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Q-Madaline: Madaline Based On Qubit

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Abstract

This research focuses on developing the MADALINE algorithm using quantum computing. Quantum computing uses binary numbers 0 or 1 or a combination of 0 and 1. The main problem in this research is how to find other alternatives to the MADALINE algorithm to solve pattern recognition problems with a quantum computing approach. The data used in this study is heart failure data to predict whether a patient is at risk of death. The data source comes from KAGGLE, consisting of 299 data with 12 symptoms and one target, alive or dead. The result of this study is an alternative to the MADALINE algorithm using quantum computing. The accuracy of the test results with MADALINE with a learning rate of 0.1 = 100% with 2 epochs. The accuracy of the test results using a quantum approach with a learning rate of 0.1 is 85.71%. The results of this study can be an alternative to the MADALINE algorithm with a quantum computing approach, although it has not shown better accuracy than the classical MADALINE algorithm. Further research is needed to produce better accuracy with larger data.

Keywords: pattern recognition; quantum computing; neural networks; MADALINE

1. Introduction

Quantum systems involve counter-intuitive patterns that classical systems cannot manufacture properly, and this is acceptable to speculate that computer programs may outperform classical computers on computer vision tasks [1]. The authors of this paper [2] presented a spin-star model for spin-(1/2) particles to investigate the unit coherence dynamics of a quantum neural network (QNN). The authors investigated the time domain core spin consistency of a spin system approach in a dissipative system, with a concentration on quantum consistency as a natural resource for quantum mechanics. The scientists discovered that the Heisenberg XX-type clutch was preferable for the spin calibration period and that increasing ambient spins merely prolonged coherence duration in this coupling strategy.

This research [3] develops a quantum circuit architectural model on the perceptron algorithm that can solve problems in data classification. This architecture was tested using IBM Quantum Experience. The results of this study are the quantum perceptron architecture with the quantum circuit with four data inputs showing a probability value of 100% with an average error of training and testing = 0. This architectural model is feasible for classifying data. This paper [4] presents a quantum algorithm to train and evaluate a feed forward neural network. Our algorithm relies on efficient quantum subroutines to robustly estimate the inner product between vectors. It implicitly stores large intermediate values in quantum random access storage for later efficient retrieval. The running time of the author's algorithm can be faster squared in network size than the standard classical algorithm.

The authors [5] have provided two different ways of looking at quantum perceptron training, each resulting in a different acceleration relative to the other. The first gives a quadratic acceleration concerning the size of the training data. Furthermore, offers a squared reduction in the training time scale (as measured by the number of contacts with training data) with a margin between the two classifications.

The authors [6] offer a quantum privacy-preserving approach for machine learning with perception in this research. To safeguard original training examples, there are primarily two procedures. When testing the present classifier, quantum tests are used to detect data user dishonesty. Second, private random noise is employed to secure the original data when upgrading the current classifier. Our algorithm has the following benefits: (1) it protects training examples more effectively than

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current classical methods; (2) it involves no quantum database and is simple to implement.

The research authors [7] describe various innovative methods that integrate traditional machine learning algorithms and quantum computing. We presented a multiclass tree tensor network approach and its implementation on an IBM quantum processor. In addition, we provided a neural network method for the quantum tomography issue. Our tomography approach predicts the quantum state while excluding the noise's effect. This classical-quantum technique can be used in type studies to uncover latent dependencies between input information and investigation findings.

Research [8], a theoretical analysis demonstrated that the p-delta rule does perform gradient descent in terms of an acceptable error measure, even though derivatives are not required. Furthermore, investigations on typical real-world benchmark datasets reveal its performance is competitive with other neural network and algorithm learning methodologies. As a result, our method offers an intriguing new explanation for the structure of learning in biological neural mechanisms.

Research [9], this research departs from the usual school-business collaboration in higher secondary qualifications. Instead, it employs a sensitive neural network to build a school-enterprise collaboration development model in higher secondary qualifications. Depending on the intensity of ADALINE neurons, this research considered the sensitivity of the MADALINE network structure calculated the sensitivity of the MADALINE network structure without imposing that many restrictions, and built a model of intelligence. We know from experimental research that the school-enterprise collaboration development model of higher secondary qualifications described in this research had satisfactory accuracy.

