Image Recognition by Quantum Annealing Using Multi-bit Spin Variables

Kazutake Uehira*
Kanagawa Institute of Technology
uehira@nw.kanagawa-it.ac.jp

Hiroshi Unno
Kanagawa Institute of Technology
unno@nw.kanagawa-it.ac.jp

ABSTRACT

This paper presents an image-recognition technique using quantum annealing. We used four handwritten numbers of 0, 1, 2, and 3 from the MNIST (Modified National Institute of Standards and Technology) digit classification dataset as images to be recognized. We used two models in this study which were basically the same as a simple neural network, one had one fully connected layer and the other had 3x3 Sobel filters in front of that layer. The images were first resized to 1/2 the original in both directions, and pixel data were converted to 196 one-dimension data then output to four outputs through a fully coupled neural network. The optimum values of 196 x 4 weights and 4 bias values of the fully connected layer were obtained by quantum annealing in which the loss function is expressed as Hamiltonian of the Ising model. The weights and biases are multi-valued variables consisting of multiple spin variables in the Ising model. Quantum annealing was simulated using Pyqubo to create Ising models from flexible mathematical expressions. Prediction accuracy when using the Sobel filters reached about 95% and Sobel filter improved it by about 5%.

CCS CONCEPTS

• **Machine learning**; • **Artificial intelligence**; • **Information systems applications**;

KEYWORDS

Quantum annealing, Neural network, Image recognition

ACM Reference Format:
Kazutake Uehira* and Hiroshi Unno. 2021. Image Recognition by Quantum Annealing Using Multi-bit Spin Variables. In *2021 the 5th International Conference on Graphics and Signal Processing (ICGSP 2021), June 25–27, 2021, Nagoya, Japan.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3474906.3474911

1 INTRODUCTION

With the increase in computer performance, machine learning has become more sophisticated, thus rapidly expanding the range of its applications. The increase in computer performance also made it possible to handle enormous amounts of data, enhancing machine learning for image recognition, natural language processing, etc. However, machine learning is requiring even higher-performance computers. The reason is that the amount of data used for learning is increasing infinitely, and models such as deep learning used for machine learning are becoming more complicated. Such a continuous increase in data and complexity of machine learning will continue to increase the processing time for learning. Computational performance has continuously improved for decades as well as the evolution of the architecture from single core to multi-core and graphics, but that progress has begun to slow. Future improvements in computer performance are not expected to keep up with the increased performance required for machine learning [1]. Conversely, if the performance of computers dramatically improves, it may be possible to achieve much more advanced machine learning.

Quantum computers are attracting attention for dramatically improving computer performance in the future [2]. Studies on the application of quantum computers have been progressing in various fields including machine learning [3–8]. Progress is expected in fields that require enormous time-consuming calculations, and machine learning is one of them. There are two types of quantum computers, gate-based and quantum-annealing-based. Gate-based quantum computers [3–8] can be used for general purposes like a conventional computer. However, the practical hardware of quantum computer has not yet been developed, although the principle of it has been proven. The research thus far has been simulation based on its principle.

A quantum-annealing-based computer [9], which is also a computer using quantum physics but works on different principles, has already been put to practical use and can be used commercially [10]. Since it operates on the principle of quantum mechanics, its processing speed is far faster than conventional computers. However, its use is limited to problems that seek optimal solutions of combinatorial problems. Despite this limitation, it is possible to use such a computer if we can transform the problem we want to address into a problem that finds the optimal solution in combination problem, and many studies that use quantum annealing for machine learning have been conducted [11–14]. In many of these studies, Boltzmann machines were used for machine learning. The reason is that since quantum annealing is based on the Ising model and the network configuration is an undirected graph, Boltzmann machines have good compatibility with quantum annealing.

In this study, we examined the feasibility of applying quantum annealing to image recognition using a simple neural network. Machine learning by using neural networks can be regarded as finding the optimal combination of connection weights between neurons, which is expected to be solved by quantum annealing. We conducted simulations of simple networks represented by the Hamiltonian of the Ising model that correspond to fully connected neural network. The spin variables used in the Ising model are

ICGSP 2021, June 25–27, 2021, Nagoya, Japan

ACM ISBN 978-1-4503-8941-9/21/06…$15.00
https://doi.org/10.1145/3474906.3474911

binary, but in this study, the coupling weights and biases were expressed as multi-valued variables using multiple spin variables. The main purpose of this study was to investigate how much prediction accuracy can be with quantum annealing.

