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COMPARISON OF ADALINE AND HEBBIAN ALGORITHMS ON PATTERN RECOGNITION WITH QUANTUM COMPUTING APPROACH

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Abstract— *In this research, a quantum computational approach was employed to enhance the Adaline and Hebbian algorithms. A comparative analysis of these algorithms was conducted, focusing on their performance, specifically the accuracy of test outcomes. The investigation was carried out utilizing a hepatitis prediction dataset comprising data related to individuals diagnosed with hepatitis, with observations on whether they were alive or deceased. The dataset encompassed 19 distinctive symptoms, with 18 symptoms utilized for hepatitis pattern recognition and ten symptoms employed as simulated test data for the Adaline and Hebbian algorithms integrated with quantum computation methodologies. The findings of the study revealed advancements in the Adaline and Hebbian algorithms, as influenced by the integration of a quantum computational framework. Notably, the simulation testing outcomes exhibited a remarkable accuracy rate of 100% for both the Adaline and Hebbian algorithms. Consequently, the results underscore the comparable performance of the two algorithms, highlighting their identical accuracy levels.*

Keywords: *Adaline, Hebbian, Pattern Recognition, Quantum Bit, Quantum Computing.*

Intisari— *Dalam penelitian ini, pendekatan komputasi kuantum digunakan untuk meningkatkan algoritma Adaline dan Hebbian. Analisis komparatif terhadap algoritme ini dilakukan, dengan fokus pada kinerjanya, khususnya keakuratan hasil tes. Investigasi dilakukan dengan menggunakan kumpulan data prediksi hepatitis yang terdiri dari data yang terkait dengan individu yang didiagnosis dengan hepatitis, dengan pengamatan apakah mereka masih hidup atau sudah meninggal. Dataset ini mencakup 19 gejala yang berbeda, dengan 18 gejala yang digunakan untuk pengenalan pola hepatitis dan sepuluh gejala yang digunakan sebagai data uji simulasi untuk algoritma Adaline dan Hebbian yang diintegrasikan dengan metodologi perhitungan kuantum. Temuan dari penelitian ini mengungkapkan kemajuan dalam algoritma Adaline dan Hebbian, yang dipengaruhi oleh integrasi kerangka kerja komputasi kuantum. Khususnya, hasil pengujian simulasi menunjukkan tingkat akurasi yang luar biasa yaitu 100% untuk algoritma Adaline dan Hebbian. Hasilnya, hasil tersebut menggarisbawahi kinerja yang sebanding dari kedua algoritma tersebut, yang menyoroti tingkat akurasi yang sama.*

Kata Kunci: *Adaline, Hebbian, Pengenalan Pola, Bit Kuantum, Komputasi Kuantum.*

INTRODUCTION

Contemporary conventional computing operates by manipulating binary bits, representing information as either 0 or 1. The collective action of millions of these bits enables the rapid processing and presentation of data, a familiar experience on devices like smartphones, laptops, and cloud servers. In contrast, quantum computers leverage principles from quantum mechanics to process information. At the core of this quantum computing paradigm are qubits, which, unlike classical bits limited to 0 or 1 (or their probabilistic blend), can exist in a superposition—a complex combination of states weighted by their respective values [1].

Emerging quantum computational technology harnesses quantum phenomena to expedite algorithms significantly, often achieving exponential acceleration compared to their classical counterparts. Within the framework of quantum computing, particles exhibit superposition as qubits, analogous to classical bits, with the potential to form entangled states. For instance, the representation of |11000110> demonstrates the utilization of qubits. Furthermore, qubits can assume a superposition state, as denoted in the equation [2] [3].

There are many studies on the Adaline algorithm, including research that uses the ADALINE neural network to detect harmonics in shunt active power filters. This method is intended to improve the efficiency and accuracy of harmonic detection in power systems. By implementing ADALINE neural network technology, this research has contributed to developing better technology to overcome harmonic problems in power systems[4].

This paper introduces a novel prototype for an enhanced smart home controller, which incorporates a neural network-based algorithm to facilitate decision-making and actions based on current conditions. Diverging from prior approaches, this design harnesses IoT (Internet of Things) technology alongside a neural network-based algorithm to refine controller functionality. Given the diverse array of sensors, actuators, smart appliances, and mobile terminals typically present in a smart home, internet connectivity is imperative to enable communication and service provision for occupants. The development of the proposed controller involves several stages, including the implementation of the ADALINE (Adaptive Linear) neural network method, prototype design, and validation via mean average percentage error (MAPE) calculation. This prototype amalgamates the functionalities of multiple household appliances into a single application controllable via smartphone. ADALINE serves as the algorithm for output prediction when the controller operates in automatic mode. While the accuracy attained may not currently meet expectations, further testing on larger datasets is anticipated to yield improved results. The findings presented in this paper aim to foster the adoption of smart technology in more Indonesian households [5].

