UDC 004.885.5(045)
DOI:10.18372/1990-5548.76.17667

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QUANTUM CONVOLUTION NEURAL NETWORK

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Abstract—*In this work, quantum convolutional neural networks are considered in the task of recognizing handwritten digits. A proprietary quantum scheme for the convolutional layer of a quantum convolutional neural network is proposed. A proprietary quantum scheme for the pooling layer of a quantum convolutional neural network is proposed. The results of learning quantum convolutional neural networks are analyzed. The built models were compared and the best one was selected based on the accuracy, recall, precision and f1-score metrics. A comparative analysis was made with the classic convolutional neural network based on accuracy, recall, precision and f1-score metrics. The object of the study is the task of recognizing numbers. The subject of research is convolutional neural network, quantum convolutional neural network. The result of this work can be applied in the further research of quantum computing in the tasks of artificial intelligence.*

Index Terms—Quantum computer; quantum method of support vectors; quantum convolutional neural network; quantum computing; classification; machine learning.

I. INTRODUCTION

Today, there are many methods of classifying non-linearly separable data. For example, neural networks. But these methods have one significant drawback — it's training time. Quantum machine learning should solve this problem in the future, namely training speed. We already have enough scientific works on quantum machine learning. Guillaume Verdon, Michael Broughton, and Jacob Biamonte demonstrate neural network training on a quantum computer [1]. Maria Schuld, Alex Bocharov, Krista Svore, and Nathan Wiebe demonstrated a variational quantum classifier [2].

But all these works have one thing in common, the optimization takes place on a classic computer. So far, leading scientists have not been able to optimize on quantum computers for several reasons:

- noise immunity of quantum computers;
- property of superposition of qubits.

The noise immunity problem has already been improved on April 12, 2021. Scientists have developed quantum error correction, which works with twice as much noise [3].

II. QUANTUM COMPUTING

Quantum computing is a branch of computer science that uses the principles and effects of quantum physics to perform calculations. In order for a quantum computer to be able to perform calculations, a quantum circuit must be developed.

Quantum circuit is a model for quantum computing, in which the computation is a sequence of quantum gates [4].

Quantum gate is a quantum logic element. It is described using unitary matrices [4].

Unitary matrix (English unitary matrix) is a square matrix U, in which the elements of this matrix are complex numbers and has the following property

$$U^{*}U = UU^{*} = I, \tag{1}$$

where U is a square matrix; U^{*} is the transposed matrix U with complex-conjugate numbers; I unit matrix.

To date, the following quantum gates are known:

- Pauli X;
- Pauli Y;
- Pauli Z;
- Hadamard;
- CNOT;
- Toffoli.

The Bloch sphere is used to display the quantum state of the qubit.

The state of the qubit is described using bracket notation.

Two base qubits are used:

- $\left|0\right\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ – zero state;

- $|1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ – one state.

On the Bloch sphere, they reflect as follows (according to Fig. 1)

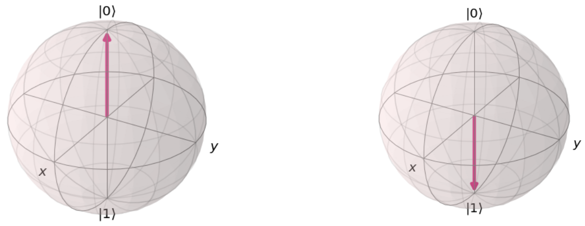

Fig. 1. Representation of basis qubits using on the Bloch sphere

When a quantum system has two qubits, it is mathematically denoted as follows:

$$|00\rangle = |0\rangle \otimes |0\rangle = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \quad (2)$$

That is, the size of the vector that describes the state of the quantum system is equal to

$$m = 2^n, \quad (3)$$

where m is the size of the vector that describes the quantum system; n number of qubits.

Therefore, one qubit corresponds to two classical bits. If there are two qubits, then 4 bits are needed to interpret it in a classical computer.

III. QUANTUM MACHINE LEARNING

Quantum machine learning combines the principles of quantum physics and machine learning methods to solve data analysis and model training tasks on quantum computers. It is seen as a transition from classical machine learning algorithms to the use of quantum computing to improve computational speed and the ability of models to recognize complex patterns in data.