2 QUANTUM ANNEALING

A quantum-annealing-based computer is specialized for solving combinatorial optimization problems. Although there are restrictions, it is possible to obtain realistic solutions. Annealing is "annealing" in which a material such as metal is heated then slowly cooled. It is an operation to homogenize the internal structure, which is the lowest energy state. Quantum annealing is a method of obtaining a solution as the lowest energy state by executing annealing processing in the process of fluctuations accompanied by quantum superposition and quantum entanglement. The effect of quantum tunneling should avoid local solutions and reach the global optimal solution. The annealing structure can be represented by a simple model called the Ising model. Equation 1 indicates the energy of the Ising model.

$$\mathrm{H} = \sum_{i=1}^{N} h_i s_i + \sum_{i<j}^{N} J_{i,j} s_i s_j \tag{1}$$

where energy function H is called a Hamiltonian, s_i and s_j respectively indicate the spin variables at positions i and j, which take +1 or -1 when the direction of the spin is upward and downward, and N is the number of spins. The first term in the equation shows the energy of spins due to the external magnetic field h, and the second term shows the energy due to the interaction between spins. The notation J is a coefficient indicating the magnitude of the interaction.

The state in which the external magnetic field is large corresponds to the high temperature state in annealing, and the process of gradually reducing h corresponds to the annealing process. With this annealing process, the values of every spin that give the minimum H in Eq. 1 can be obtained. Therefore, if the problem to be solved can be expressed with Eq. 1 and if we can make it a problem to find the minimum H by changing all spin variables, a quantum-annealing-based computer can be applied to any problem. The s_i, and s_j in Eq. 1 are either +1 or -1, but it is also possible to make them into binary numbers of 1 and 0 through modification using the following equation.

$$x_i = \frac{s_i + 1}{2} \tag{2}$$

3 SIMULATIONS

3.1 Data preparation

We conducted simulations to address the problem of recognizing a specific image category from four image categories. Four types of images of handwritten numbers 0 to 3 from the MNIST (Modified National Institute of Standards and Technology) digit classification dataset were used as the four categories. These data are monochrome image data of 28 x 28 pixels. Pixel value is 8 bits of which maximum is 255. To reduce the number of spin variables, these images were reduced by half in both the horizontal and vertical directions, as described below. They were then normalized by dividing by 255 in a similar manner to what is done with conventional neural networks. Label data showing the numbers corresponding to each image were also used for learning and evaluation of prediction accuracy.

3.2 Model and loss function

Figure 1 shows the models used in the simulations. Model 1 was basically the same as a conventional neural network having one fully connected layer, as shown in Figure 1 (a). Model 2 used Sobel filters placed in front of the fully connected layer, as shown in Figure 1 (b). These Sobel filters were for horizontal and vertical edge detection, as shown in Figure 2. The two two-dimension data convolved by these two filters are converted into one-dimension 196 data after passing through the activation function, Relu. In both models, images were input after resizing to 1/2 in height and width. All one dimension data in the fully connected layer were linearly combined to 4 neurons in the output layer. i th outputs fi are given by Eq. 3.

$$f_i = \sum_{j=0}^{n} w_{i,j} x[j] + b_i \tag{3}$$

where n is the number of pixels of the image after being converted to one dimension, x[j] is the value of the i-th pixel, $w_{i,j}$ are the weight factors, and b_i is the bias. The weight factor and biases are given by Eqs. 4 and 5, respectively, using multiple spin variables.

$$\begin{aligned} w_{i,j} &= c_w s_{i,j,m-1} \quad \text{for m = 1} \\ &= c_w \left(\textstyle\sum_{k=0}^{m-2} 2^k s_{i,j,k} - \left(2^{m-1} - 1\right) s_{i,j,m-1} \right) \quad \text{for m > 1} \end{aligned} \tag{4}$$

$$\begin{aligned} b_i &= c_b t_{i,m-1} \quad \text{for m = 1} \\ &= c_b \left(\textstyle\sum_{k=0}^{m-2} 2^k t_{i,k} - \left(2^{m-1} - 1\right) t_{i,m-1} \right) \quad \text{for m > 1} \end{aligned} \tag{5}$$

Here, m is the number of bits, c_w, c_b are coefficients, and $s_{i,j,m}$, $t_{i,m}$ are spin variables, which are 0 or 1. Therefore, $w_{i,j}$ and b_i take integer values from -2^{m-1} -1 to 2^{m-1}-1 for m larger than one.