Quantum computing stands among the burgeoning technologies, with various communities and research institutions striving to translate theoretical advancements into tangible applications. Concurrently, Artificial Intelligence (AI) represents another rapidly evolving domain, gaining stability over time. The primary focus of this paper is to assess the influence of quantum computing research on the development of AI applications. To achieve this objective, computational methodologies are employed, enabling a conclusive analysis of the escalating impact of quantum computing research on specific AI applications. Furthermore, this paper explores the potential implications of quantum computing within the realm of artificial intelligence [6].

This review paper offers an original examination of quantum computing's potential contributions to healthcare systems, focusing on its capacity to transform compute-intensive healthcare activities like drug discovery, personalized medicine, DNA sequencing, medical imaging, and operational optimization. By thoroughly analyzing existing literature, we have constructed categorizations spanning various aspects, including background and enabling technologies, applications, prerequisites, architectures, security considerations, unresolved issues, and future research trajectories. This comprehensive approach provides a panoramic overview of quantum computing's role in healthcare. Our review aims to assist both novice and seasoned researchers in quantum computing and healthcare, facilitating their comprehension of the current research landscape, identification of potential opportunities and obstacles, and informed decision-making in the development of new architectures and applications for quantum computing within healthcare settings [7].

We introduce a novel quantum algorithm designed for data classification, drawing upon the nearest-neighbor learning approach. Our classification process unfolds in two key phases: initially, data within identical classes are segmented into smaller clusters, facilitated by sublabels that aid in delineating boundaries

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between data points bearing different labels. Subsequently, we devise a quantum circuit for classification, incorporating multi-control gates. Notably, our algorithm stands out for its ease of implementation and efficiency in predicting labels for test data. To underscore the efficacy of our approach, we employ it to construct a phase transition diagram for the metal-insulator transition of VO2. Despite utilizing limited experimental data for training, VO2, a prototypical strongly correlated electron material, our algorithm demonstrates promising results. This transition between metallic and insulating phases has garnered significant interest in condensed matter physics. Furthermore, we validate our algorithm through experiments involving the classification of randomly generated data and the classification of entanglement for various Werner states. Notably, our algorithm successfully handles scenarios where training sets cannot be partitioned by a single curve, necessitating the use of multiple curves for perfect separation. These initial findings highlight the substantial potential of our approach for addressing diverse classification problems, particularly in delineating different phases in materials[8].

This study introduces a novel approach for efficient harmonic detection to enable real-time generation of the reference current supplied to a shunt active power filter. Utilizing the ADALINE neural network, our proposed method consists of a single layer comprising 101 nodes responsible for generating coefficients, known as weights, for the reference current model. This innovation effectively addresses the limitations of existing technology, such as the instantaneous power theory (PQ). We implemented the proposed method on the TMS320F28335 DSP board and evaluated its performance against MATLAB with Simulink in a hardware-in-loop (HIL) setup. Our method demonstrates excellent performance by generating precise reference current rapidly with minimal computational complexity. Additionally, it efficiently mitigates individual harmonic currents, resulting in a significant reduction in the percentage of total harmonic distortion (%THD) in the current, aligning with IEEE standards, while maintaining power factor unity. [9].

This research discusses the evolution and combination of Hebbian learning rules to increase generalization by reducing the number of regulations. This research focuses on developing an effective learning strategy for neural networks by integrating various Hebbian learning rules into a smaller number but with better generalization capabilities. This approach has important implications in the development of artificial intelligence, especially in understanding how to improve the learning capabilities of neural networks in handling complex and varied information. Thus, this research can significantly contribute to the fields of artificial intelligence and cognitive science[10].

This research develops synaptic plasticity rules that consider the strong Allee effect applied in an unsupervised learning environment. This aims to increase our understanding of how such authorities can improve automatic learning and adaptation capabilities in neural networks or other artificial intelligence systems. This research has the potential to provide valuable insight into how the Allee effect can be exploited in unsupervised learning environments, which could have a significant impact on the fields of artificial intelligence and cognitive science[11].