Researchers [10], employed two machine hypothesis features in this research: the NEURO-fuzzy interval regression model and the MADALINE. Three time periods were used in this research to establish the ideal parameters for accuracy. It provided the Mean Squared Error (MSE) measurement to examine the performance of this system. The findings demonstrated that the interval regression model with NEURO-fuzzy performed better than the MADALINE with a learning parameter value of 0.09. The regression interval approach with NEURO-fuzzy is one of the world's most substantial machine prediction models, which is one of the strengths of our technique.

Research [11], this paper emphasized two novel elements. First, it sets up an advanced feature set consisting of seven different elements yet to be widely used for sign language interpretation purposes. Furthermore, using such features eliminates the time-consuming step of cropping irrelevant background images, decreasing network architecture. Second, it argued that a viable solution to the issue could be reached by extending the typical ADALINE network, technically known as the MADALINE Network. Furthermore, the notion of the MADALINE network dates back much further, the utilization of this framework in this sector will undoubtedly aid in building a superior sign language interpretation interface. The newly developed framework has been deployed to acknowledge standardized American Sign Language, which contains 26 English alphabets beginning with 'A' to 'Z.' The proposed algorithm's performance was also compared to that of standardized algorithms. In each case, the former surpassed its competitors by a considerable margin, demonstrating the algorithm's efficiency.

Research [12], this research offered a new adaptive learning technique for MADALINE depending on a sensitivity scale developed to examine the influence of a MADALINE weight modification on its performance. Employing the same basic notion as the MRII, the technique involved an adaptation selection rule via the sensitivity measure to more correctly locate the weights in actual need of adaptation. Experiment results on some benchmark data indicated that the suggested algorithm outperforms the MRII and BP algorithms regarding learning capability.

According to research [13], statistical models for stock market prediction primarily depending information with specific features that are disorderly and disorganized, or incorrectly produced are insufficient. Numerous studies have shown that the neural network's most essential capability is its ability to discover patterns and deformities in data and identify multi-dimensional, non-linear co-relationships. Artificial Neural Networks (ANNs) could indeed easily distinguish unknown and invisible characteristics of information data, which is sufficient for predicting the stock market and stock exchange index. For stock market forecasting, technical analysis, fundamental analysis, and traditional time series forecasting are inappropriate. Then, Standard Supervised BACKPROPAGATION Neural Network Learning Methodology where Boltzmann Machine, ADALINE, and MADALINE will be utilized in the investigation.

Research [14], this article attempts to approach two of the many existing models of Artificial Neural Networks (ANN), comparing different parameters of the ANN and showing each equation, all applied to a binary decoder 9 bits. The two neural models tested were: MADALINE and radial basis neural network (RBN networks), training these with 50% of the data, leaving the remaining 50% for validation, yielding results in the ANN MADALINE with sigmoidal activation function and learning time gave the lowest mean square error (ERS) among the tested with a value of 0.01.

Research [15], fundamental advances in feed forward artificial neural networks during the last 30 years are discussed. This writer's core focus is a summary of the Perceptron rule, the LMS technique, three MADALINE rules, and the BACKPROPAGATION technique, as well as the history, inception, operating features, and basic concept of various supervised neural network training algorithms. These strategies were invented independently, but when viewed through the lens of history, they can all be linked. The "minimum disturbance principle" underpins these algorithms, which argues that during training, it is best to insert new input into such a connection that disrupts stored data as little as practicable.

Research [16], a fresh strategy has been devised for training multi-layer fully linked feed forward networks of ADALINE neurons. Because the ADALINE processing element uses the non DIFFERENTIABLE sign function for its nonlinearity, such networks cannot be trained using the standard BACKPROPAGATION approach. The algorithm is known as MRJI, which stands for Madaline Rule 11. MRII previously successfully trained the adaptive "descrambler" element of a neural data network used for translation invariant pattern identification.

According to research [17], optical character recognition is one of the primary uses of Artificial Neural Networks that mimic human thinking in artificial intelligence. The use of neural networks to identify English machine-printed characters in an automated manner is discussed in this research. To distinguish each character from the others, a preprocessing step is used. Then, utilizing Mean, Standard Deviation, and Variance, a feature extraction procedure is done for each character to generate the fewest nodes. MADALINE was conditioned on 26 alphabetical English characters in a standardized size and font. Furthermore, checked on these characters to ensure that each coded picture corresponds to the correct code.