The loss function H is expressed as

$$\mathrm{H} = H_0 + H_1 + H_2 + H_3, \tag{6}$$

where, H_0, H_1,H_2, and H_3 are given following equations.

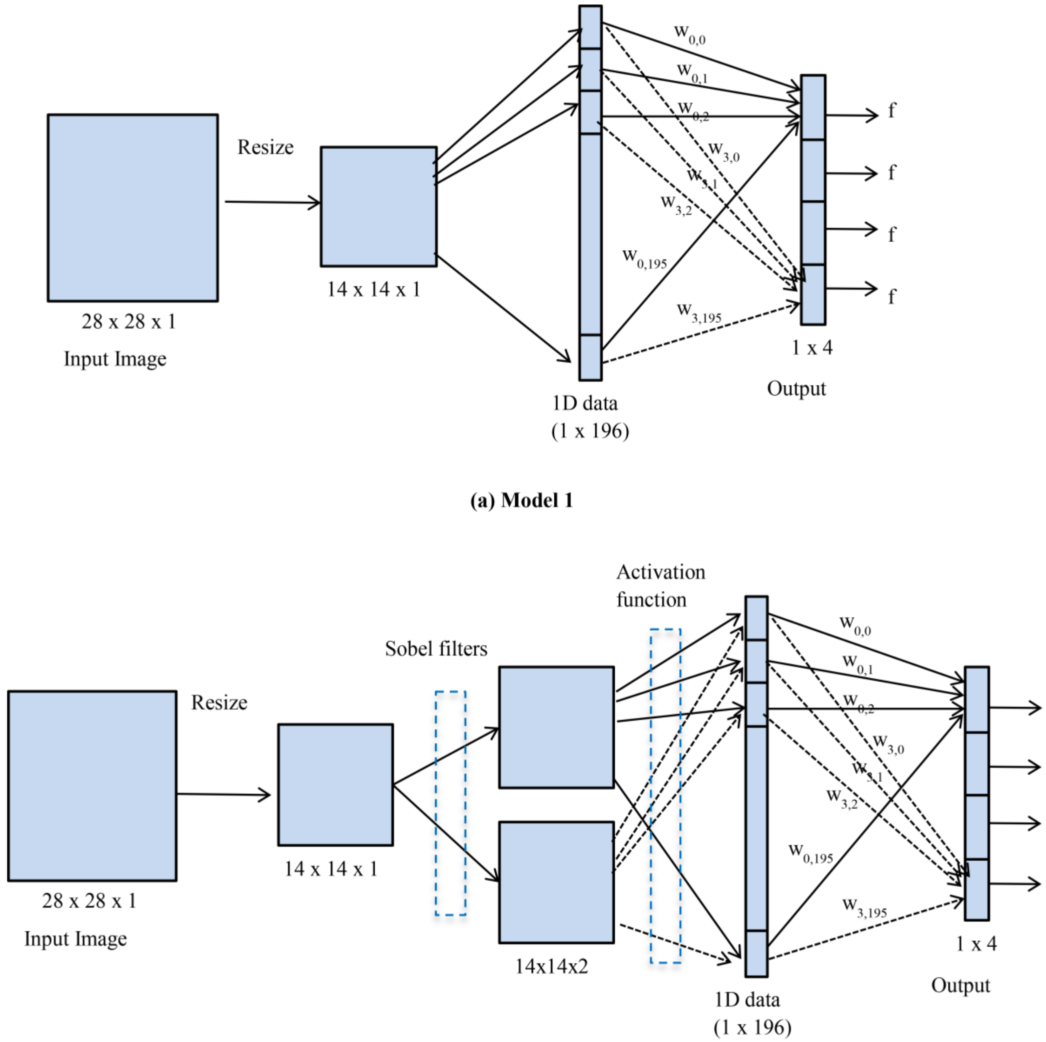
$$H_0 = \sum_{i=0}^{n} \left(f_0[i] - y_i[0]\right)^2 \tag{7}$$