Research discusses learning rules for quantum neural networks inspired by Hebbian learning. This research aims to develop a learning method that suits the characteristics of quantum neural networks by utilizing Hebbian learning principles, which have been proven effective in classical neural networks. By integrating Hebbian learning concepts into quantum neural networks, this research may contribute to understanding how classical learning principles can be applied in quantum computing. The implications of this research could be related to developing more sophisticated and practical applications of quantum neural networks in various fields, including computing and artificial intelligence[12].

Research analyzes the feedforward compensation of piezoelectric actuators using artificial neural networks with conventional PID and single-neuron PID controllers based on Hebb's learning rule. This research aims to develop an effective compensation method to improve the performance of piezoelectric actuators by using artificial neural networks and the mentioned PID controller. By integrating Hebb's learning principles into a PID controller, this research has provided a better understanding of how to leverage artificial intelligence to improve the performance of piezoelectric actuator control systems. The implications of this research relate to developing more sophisticated and efficient control technologies in various applications, including precision techniques in fields such as robotics, automation, and mechatronics technology[13].

Based on Hebb's learning rule, research focuses on single-neuron adaptive hysteretic compensation of piezoelectric actuators. This research aims to develop an effective method to overcome the hysteretic problem in piezoelectric actuators by applying Hebb's learning principles at the single neuron level. By using Hebb's learning principles for actuator hysteretic compensation, this research contributed to our understanding of optimizing piezoelectric actuators' performance through artificial intelligence techniques. The implications of this research can be related to developing more sophisticated and efficient control technologies, especially in applications that require high accuracy and fast responsiveness, such as precision, sensory and industrial automation technologies[14].

This research uses an artificial neural network with the Hebb algorithm to optimize employee ability assessment. This research aims to develop an efficient method for transmitting employee abilities by applying Hebb's learning principles to artificial neural networks. By utilizing Hebb's algorithm in the assessment process, this research has provided valuable insight into how artificial intelligence can be applied in human resource management environments to increase accuracy and efficiency in assessing employee capabilities. The implications of this research relate to more sophisticated and efficient development assessment methods in human resource management, which can positively impact organizational human resource development and strategic planning[15].

This research focuses on the ability of local plasticity rules to learn deep representations using independent contrastive predictions. This research aims to develop a practical learning approach for building complex data representations by applying local plasticity rules and contrastive prediction. By exploiting local plasticity rules and contrastive prediction, this research has provided a better understanding of optimizing representation learning in the context of artificial intelligence. The implications of this research could be related to developing more sophisticated and efficient machine learning techniques, especially in applications that require a deep understanding of complex data representation, such as natural language processing, computer vision, and big data processing[16].

This research compares stacking modeling and the Cannistraci-Hebb adaptive automata network in predicting links in complex networks. This research aims to compare the performance of the two methods in predicting links in complex networks, focusing on the accuracy and efficiency of each approach. Through this comparison, this research provides valuable insight into the strengths and weaknesses of each method in dealing with link prediction problems in complex networks. The implications of this research can provide direction for developing more effective and accurate prediction methods in the context of complex network analysis, which can be helpful in various applications, such as social analysis, biological networks, and information systems[17].

This research discusses RS-HeRR, a neuro-fuzzy system based on rough set-based Hebbian rule reduction. This system was developed to improve the ability of neuro-fuzzy systems to handle complex problems through the application of Hebbian rule reduction and the concept of rough sets. Through this approach, this research has made an essential contribution to developing intelligent systems that are more adaptive and responsive in handling complex and uncertain data. Combining the principles of Hebbian rule reduction and rough sets into a neuro-fuzzy system, this research has important implications in various applications that require complex data analysis, including in artificial intelligence, data analysis, and information systems[18].

This research discusses multi-context blind source separation using error-governed Hebbian rules. This approach may be developed to enable more accurate and efficient source separation in scenarios where the source is unknown or not directly accessible. This research has contributed to our understanding of effectively separating seeds in various complex and uncertain contexts using error-governed Hebbian rules. The implications of this research can be applied in multiple applications, including signal processing, audio processing, and data analysis involving the search or identification of hidden sources[19].

This research discusses meta-learning through Hebbian plasticity in random networks. Using this approach, this research aims to explore the ability of random networks to perform meta-learning via Hebbian plasticity mechanisms. Through the use of Hebbian plasticity, this research provides insight into how to increase network adaptability in the face of different tasks and learning environments. The implications of this research could be related to the development of more adaptive and responsive machine learning techniques, especially in the context of artificial intelligence and automated learning[20].