This research [18], studies approach for building decision trees made out of linear threshold units and a unique algorithm for learning non-linearly separable boo-lean functions using MADALINE -style networks that are isomorphic to decision trees. The design of such networks is explored, and their learning performance is compared to normal Back-Propagation on a sample issue with numerous irrelevant features inserted. Little stone's Winnow algorithm is also investigated in this architecture as a learning method in the presence of a significant number of unnecessary qualities. This MADALINE -style architecture's learning ability on non-optimal networks is also investigated. Fundamental breakthroughs in feed forward artificial neural networks during the last thirty years are summarized in research [19]. This writer's primary emphasis is a summary of the history, genesis, operational features and fundamental concept of numerous supervised neural network training algorithms, along with the Perceptron rule, the LMS algorithm, three MADALINE rules, and the BACKPROPAGATION [20] approach. These strategies were invented. However, when viewed through history, they can be linked.

This research provided research [21] to develop a new adaptive intelligent system for a robot work cell capable of visually following and intercepting an invariant stationary HGA component through arbitrary orientation at any place in the robot's workplace. For recognizing the stationary HGA at any rotation angle without overlaying and creating the projected robot route, a combination of the seven invariant moment techniques, image feature technique, and MADALINE network is employed.

Based on previous studies, quantum computing promises speed in the algorithm process. The problem in this research is that the higher the need for data processing, the researcher must be able to provide other alternatives of an algorithm to produce a reliable one. This study aims to find other alternatives to the MADALINE algorithm using quantum computing. This research develops the MADALINE algorithm from classical computing to quantum computing.

2. Research Methods

To complete this research, the researcher made work steps from the study, Dataset: The information utilized in this research is a prediction dataset of heart failure concerning patients who have heart failure and are either alive or dead. The data on heart failure is made up of 12 symptoms; Data Transformation: Data is transformed into binary form, namely 0 and 1 according to the rules of each symptom; Transformation to Quantum Bit: After transforming the data to binary, the data is transformed into quantum bits. To do the testing process; Learning Algorithms: The data is processed into the MADALINE algorithm using binary data and the MADALINE algorithm with a quantum approach using the results of quantum bit transformation data; Evaluation: At this stage, an evaluation process is carried out on learning the MADALINE and MADALINE algorithms with a quantum approach. Can the proposed algorithm provide another alternative to the classic MADALINE algorithm?

The dataset used in this study is a predictive dataset of heart failure about people who suffer from heart failure, life or death. Heart failure data consists of 12 symptoms. There are 11 symptoms used for pattern recognition of heart failure and 299 records. The data transformation rule is age-related: if the age is 0 to 21 years, then the weight is 0; if the age is over 46 years, then the weight is 1. Symptoms of anemia: if normal, 0; if not, 1. Creatinine phosphokinase: if normal, then 0. If

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not, then 1. Diabetes: if normal, then 0. If not, then 1. Ejection fraction: if normal, 0. If not, then 1. High blood pressure: if normal, then 0; if not, 1. Platelets: if normal, then 0; if not, 1. Serum creatinine: if normal, then 0; if not, 1. Serum sodium: if normal, 0; otherwise, 1. Sex: if male, then 1; if female, then 0. Smoking: if smoking, then = 1; if not smoking, = 0. Target life = 0, die = 1. The data used for simulating the MADLINE algorithm and developing the MADALINE algorithm are 10 records.

3. Results and Discussions

The result of this research is the development of the MADALINE algorithm using quantum computing as an alternative to the classical MADALINE algorithm. This novelty is the MADALINE quantum algorithm.