$$H_1 = \sum_{i=0}^{n} \left(f_1[i] - y_i[1]\right)^2 \tag{8}$$

$$H_2 = \sum_{i=0}^{n} \left(f_2[i] - y_i[2]\right)^2 \tag{9}$$

$$H_3 = \sum_{i=0}^{n} \left(f_3[i] - y_i[3]\right)^2 \tag{10}$$

Here, $y_i[j]$(j=0-3) is the label data indicating the classification of the i-th image in the form of a one-hot vector, $f_0[i] - f_3[i]$ are in the form of a first-order polynomial with respect to s_i and t_i; therefore, since $H_0 - H_3$, and H given by Eqs. 6–10 are in the square form of their first-order polynomials, they are second-order polynomials of spin variables. Then, H in Eq. 6 can be transformed to form the Hamiltonian of the Ising model given by Eq. 1. Therefore, it



(a) Model 1

(b) Model 2

Figure 1: Models used in simulations

-1	0	1
-2	0	2
-1	0	1

-1	-2	-1
0	0	0
1	2	1

Figure 2: Sobel filters used in Model 2

is possible to find a combination of spin variables that gives the minimum H by quantum annealing.

3.3 Simulation of quantum annealing

Using H in Eq. 10 as the Hamiltonian, we conducted a simulation of quantum annealing using Pyqubo [11]. Pyqubo is a package that creates Ising models from flexible mathematical expressions. We conducted the simulation five times for each condition. We chose the number of training images and number of bits for the weights as the simulation parameters. The c_w and c_b of Eqs. 4 and 5 were both set to 0.05.

Using the optimal weights obtained from this simulation, we calculated four outputs given by Eq. 3 and predicted the category corresponding to the maximum output as the correct category. Prediction accuracy was obtained for both training and test datasets. We used 500 images as test data.

For comparison, recognition accuracy was also obtained using conventional neural networks that had the same configuration as the two models using the quantum annealing shown in Figure 2. Here, the conventional network refers to a network in which the optimal weights and biases is obtained by backpropagation and gradient descent, and so on.