This study's main problem is finding other alternatives to the Adaline and Hebbian algorithms

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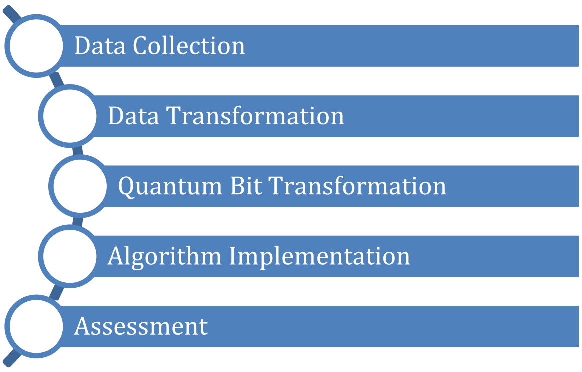
by comparing the two algorithms using a quantum computation approach. Quantum computing in operation uses bits 1 or 0 or a combination of both with the hope that the algorithm's performance will increase. The main problem in this study is to find other alternatives to the Adaline and Hebbian algorithms by comparing the two algorithms using a quantum computation approach. Quantum computing in operation uses bits 1 or 0 or a combination of both with the hope that the algorithm's performance will increase.

MATERIALS AND METHODS

Here are the research stages that have been conducted, as shown in Figure 1. Research stages:



Source: (Research Results, 2024)

Figure 1.Research Stage

The following is an explanation of figure 1 regarding the research stage:

a. Data Collection:
The study involves the compilation of data on hepatitis symptoms, focusing on the binary outcomes of survival or fatality. Sourced from Kaggle, the dataset encompasses 155 entries, featuring 19 attributes and a singular target variable denoting survival status. Prior to the data transformation phase, meticulous data cleansing procedures are employed to eliminate any erroneous or invalid entries. Specifically, the test subset comprises 10 data points alongside 18 distinct symptoms associated with hepatitis.

b. Data Transformation:
This phase primarily involves the conversion of the hepatitis prediction dataset into binary representations (1 or 0) for streamlined processing.

c. Quantum Bit Transformation:
Subsequently, the binary data undergoes a transformation into quantum bits, paving the way for the application of the Adaline algorithm.

d. Algorithm Implementation:
This stage entails two key processes. The initial step revolves around the implementation of the Adaline algorithm using quantum computing techniques, followed by the subsequent deployment of the Hebbian algorithm also leveraging quantum computing methodologies.

e. Assessment:
The study culminates in the development and assessment of the Adaline and Hebbian algorithms. Researchers conduct a comprehensive evaluation by comparing the performance of the two algorithms, emphasizing the accuracy of the test outcomes.

The data set employed in this investigation concerns the prognosis of hepatic conditions among individuals, categorizing them based on their vitality status (i.e., survival or fatality). The data encompassed a comprehensive representation of 19 distinctive symptoms. Among these, 18 signs were utilized specifically to recognize patterns associated with hepatitis, while 10 data points were employed for further analysis.

To transform the data, specific rules were applied. These included criteria based on various symptoms such as age, steroid usage, antivirus medication, fatigue, malaise, anorexia, liver size, liver firmness, palpable spleen, presence of spider nevi, ascites, and varices.

Moreover, parameters like bilirubin levels, alkaline phosphatase, serum glutamic oxaloacetic transaminase (SGOT) levels, albumin concentrations, and prothrombin time were considered in the data transformation process. The ultimate objective was to establish a clear distinction between patients deemed 'live' (0) and those marked as 'die' (1). Here is table 1 representing the rules for data transformation.

Table 1. The rules for data transformation

No	Symptoms	Condition	Weight
1	Age	0-21 years	0
		Greater than 46 years	1
2	Steroid	Normal	0
		Abnormal	1
3	Antivirus	False	1
		True	0
4	Fatigue	True	1
		False	0
5	Malaise	True	1
		False	0
6	Anorexia	No	1
		True	0
7	Liver big	False	0
		True	1
8	Liver firm	True	1
		False	0
9	Spleen palpable	False	0
		True	1
10	Spiders	False	0
		True	1
11	Ascites	True	1
		False	0

No	Symptoms	Condition	Weight
12	Varices	True	1
		False	0
13	Bilirubin	Normal (0.4)	0
		Abnormal	1
14	Alkphosphate	Normal (20-240 IU/L)	0
		Abnormal	1
15	Sgot	Normal (5-40 micro per liter)	0
		Abnormal	1
16	Albumin	Normal Adult (3.8-5.1 gr/dl)	0
		Abnormal, Normal Children (4.0-5.8 gr/dl), Normal Infant (4.4-5.4 gr/dl)	1
17	Protime Women	(46-50 grams)	0
	Protime Men	(60 grams)	1
18	Target	Live	0
		Die	1

