

$$= \begin{bmatrix}1&0\\0&1\end{bmatrix} \cdot \begin{bmatrix}4\\7\end{bmatrix} + \begin{bmatrix}0&0\\1&0\end{bmatrix} \cdot \begin{bmatrix}4\\8\end{bmatrix} = \begin{bmatrix}4\\7\end{bmatrix} + \begin{bmatrix}0\\4\end{bmatrix} = \begin{bmatrix}4\\11\end{bmatrix}$$

Output $Y_2 = V_{1,2}.|Z_1> + V_{2,2}.|Z_2>$

$$= \begin{bmatrix}0&0\\1&1\end{bmatrix} \cdot \begin{bmatrix}4\\7\end{bmatrix} + \begin{bmatrix}1&0\\0&0\end{bmatrix} \cdot \begin{bmatrix}4\\8\end{bmatrix} = \begin{bmatrix}0\\11\end{bmatrix} + \begin{bmatrix}4\\0\end{bmatrix} = \begin{bmatrix}4\\11\end{bmatrix}$$

Subsequently, the interim results Y_1 and Y_2 are compared with the expected outcome of $Y_1 = |1> = \begin{bmatrix}0\\1\end{bmatrix}$ and $Y_2 = |0> = \begin{bmatrix}1\\0\end{bmatrix}$ where $\begin{bmatrix}0\\1\end{bmatrix} \neq \begin{bmatrix}4\\11\end{bmatrix}$ and $\begin{bmatrix}1\\0\end{bmatrix} \neq \begin{bmatrix}4\\11\end{bmatrix}$ Then, the weights $W_{i,j}$ and $V_{i,j}$ from $|X_1>$ to $|X_{12}>$ are adjusted, and the error value is computed. Initially, the weights for $W_{1,1}$ to $W_{12,1}$ and $V_{1,1}$ to $V_{2,1}$ are adjusted when $Y_1 \neq T_1$.

New $W_{1,1}$ weights = $W_{1,1}$ old + $\alpha.(|Y_1> - |T_1>).<X_1|$

$$= \begin{bmatrix}0&1\\1&0\end{bmatrix} + 0,1 . \left(\begin{bmatrix}4\\11\end{bmatrix} - \begin{bmatrix}0\\1\end{bmatrix}\right) . <1|$$

$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1,4 \\ 1 & 1 \end{bmatrix}$$

New $W_{2,1}$ weights = $W_{2,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_2|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 0|$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 & 0 \\ 10 & 0 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0,4 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1,4 & 0 \\ 1 & 1 \end{bmatrix}$$

New $W_{3,1}$ weights = $W_{3,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_3|$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0,4 \\ 0 & 2 \end{bmatrix}$$

New $W_{4,1}$ weights = $W_{4,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_4|$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 0|$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 & 0 \\ 10 & 0 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 0,4 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 0,4 & 1 \\ 2 & 1 \end{bmatrix}$$

New $W_{5,1}$ weights = $W_{5,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_5|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0,4 \\ 0 & 1 \end{bmatrix}$$

New $W_{6,1}$ weights = $W_{6,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_6|$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 0|$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 & 0 \\ 10 & 0 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0,4 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 0,4 & 1 \\ 2 & 0 \end{bmatrix}$$

New $W_{7,1}$ weights = $W_{7,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_7|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0,4 \\ 0 & 2 \end{bmatrix}$$

New $W_{8,1}$ weights = $W_{8,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_8|$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 4 \\ 0 & 2 \end{bmatrix}$$

New $W_{9,1}$ weights = $W_{9,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_9|$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1,4 \\ 1 & 2 \end{bmatrix}$$

New $W_{10,1}$ weights = $W_{10,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_{10}|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0,4 \\ 0 & 1 \end{bmatrix}$$

New $W_{11,1}$ weights = $W_{11,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_{11}|$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1,4 \\ 1 & 1 \end{bmatrix}$$

New $W_{12,1}$ weights = $W_{12,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle X_{12}|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \langle 1|$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 0 & 4 \\ 0 & 10 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0,4 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0,4 \\ 0 & 2 \end{bmatrix}$$

New $V_{1,1}$ weights = $V_{1,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle Z_1|$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \begin{bmatrix} 4 & 7 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 4 & 7 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 16 & 20 \\ 40 & 70 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 1,6 & 2 \\ 4 & 7 \end{bmatrix} = \begin{bmatrix} 2,6 & 2 \\ 4 & 8 \end{bmatrix}$$

New $V_{2,1}$ weights = $V_{2,1}$ old + $\alpha.(|Y_1\rangle - |T_1\rangle).\langle Z_2|$
$$= \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \left(\begin{bmatrix} 4 \\ 11 \end{bmatrix} - \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) . \begin{bmatrix} 4 & 8 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 4 \\ 10 \end{bmatrix} . \begin{bmatrix} 4 & 8 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + 0,1 \,.\, \begin{bmatrix} 16 & 32 \\ 40 & 80 \end{bmatrix}$$
$$= \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 1,6 & 3,2 \\ 4 & 8 \end{bmatrix} = \begin{bmatrix} 1,6 & 3,2 \\ 5 & 8 \end{bmatrix}$$

The next step is to adjust the weights from $W_{1,2}$ to $W_{12,2}$, and from $V_{1,2}$ to $V_{2,2}$. After the adjustment of weights W and V, the learning process continues with the second set of data. The algorithm iteratively adjusts the weights until the expected output (T) matches the interim output (Y) or until the error value reaches 0. Weight adjustments will continue until the set goal is achieved.

4. Conclusions

This research is still in the initial analysis stage, with a focus on the use of quantum perceptron algorithms and quantum computing. However, further steps are needed to test its validity and effectiveness more deeply. Further research will be key to understanding the extent to which the application of this method can make a significant contribution. Nevertheless, this research has succeeded in identifying unemployment patterns and trends in North Sumatra. The analysis results show that this method is able to process and analyze unemployment data more efficiently and in-depth. The application of optimized quantum perceptron neural networks with the help of quantum computing has provided a more accurate picture of unemployment trends in the region. This research also shows that quantum technology has great potential to help policymakers, economists and other stakeholders overcome the challenge of unemployment. With more precise data analysis, the policies developed can be more targeted, training programs can be more effective, and the creation of new jobs can be more innovative. However, to achieve successful practical implementation, large investments in quantum technologies are required as well as the development of relevant skills among professionals in this field. Thus, this research not only provides more detailed insight into unemployment trends in North Sumatra but also paves the way for a deeper understanding of the region's economic dynamics. The next step is to implement these findings in real policies and programs to reduce the unemployment rate in the region.

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