MADALINE's quantum algorithm are: All weights and biases should be set to small random values. Begin by entering a modest number; As long as the weight change is greater than the tolerance, perform steps a to e (Set of input unit activations: $xi = s_i$ for all I; Compute the net input for each ADALINE hidden unit (z_1, z_2,..) using Formula 1.

$$Z_{in_j} = b_j + \sum_i |X_i >< W_{ji}| \quad (1)$$

Using the identity activation function, compute the output of each hidden unit using Formula 2.

$$Z_j = f(Z_{inj}) = \begin{cases} 1 & jika\ Z_{inj} > 0 \\ 0 & jika\ Z_{inj} \le 0 \end{cases} \quad (2)$$

Define network output using Formula 3 and 4.

$$Y_{in} = b_k + \sum_j |Z_j >.< V_j| \quad (3)$$

$$Y = f(Y_{in}) = \begin{cases} 1 & jika\ Z_{inj} > 0 \\ 0 & jika\ Z_{inj} \le 0 \end{cases} \quad (4)$$

Compute the error and determine the weight change. If y = target, then the weight is not changed. If $|y> \neq |target>$: For t = 1, change the weight to units whose is closest to 0 using Formula 5 until 8.

b(new)= b (old) + Δb

w_i(new)= w_i (old) + Δw

$$\Delta b = \alpha\ (1 - Z_p) \quad (5)$$

$$\Delta w = \alpha\ (|1> - |Z_p>) <X_i| \quad (6)$$

For t = 0, convert all weights to Z_k units with positive Z_{in}:

$$\Delta b = \alpha\ (0 - Z_k) \quad (7)$$

$$\Delta w = \alpha\ (|0> - |Z_k>) <X_i| \quad (8)$$

This research is looking for another alternative to the MADALINE algorithm with a quantum computation approach. The data used to predict heart failure is converted into binary and then processed using the MADALINE and Quantum MADALINE algorithms. The test results will be evaluated with the results of performance and speed or the number of iterations obtained. Table 1 is the raw data resulting from the transformation into binary.

Table 1. Heart Failure Prediction Data

X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	T
1	1	0	1	1	1	0	0	1	1	0	1
1	1	1	0	1	0	0	0	0	1	0	1
1	0	1	1	1	0	1	0	0	0	0	1
1	1	0	1	1	1	0	0	1	0	0	0
1	0	0	1	1	1	0	0	1	0	0	1
1	1	0	1	0	1	1	1	1	0	1	1
1	0	0	0	1	1	1	0	1	0	1	1
1	1	0	1	1	1	1	0	0	0	1	1
1	1	0	0	1	0	1	0	0	0	0	0
1	0	1	1	1	1	0	0	0	0	0	1
1	1	0	1	1	1	0	0	1	0	1	1
1	1	0	1	0	1	1	0	0	0	0	1
1	1	0	1	1	1	1	1	1	0	1	1
1	1	1	1	0	1	1	0	1	1	0	1

Where X1 is the Age, X2 is Anemia, X3 is Creatinine phosphokinase; X4 is Diabetes; X5 is the Ejection fraction high bold; X6 is the Blood Pressure; X7 is the Platelets; X8 is the Serum creatinine; X9 is the Serum sodium; X10 is the Sex; X11 is Smoking; T is the Death event.

The MADALINE algorithm testing simulation results show 100% accuracy in epoch 2 with the result y=t. In epoch 1, it offers an accuracy of 92.86%. One record reaches the goal (y=t) at epoch 2—error tolerance value = 0.1. The test results at epoch 2 for weight change can be seen in Table 2, Table 3, Tabel 4 and the results comparison table between madaline and madaline quantum in Table 5.

Table 2. 2nd Iteration Weight Change of the MADALINE Algorithm

Type Of Weight	Initial Weight	Change Of Weight	New Weight	Type Of Weight	Initial Weight	Change Of Weight	New Weight
b1	0.3	-0.10	0.06	b2	0.4	-0.1	0.23
W1,1	0.1	-0.24	-0.14	W2,1	0.9	-0.24	0.66
W1,2	0.9	-0.24	0.66	W2,2	0.1	-0.24	-0.14
W1,3	0.2	0.24	0.44	W2,3	0.5	0.24	0.74
W1,4	0.8	-0.24	0.56	W2,4	0.6	-0.24	0.36
W1,5	0.3	-0.24	0.06	W2,5	0.4	-0.24	0.16
W1,6	0.7	-0.24	0.46	W2,6	0.7	-0.24	0.46
W1,7	0.4	0.24	0.64	W2,7	0.3	0.24	0.54
W1,8	0.6	0.24	0.84	W2,8	0.8	0.24	1.04
W1,9	0.5	-0.24	0.26	W2,9	0.2	-0.24	-0.04
W1,10	0.1	0.24	0.34	W2,10	0.9	0.24	1.14
W1,11	0.9	0.24	1.14	W2,11	0.1	0.24	0.34