Source: (Research Results, 2024)

The following is the formula for the development of Adaline and Hebbian's algorithm with quantum computing:

Adaline algorithm formula with quantum computing:

1. Determine the value of weight (wi), bias (b), learning rate (α), and tolerance limits according to circumstances. The learning rate is between 0.1 and 1 => 0 < α ≤ 1).
2. As long as max Δwi > tolerance limit, then:
   a. Calculate net=
   $$\sum_i |X_i >. | W_{ji} > + b \tag{1}$$
   b. Calculate y with:
   $$\mathrm{y} = \mathrm{net} \tag{2}$$
   c. Perform weight correction if y ≠ t :
   $$\mathrm{wi\ (new)} = \mathrm{wi\ (old)} + \Delta\mathrm{w}$$
   $$\mathrm{b(new)} = \mathrm{b\ (old)} + \Delta\mathrm{b} \tag{3}$$
   where :
   $$\Delta\ \mathrm{w} = \alpha. (|\mathrm{t}\rangle\text{-}|\mathrm{y}\rangle). \langle \mathrm{xi}|$$
   $$\Delta\ \mathrm{b} = \alpha\ . (|\mathrm{t}\rangle\text{-}|\mathrm{y}\rangle) \tag{4}$$
   d. Repeat steps a to c if the maximum value of Δwi is still greater than the tolerance value (entering the next epoch).
   e. This process stops when the maximum Δwiv is less than or equal to the tolerance limit.
3. For pattern recognition, perform net calculations with the new w1 , w2 , and bias weights.
4. Calculate the training output with the threshold activation function.

Hebbian algorithm formula with quantum computing:

1. Initialize weight (wi) and bias (b).
2. For all s and t input vectors and target units, do:
   a. Set input unit activation xi=si (i=1,...,n).
   b. Output unit activation set: y=t, where t is activated by bipolar
   $$\mathrm{t} = f\ (t) = \begin{cases} 1, & x \geq 0 \\ -1, & x < 0 \end{cases} \tag{5}$$
3. Fix the weights regarding the equation w new =w old + Δw (i=1,...,n) with the equation
   $$\Delta\mathrm{w} = |\mathrm{xi}\rangle.\ \mathrm{y} \tag{6}$$
4. Correct the bias regarding the equation new b = old b + y.
5. Calculate the net with the equation
   $$y = \sum |wi >. < xi + b \tag{7}$$
   Activate y with bipolar activation.
   $$\mathrm{y} = f(y) = \begin{cases} 1, & x \geq 0 \\ -1, & x < 0 \end{cases} \tag{8}$$
   If y=t then stop.

RESULTS AND DISCUSSION

The research finding is a development of Adaline and Hebbian's algorithm with a quantum computation approach. This research focuses on the development of the Adaline and Hebbian algorithms using quantum computing techniques. For the Adaline algorithm with quantum computing, the following steps are undertaken: Initially, determine the weight (wi), bias (b), learning rate (α), and tolerance limits under specific circumstances, with α falling within the range of 0.1 and 1 (0 < α ≤ 1). Proceed to iterate the subsequent steps until the maximum weight change (Δwi) surpasses the tolerance limit: (A) Calculate net input using Equation (1). (B) Compute output (y) using Equation (2). (C) Adjust weights and bias based on Equation (3) if y does not match the target value (t). Continue repeating steps A to C if the maximum Δwi remains above the tolerance value, advancing to the next epoch. Terminate the process when the maximum weight change (Δwiv) falls below or equals the tolerance limit. Additionally, for

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pattern recognition, compute the clean input utilizing the updated weights and bias, and determine the training output utilizing the threshold activation function.

Regarding the Hebbian algorithm with quantum computing, the procedure unfolds as follows: Initially, initialize the weight (wi) and bias (b). Then, iterate over the entire input vector (s) and target units (t), with the following sub-steps: (A) Set the input unit activation (xi) to the corresponding value (si). (B) Determine the output unit activation (y) according to Equation (5), where t adopts bipolar notation. Proceed to update the weights using Equation (6), accounting for input-output correlation, and adjust the bias as per Equation (4). Compute the net input utilizing Equation (7) and activate the output (y) through bipolar activation, defined by Equation (8). Finally, if the output matches the target (y=t), cease the process.