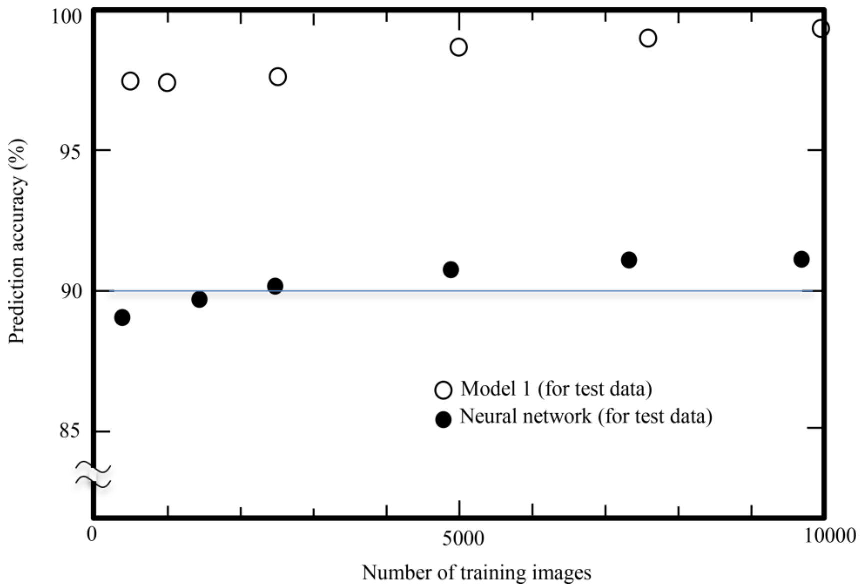


Figure 3: Simulation results on prediction accuracy of Model 1

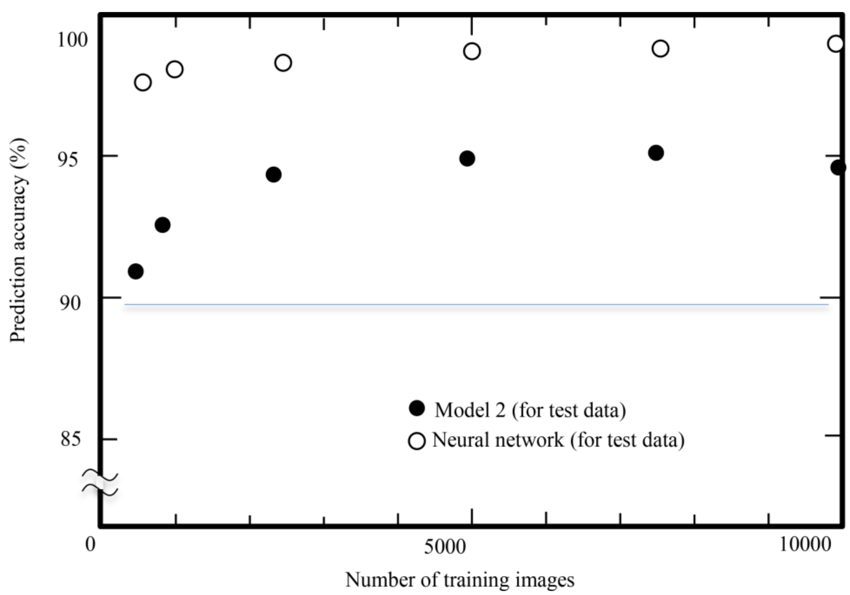


Figure 4: Simulation results on prediction accuracy of Model 2

4 RESULTS AND DISCUSSION

Figures 3 and 4 show the simulation results of prediction accuracy of Models 1 and 2 for 500 test images. The x-axis of these graphs indicate the number of training images The prediction accuracy of the corresponding neural networks to these models are also shown with white circle. These prediction accuracies are the average of the five trials. Prediction accuracy increased as the number of training images increased, as expected. For Model 2, when the number of training images was 2500 or more, prediction accuracy was over 95%. This value is high, but lower than that of a conventional neural network.

By comparing Figures 3 and 4, prediction accuracy improved using Sobel filtering and non-linear processing by the activation function as preprocessing. It would be desirable if the weighting coefficient in these filtering processes could also be optimized by quantum annealing. In quantum annealing, however, the weights in the loss function is limited to the second order because it must be able to transform into the form of the Hamiltonian equation given as Eq. 1, so only the weight of the fully connected layer can

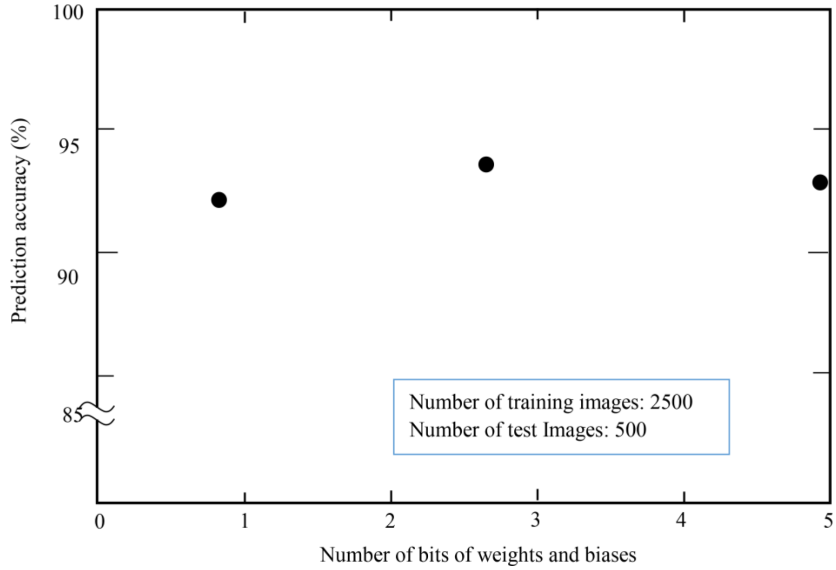


Figure 5: Prediction dependence on the number of bits of weights and biases

be optimized by quantum annealing. Therefore, preprocessing 3x3 filter weights had to be hyper parameters. In this simulation, a general Sobel filters used for horizontal and vertical edge detection was used. However, prediction accuracy should further improve if we can find a more suitable filter.