Basic concepts and methods of quantum machine learning include:

1) Quantum computing models: Quantum neural networks and algorithms such as quantum gradient descent, quantum variational algorithm, and quantum cluster analysis are used. These models and algorithms are used for learning on quantum data and performing quantum calculations using the principles of quantum information processing;

2) Quantum entanglement and superposition: Quantum systems can exist in an entangled state where the states of different qubits are interdependent and indivisible. This allows quantum models to perform calculations in parallel and handle many possible options simultaneously;

3) Quantum Measurements and Quantum Properties: Using quantum measurements and quantum properties such as superposition and entanglement to gain insight into the raw data and improve pattern recognition;

4) Quantum data processing: Application of quantum algorithms for efficient processing and analysis of large volumes of data, in particular in clustering, classification and regression tasks.

Advantages of quantum machine learning include the potential for rapid advances in complex data processing, optimization, and artificial intelligence tasks. However, at present, quantum machine learning remains an active field of research, and requires further development of algorithms, hardware and infrastructure for practical implementations and use in real applications.

IV. QUANTUM CONVOLUTION NEURAL NETWORK

Convolutional neural networks (CNN) are a special class of multilayer perceptrons for data processing with a network topology (LeCun, 1989). CNNs were created to recognize images represented by a two-dimensional matrix of pixels, with a high degree of invariance to transformations, scaling, distortions, and other types of input data deformation [4].

Convolution is an operation used in signal processing and image processing. It is used to combine two functions or signals to create a new signal.

Let's consider an example. We have a sensor that outputs a single value $u(t)$ – this is the position of the ship at time t:

- sensor measurements contain noise;
- to obtain a more accurate estimate of the ship's position, we will take several measurement results and average them;
- the last measurements are more important, so we calculate the weighted average, giving more weight to the last measurements;
- take the weight function $w(a)$, where a is the age of the dimension.

We will get a new function that gives a smoothed estimate of the ship's position and is called convolution:

$$s(t) = \int u(a)w(t-a)da, \quad (4)$$

where $u(a)$ is input function, $w(a)$ is kernel function. The output is called a feature map.

Let the sensor provide the result after certain intervals, and the functions are defined only for the integer indices of the moment of time t. We obtain a discrete convolution [4]:

$$s(t) = (u * w)(t) = \sum_{a=-\infty}^{\infty} u(a)w(t-a). \quad (4)$$

An example of convolution in a neural network is shown in Fig. 2.

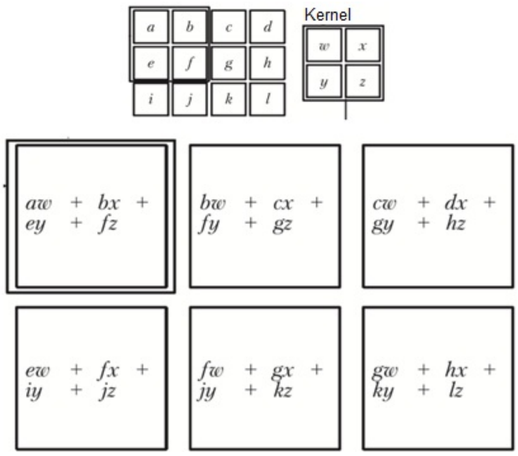

Fig. 2. An example of convolution

Also, the convolutional layer has properties of stride and padding.

Padding is a technique used in signal processing and image processing, particularly in convolutional neural networks. It involves adding extra values or pixels to the edges of the input image or signal before applying convolution.

Stray is a parameter used in convolutional operations such as convolution of images or signals in convolutional neural networks. It defines the step or distance the kernel moves during convolution over the input signal.

Also, a convolution neural network has a pooling layer.

A pooling layer is one of the types of layers used in convolutional neural networks to reduce the spatial dimensions of the input data. Its main function is to summarize information from a certain area of the input signal and compress this information to a single value. The output image is divided into blocks of size w by h and some function is calculated for each block. The function of maximum (max pooling) or (weighted) average ((weighted) average pooling) is most often used. There are no learning parameters for this layer. The main goals of the pooling layer:

- reducing the image so that subsequent convolutions operate over a larger area of the original image;
- increasing the invariance of the network output with respect to small input transfer;
- acceleration of calculations.