The simulation results of Adaline's algorithm testing with quantum computation show 100% accuracy with epoch 1. The following are the results of testing the epoch-1 data:

Table 1. First Data Adaline Epoch-1 Test Results

Target (t)	y=net	First New Weight(w,b) Data		Target (t)	Y=net	First New Weight(w,b) Data	
b=0		b=-1		b=0		b=-1	
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W1	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W10	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W2	0	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W11	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W3	0	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W12	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W4	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W13	0
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W5	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W14	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W6	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W15	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W7	0	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W16	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W8	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W17	-14
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W9	-14	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W18	-14

Source: (Research Results, 2024)

Table 2. Second Data Adaline Epoch-1 Test Results

Target(t)	y=net	New Weight(w,b) Second Data		Target(t)	Y=net	New Weight(w,b) Second Data	
b=0		b=-1		b=0		b=-1	
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W1	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W10	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W2	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W11	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W3	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W12	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W4	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W13	0
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W5	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W14	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W6	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W15	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W7	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W16	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W8	0	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W17	-1.6
$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W9	-1.6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\0\end{bmatrix}$	W18	-1.6

Source: (Research Results, 2024)

The simulation results of testing the Hebbian algorithm with quantum computing show 100% accuracy with epoch 1. Following are the results of testing the epoch-1 data:

Table 3. First Data Hebbian Epoch-1 Test Results

Target(t)	y=net	New Weight(w,b) Data Pertama		Target(t)	Y=net	New Weight (w,b) Data Pertama	
b=0		b=-1		b=0		b=-1	
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W1	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W10	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W2	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W11	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W3	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W12	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W4	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W13	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W5	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W14	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W6	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W15	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W7	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	$\begin{bmatrix}1\\-1\end{bmatrix}$	W16	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W8	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W17	$\begin{bmatrix}1\\0\end{bmatrix}$
$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W9	$\begin{bmatrix}1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\end{bmatrix}$	W18	$\begin{bmatrix}1\\0\end{bmatrix}$

Source: (Research Results, 2024)

Table 4. Second Data Hebbian Epoch-1 Test Results

Target(t)	y=net	New Weight(w,b) Second Data		Target(t)	Y=net	New Weight(w,b) Second Data	
b=0		b=-1		b=0		b=-1	
-1	-1	W1	$\begin{bmatrix}-1\\0\end{bmatrix}$	-1	-1	W10	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W2	$\begin{bmatrix}0\\-1\end{bmatrix}$	-1	-1	W11	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W3	$\begin{bmatrix}0\\-1\end{bmatrix}$	-1	-1	W12	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W4	$\begin{bmatrix}-1\\0\end{bmatrix}$	-1	-1	W13	$\begin{bmatrix}1\\-2\end{bmatrix}$
-1	-1	W5	$\begin{bmatrix}-1\\0\end{bmatrix}$	-1	-1	W14	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W6	$\begin{bmatrix}-1\\0\end{bmatrix}$	-1	-1	W15	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W7	$\begin{bmatrix}0\\-1\end{bmatrix}$	-1	-1	W16	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W8	$\begin{bmatrix}0\\-1\end{bmatrix}$	-1	-1	W17	$\begin{bmatrix}-1\\0\end{bmatrix}$
-1	-1	W9	$\begin{bmatrix}-1\\0\end{bmatrix}$	-1	-1	W18	$\begin{bmatrix}-1\\0\end{bmatrix}$

Source: (Research Results, 2024)

The research findings signify a significant progression in the Adaline and Hebbian algorithms facilitated by the implementation of quantum computation methodology. The simulation results illustrate that when subjected to quantum computation, Adaline's algorithm achieves a remarkable 100% accuracy rate within a single epoch. Following this, the outcomes of testing the data from epoch 1 are detailed. Similarly, the simulation outcomes for evaluating the Hebbian algorithm using quantum computing depict a perfect 100% accuracy rate in epoch 1. Subsequently, the subsequent section elaborates on the findings obtained from testing the data of epoch 1.

CONCLUSION

The researchers achieved a significant breakthrough by effectively leveraging quantum computing to advance the Adaline and Hebbian algorithms. Notably, the experimental results revealed that both the Adaline and Hebbian algorithms exhibit comparable levels of accuracy, demonstrating their proficiency in effectively recognizing patterns within datasets. This research marks a pivotal contribution to the field, introducing a novel dimension through the utilization of quantum computing in the development of the Adaline and Hebbian algorithms.

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