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EFFECTIVENESS OF HYBRID QUANTUM-CLASSICAL AND QUANVOLUTIONAL NEURAL NETWORKS FOR IMAGE CLASSIFICATION

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The article focuses on studying the effectiveness of two different Hybrid Neural Networks (HNNs) architectures for solving real-world image classification problems. The first approach investigated in the research is a hybridization technique that allows creation of HNN based on a classical neural network by replacing a number of hidden layers of the neural network with a variational quantum circuit, which allows to reduce the complexity of the classical part of the neural network and move part of computations to a quantum device. The second approach is a hybridization technique based on utilizing quanvolutional operations for image processing as the first quantum convolutional layer of the hybrid neural network, thus building a Quanvolutional Neural Network (QNN). QNN leverages quantum phenomena to facilitate feature extraction, enabling the model to achieve higher accuracy metrics than its classical counterpart.

The effectiveness of both architectures was tested on several image classification problems. The first one is a classical image classification problem of CIFAR10 images classification, widely used as a benchmark for various imagery-related tasks. Another problem used for the effectiveness study is the problem of geospatial data analysis. The second problem represents a real-world use case where quantum computing utilization can be very fruitful in the future. For studying the effectiveness, several models were assembled: HNN with a quantum device that replaces one of the hidden layers of the neural network, QNN based on quanvolutional operation and utilizes VGG-16 architecture as a classical part of the model, and also an unmodified VGG-16 was used as a reference model. Experiments were conducted to measure the models' key efficiency metrics: maximal accuracy, complexity of a quantum part of the model and complexity of a classical part of the model.

The results of the research indicated the feasibility of both approaches for solving both proposed image classification problems. Results were analyzed to outline the advantages and disadvantages of every approach in terms of selected key metrics. Experiments showed that QNN architectures proved to be a feasible and effective solution for critical practical tasks requiring higher levels of model prediction accuracy and, simultaneously, can tolerate higher processing time and significantly increased costs due to a high number of quantum operations required. Also, the results of the experiments indicated that HNN architectures proved to be a feasible solution for time-critical practical tasks that require higher processing speed and can tolerate slightly decreased accuracy of model predictions.

Key words: Neural Networks, Quantum Computing, Hybrid Neural Networks, Image Classification.

1. Introduction

Machine learning and deep learning, in particular, are established but still incredibly dynamic and rapidly growing fields of study that have revolutionized numerous domains, including computer vision, among many others. Classical deep neural models have achieved extraordinary levels of accuracy in various computer vision tasks, including image classification, due to their ability to detect complex patterns in data. However, with today's growing demands and increasing scale of datasets, classical machine learning algorithms encounter challenges in performance and energy consumption. The aforementioned limitations are a driving force in the exploration of alternative computational paradigms.

Quantum computing has emerged as a promising solution capable of addressing some of the bottlenecks classical approaches face. By leveraging the phenomena of quantum mechanics, such as superposition and entanglement, quantum computing can perform computations impossible or infeasible for classical systems. The hybrid quantum-classical model's domain lies at the edge between classical and quantum computing and allows the combination of the strengths of classical neural networks with quantum algorithms. This field has gained attention recently as a most practical approach to utilizing today's quantum computing capabilities, providing a pathway to more efficient and robust machine learning models.

Within this context, Hybrid Quantum-Classical Neural Networks (HNNs) have shown significant promise for image classification tasks in particular. HNNs integrate quantum devices into classical architectures, enhancing feature extraction from images of various complexity. Recent advancements, such as the development of quantum convolutional layers, have demonstrated the ability to improve feature extraction and enhance classification performance on complex classical datasets. However, this field still remains in its early stages of research with numerous challenges related to quantum hardware constraints, scalability issues and a lack of theoretical understanding of quantum neural network behaviors.

2. Literature review and problem statement

One of the most notable contributions of HNNs is the introduction of quantum convolutional neural networks (QCNNs), which replace classical convolutional layers with quantum circuits to extract complex features [1]. QCNNs have shown the ability to process data fundamentally differently by leveraging quantum parallelism, which allows simultaneous evaluation of multiple states. This architecture has been explored on image classification problems, including the MNIST dataset, where hybrid models demonstrated competitive performance with reduced classical computational complexity compared to purely classical networks.