Figure 5 shows the prediction-accuracy dependence on the number of bits of weights and biases. Prediction accuracy was higher for 3 and 5 bits than for 1 bit, that is, multi-valued weights and biases using multiple spin variables are effective in improving accuracy, but not significantly compared to when using a single spin variable. Therefore, it seems appropriate to express the weights and biases in about 3 bits.

5 CONCLUSION

We investigated an image-recognition technique using quantum annealing. We used four types of handwritten numbers of 0, 1, 2, and 3 from the MNIST dataset as images to be recognized. The models were basically the same as a simple neural network, and one with a fully connected layer and the other with 3x3 Sobel filters in front of this layer. The images were first resized to 1/2 in both directions, and the pixel data were converted to one-dimension196 data, then output to four outputs through a fully coupled neural network. The optimum values of 196 x 4 weights and 4 bias of the fully connected layer were obtained by quantum annealing in which the loss function was expressed as the Hamiltonian of the Ising model. We conducted simulations using Pyqubo, and the results revealed the following. 1) High prediction accuracy of over 95 % was obtained when using over 2500 training images. 2) Prediction accuracy improved by placing the Sobel filters in front of the fully connected layer and 3) by expressing weights and biases using multiple spin variables.

Prediction accuracy may be improved by placing a filter other than a Sobel filter in front of the fully coupled layer. Finding the best filter is for future work.

REFERENCES

[1] N. C. Thompson, K. Greenewald, K. Lee, and G. Manso. 2020. The Computational Limits of Deep Learning. https://arxiv.org/abs/2007.05558
[2] Rieffel E, Polak W., 2011. Quantum Computing: A Gentle Introduction. Cambridge, MA: MIT Press; 2011.
[3] Biamonte, J, Wittek, P, Pancotti, N, Rebentrost, P, Wiebe, N, Lloyd, S. 2017. Quantum machine learning, Nature, Vol. 549, No. 7671, pp. 195–202
[4] O. M Sotnikov and V. V Mazurenko. 2020. Neural network agent playing spin Hamiltonian games on a quantum computer. Journal of Physics A: Mathematical and Theoretical, Vol. 53, No. 13
[5] J. M. Arrazola, T. R. Bromley, J. Izaac, C. R. Myers, K. Br´adler, and N. Killoran. 2018. Machine learning method for state preparation and gate synthesis on photonic quantum computers, https://arxiv.org/abs/1807.10781
[6] C. S. Yen-Chi, Y. C. Huck, J. Jun, C. Pin-Yu, M. Xiaoli, G. Hsi-Sheng. 2020. Variational Quantum Circuits for Deep Reinforcement Learning, IEEE ACCESS, Vol. 8, pp. 141007–141024
[7] F. Tacchino, C. Macchiavello, D. Gerace, and D. Bajoni. 2019. An artificial neuron implemented on an actual quantum processor, NPJ QUANTUM INFORMATION, Vol. 5, 26
[8] Gao X., Zhang, Z. -Y., Duan, L. -M. 2018. A quantum machine learning algorithm based on generative models, SCIENCE ADVANCES, Vol. 4, No. 12, eaat9004
[9] Kadowaki T, Nishimori H. Quantum annealing in the transverse Ising model. Phys Rev E. 1998 Nov; 58 (5):5355±5363.
[10] https://docs.dwavesys.com/docs/latest/doc_qpu.html
[11] Willsch, D, Willsch, M, De Raedt, H, Michielsen, K. 2020. Support vector machines on the D-Wave quantum annealer, COMPUTER PHYSICS COMMUNICATIONS, Vol. 248, 107006
[12] Adachi, Steven H.; Henderson, Maxwell P. 2015. Application of Quantum Annealing to Training of Deep Neural Networks https://ui.adsabs.harvard.edu/abs/2015arXiv151006356A/abstract
[13] Manukian, H., Traversa, FL., Di Ventra, M. 2019. Accelerating deep learning with memcomputing, NEURAL NETWORKS, Vol. 110, pp. 1–7
[14] Khoshaman, A., Vinci, W., Denis, B., Andriyash, E., Amin, MH. 2019. Quantum variational autoencoder, QUANTUM SCIENCE AND TECHNOLOGY, Vol. 4, 1, 014001