Table.3. 2nd Iteration Weight Change of the MADALINE Algorithm Using Quantum Computing - 1

Type of Weight	Initial Weight	Change of Weight	New Weight	Type of Weight	Initial Weight	Change of Weight	New Weight
B1	0	-0,1	-0,1	B2	1	-0,1	0,9
W1, 1	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ 0{,}9 \end{bmatrix}$	W2, 1	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ -0{,}1 \end{bmatrix}$
W1, 2	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ -0{,}1 \end{bmatrix}$	W2, 2	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ 0{,}9 \end{bmatrix}$
W1, 3	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	0,1	$\begin{bmatrix} 0 \\ 1{,}1 \end{bmatrix}$	W2, 3	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	0,1	$\begin{bmatrix} 0 \\ 0{,}1 \end{bmatrix}$
W1, 4	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ -0{,}1 \end{bmatrix}$	W2, 4	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	-0,1	$\begin{bmatrix} 0 \\ 0{,}9 \end{bmatrix}$

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Type of Weight	Initial Weight	Change of Weight	New Weight	Type of Weight	Initial Weight	Change of Weight	New Weight
W1, 5	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$	W2, 5	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$
W1, 6	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$	W2, 6	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$
W1, 7	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$	W2, 7	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$
W1, 8	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 8	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 9	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$	W2, 9	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$
W1, 10	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 10,	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 11	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$	W2, 11,	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$

Table.4. 2nd Iteration Weight Change of the Madalne Algorithm Using Quantum Computing - 2

Type of Weight	Initial Weight	Change of Weight	New Weight	Type of Weight	Initial Weight	Change of Weight	New Weight
B1	0	-0,1	-0,1	B2	1	-0,1	0,9
W1, 1	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$	W2, 1	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$
W1, 2	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$	W2, 2	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$
W1, 3	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$	W2, 3	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$
W1, 4	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 4	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 5	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$	W2, 5	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$
W1, 6	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 6	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 7	$\begin{bmatrix}0\\1\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\0,9\end{bmatrix}$	W2, 7	$\begin{bmatrix}1\\0\end{bmatrix}$	-0,1	$\begin{bmatrix}0\\-0,1\end{bmatrix}$
W1, 8	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 8	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 9	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$	W2, 9	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$
W1, 10,	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$	W2, 10,	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$
W1, 11	$\begin{bmatrix}0\\1\end{bmatrix}$	0,1	$\begin{bmatrix}0\\1,1\end{bmatrix}$	W2, 11,	$\begin{bmatrix}1\\0\end{bmatrix}$	0,1	$\begin{bmatrix}0\\0,1\end{bmatrix}$

Table 5. the results comparison table between MADALINE and Quantum MADALINE

No	Algorithm	Accuracy	Epoch
1	MADALINE	92,85	2
2	MADALINE Using Quantum Computing	85,71	2

The simulation results of testing the MADALINE algorithm with a quantum computing approach show an accuracy of 85.71% in epochs 1 and 2 with the result y=t. The epoch stops because the tolerance value is less than the maximum weight—tolerance value = 0.1. The test results with the MADALINE algorithm with quantum computation are not better than the Classic MADALINE algorithm in terms of accuracy. However, when viewed from the epoch, it has the same epoch. Researchers managed to find another alternative to the MADALINE algorithm with classical computing, although the accuracy is not better.

5. Conclusions

The results of this study are the application of the MADALINE algorithm with a quantum computing approach as an alternative to the MADALINE algorithm. The test results using the MADALINE algorithm get an accuracy value of 92.85% with epoch 2. While the test results using the MADALINE algorithm with a quantum computing approach get an accuracy value of 85.71% in epoch 2, the error tolerance value is not greater than the maximum value of change weight. Testing the algorithm above needs further investigation using more complex data. The alternative proposed is not better in accuracy but gets the same epoch value. Researchers managed to find another option for the MADALINE algorithm with a quantum computing approach. Future researchers hope this alternative can be developed to produce better accuracy than previously obtained.

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