Another emerging promising approach involves using quanvolutional layers, which act as quantum feature extractors embedded within classical neural network pipelines [2]. These layers act similarly to classical convolutional layers and operate on small sections of images, applying a quantum transformation to generate feature maps. The outputs of the quanvolutional layers are then processed by a classical part of the model to achieve classification.

In addition to quantum convolutional approaches, researchers have explored hybrid variational quantum circuits (VQCs) to replace fully connected layers in classical networks [3]. VQCs are parameterized quantum circuits which act as a part of a neural network and take part in the training process. These circuits enable quantum models to learn advanced feature transformations that can complement the classical learning process. Studies indicated that VQC-based hybrid models achieve acceptable levels of accuracy on benchmark datasets like CIFAR10 and FashionMNIST, demonstrating the potential of quantum components to complement classical parts of hybrid models.

Moreover, hybrid quantum-classical transfer learning has emerged as a promising technique, where pre-trained classical models are used with embedded quantum layers and fine-tuned [4]. This method allows leveraging the representational power of existing classical networks while introducing quantum enhancements in downstream tasks. Such hybrid transfer learning approaches have successfully improved performance on smaller, specialized datasets.

Despite all the recent advancements in the domain of HNNs, they still face most of the limitations of current quantum computing. One of the most significant challenges in HNN development is the current state of quantum hardware. Existing noisy intermediate-scale quantum (NISQ) devices are limited by factors such as qubit count, decoherence times, and gate fidelity [5]. Quantum models often require larger quantum circuits with numerous gates to improve performance. However, hardware noise and errors significantly degrade model accuracy.

While quantum computing provides significant theoretical advantages, HNNs' scaling to handle large datasets remains challenging due to the limited computational resources of current quantum processors and very limited access to those computation resources at all. Training HNNs also requires a significant amount of quantum-classical communication, which can lead to computational bottlenecks due to significant communication overhead.

However, recent studies have proposed quite effective error-mitigation strategies and various quantum-inspired optimizations to address these challenges, paving the way for more robust and scalable hybrid models. The continuation of the evolution of quantum hardware, coupled with continuous research and advancements in quantum algorithms, is expected to continue in future and enhance quantum computing capabilities and prospects further.

3. The aim and objectives of the study

The aim of the study is to experimentally research the effectiveness of the proposed techniques of creating hybrid quantum-classical neural networks and investigate the advantages of proposed techniques in certain practical scenarios.

4. Methodology

This article is focused on researching the effectiveness of two different techniques of creating hybrid quantum-classical neural networks for solving image classification problem:

– Utilizing quantum device as one of the hidden layers of HNN. This approach is described in a detail in section 4.3.

– Utilizing quantum device as a first quantum convolutional layer of HNN. This approach is described in a detail in section 4.4.

In order to research the effectiveness of the aforementioned approaches, it is crucial to define metrics that will be used for comparisons of the approaches. Since the research has an important limitation – a quantum computing simulator was used for emulating quantum processes on classical hardware, it is impossible to compute the time complexity of each approach. So, instead of measuring time, it was decided to measure the number of quantum operations (number of executions of quantum circuits) required for training and operating the model and comparatively measure the complexity of a classical part HNNs. The number of required quantum operations is an important metric because quantum hardware is much more expensive, and access to it is much more restricted compared to classical hardware. Additionally, standard metrics such as maximal model accuracy on validation data subset, number of epochs needed for model training and minimal value of loss function during model training were used. So, a comprehensive list of effectiveness metrics used in the research is the following:

– maximal accuracy demonstrated by a model on validation data subset;

– number of epochs needed for model training;

– number of quantum operations needed for model training;

– number of quantum operations needed for producing single model prediction;

– comparative complexity of classical part of the model;

All the results were assessed and compared to an advanced model of VGG-16 architecture, which is widely used in the field of image classification and has standard pyramidal CNN architecture [6]. This classical architecture is used as a reference model for analyzing the feasibility of HNNs application for solving actual image classification problem.

4.1. Quantum circuits

In this work, the proposed HNN was based on Ry quantum circuits with four qubits. Ry quantum circuit has one trainable parameter per qubit and consists of a Hadamard gate [7] followed by a Ry gate. A diagram of the Ry quantum circuit, which was used for the experiments, is shown in Figure 1.