A quantum convolutional neural network is a convolutional neural network in which the convolution operation takes place on a quantum computer [5]. The scheme of the neural network in Fig. 3.

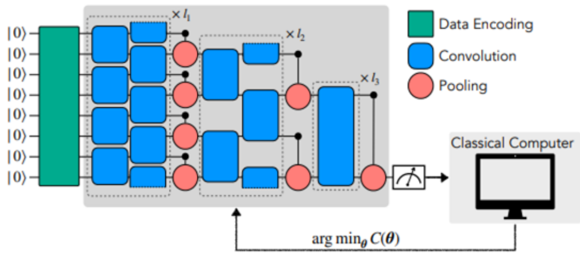

Fig. 3. Quantum convolutional neural network [5]

Such a neural network is being built on the basis of parameterized quantum gates. And then they are optimized based on the cost function:

$$C(\theta) = \sum_{i=1}^{M} \alpha_i c\left(y_i, f(x_i, \theta)\right), \quad (5)$$

where $f(x_i, \theta)$ is a machine learning model with parameters θ that gives the probability of an object label x_i; $c(a,b)$ is quantitative difference between a and b; α_i weight have property $\sum_{i=1}^{M} \alpha_i = 1$.

A. Data Encoding

Many machine learning techniques transform the input data X into another space to make the job easier. It is the same in quantum computing. We need to translate the representation of classical data into another space $X \to H$ (H – Hilbert space) so that the model can work with them. There are four ways of representation:

1) amplitude encoding;
2) qubit encoding;
3) dense qubit encoding;
4) hybrid encoding.

B. Convolutional layer

Parameterized quantum circuits for convolutional layers in a quantum convolutional neural network consist of different configurations of one-qubit and two-qubit quantum gates. Most of the known quantum circuits are shown in Fig. 4. Circuit 1 is used as a parameterized quantum scheme for training a tensor tree network [6]. Circuits 2, 3, 4, 5, 7 and 8 are taken from the work of Sim [8], which includes the analysis of expressiveness and entanglement of four-qubit parametrized quantum circuits. In article [5], circuits 7 and 8 are reduced versions of the schemes that recorded the best expressiveness in the study. Circuit 2 is a two-qubit version of the quantum scheme that has demonstrated the best entanglement capability. Circuits 3, 4 and 5 are created from circuits that have a balanced value of both expressiveness and entanglement. Circuit 6 is designed as a suitable candidate for a two-tight variational quantum eigenvalue solver (VQE) [7].

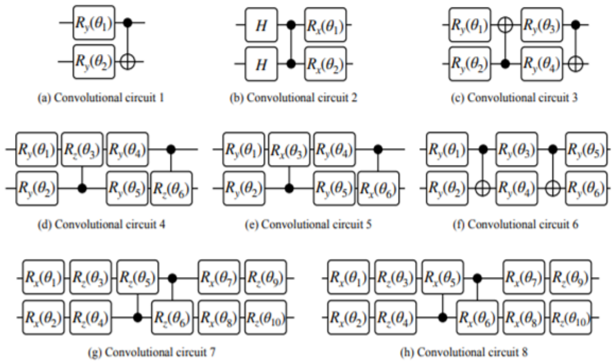

Fig. 4. An example of convolutional layers [5]

C. *Pooling layer*

The pooling layer applies parameterized quantum gates to the two qubits and tracks one of the qubits to reduce the two-qubit states to single-qubit states. An example of quantum pooling is shown in Fig. 5.

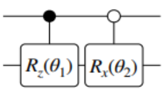

Fig. 5. An example quantum circuit for pooling layer [5]

V. RESULTS

The following quantum neural networks were implemented in our work: QCNN1 and QCNN2 (Figs 6 and 8 correspondingly).

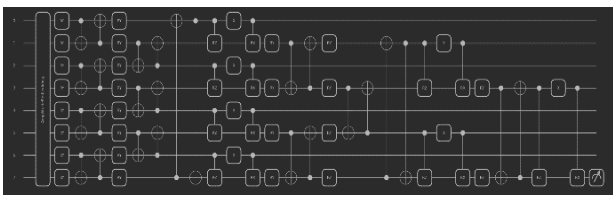

Fig. 6. Quantum circuit of quantum convolution neuron network QCNN1

In the QCNN1 network, we used the following convolutional quantum circuit in Fig. 7.

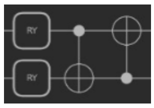

Fig. 7. Convolutional quantum circuit for QCNN1

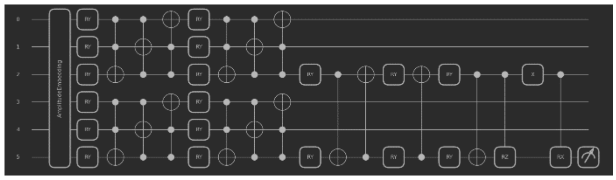

Fig. 8. Quantum circuit of quantum convolution neuron network QCNN2

The QCNN2 network has a different convolutional quantum circuit (Fig. 9).

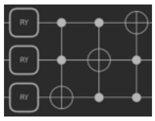

Fig. 9. Convolutional quantum circuit for QCNN2

Both neural networks have the following quantum scheme for pooling (Fig. 10).

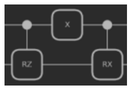

Fig. 10. Quantum circuit for pooling layer

The difference between QCNN1 and QCNN2 is that they have a different number of qubits and a different number of parameters in the Table I.

TABLE I. CHARACTERISTICS OF QUANTUM CONVOLUTIONAL NEURAL NETWORKS

Model	**Number of qubits**	**Number of parameters**
QCNN1	8	40
QCNN2	6	20

The Table II shows the results of training. Training was performed on the MNIST data set on numbers 1, 5. The size of the training sample is 1000, the test sample is 500. The training was performed using the artificial bee colony algorithm.

TABLE II. RESULTS OF LEARNING QUANTUM CONVOLUTIONAL NEURAL NETWORKS

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
QCNN1	0.832	0.884	0.764	0.8197
QCNN2	0.892	0.892	0.892	0.892

As we can see, reducing the number of parameters and the number of qubits did not affect the quality of training, but rather improved it. Also, the time spent on training has decreased.

To compare how quantum machine learning methods are superior to classical ones, let's use the classical convolutional neural network VGG19 (Table III).

TABLE III. RESULTS OF LEARNING CONVOLUTIONAL NEURAL NETWORKS VGG19

Dataset	Accuracy	Precision	Recall	F1-score
Train	1.0	1.0	1.0	1.0
Test	0.998	0.996	1.0	0.998

VI. CONCLUSIONS

In the course of the research, the properties of quantum neural networks, their advantages and disadvantages were studied on the MNIST dataset.

After many experiments, it was established that the classical method has an advantage (neuron network VGG19) over these topologies of quantum neural networks.

VGG19 has the best results, but if we further analyze the architectures, I think quantum convolutional neural network performed much better and better than classical convolutional neural network because quantum network needed less parameters to achieve great results.

So, in summary, quantum convolutional neural network has a potential advantage over classical machine learning methods, as demonstrated by the results. And recent works demonstrate that an increase in the number of parameters does not worsen the learning result [9].

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Received March 28, 2023

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У даній роботі розглянуто квантові згорткові нейронні мережі в задачі розпізнавання рукописних цифр. Запропоновано власну квантову схему для згорткового шару квантової згорткової нейронної мережі. Запропоновано власну квантову схему для пулінг шару квантової згорткової нейронної мережі. Проаналізовані результати навчання квантових згорткових нейронних мереж. Проведено порівняння побудованих моделей та вибрано найкращу за метриками accuracy, recall, precision і f1-score. Зроблено порівняльний аналіз з класичною згортковою нейроною мережею за метриками accuracy, recall, precision і f1-score. Об’єктом дослідження є задача розпізнавання цифр. Предмет дослідження – згорткова нейромережа, квантова згорткова нейромережа. Результат даної роботи можна застосувати у подальшому дослідженні квантових обчислень у задачах штучного інтелекту.

Ключові слова: квантовий комп’ютер, квантовий метод опорних векторів, квантова згорткова нейромережа, квантові обчислення, класифікація, машинне навчання.

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