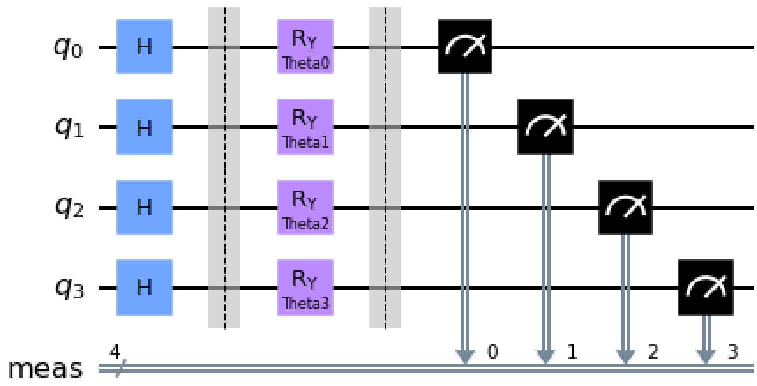

Fig. 1. Diagram of Ry quantum circuit used in a research.

As it can be seen from a diagram, number of inputs and number of outputs of the circuit is equal and corresponds to a number of qubits used in a circuit. This architecture was chosen because it proved to be the best fit for assembling HNNs based on our previous research [8].

4.2. Datasets

In this research two datasets were used:

– CIFAR10;

– Satellite Images of Hurricane Damage;

The CIFAR10 dataset is a widely used dataset in machine learning and computer vision. It consists of 60000 color images, each with a resolution of 32x32 pixels, divided into 10 mutually exclusive classes [9, 10]. Each class contains 6000 images, making the dataset balanced and representative for classification tasks. The dataset is split into 50000 training images and 10000 test images. A sample of the CIFAR10 dataset is demonstrated in Figure 2.

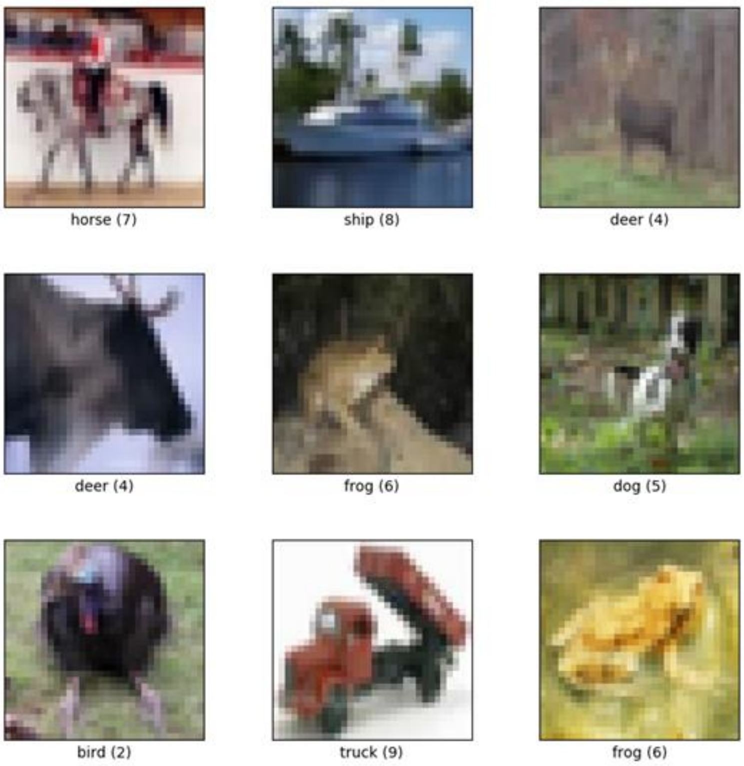

Fig. 2. Sample of CIFAR10 dataset.

The "Satellite Images of Hurricane Damage" dataset contains 23000 256x256 pixels RGB pictures of damaged and undamaged buildings taken from a satellite [11]. This dataset consists of images taken in Greater Houston area affected by 2017 Hurricane Harvey. The research used a subset of this dataset, which contains 2000 training and 200 validation images. The subset used in the research is balanced and contains an equal amount of images of damaged and undamaged buildings. A sample of the "Satellite Images of Hurricane Damage" dataset is demonstrated in Figure 3.

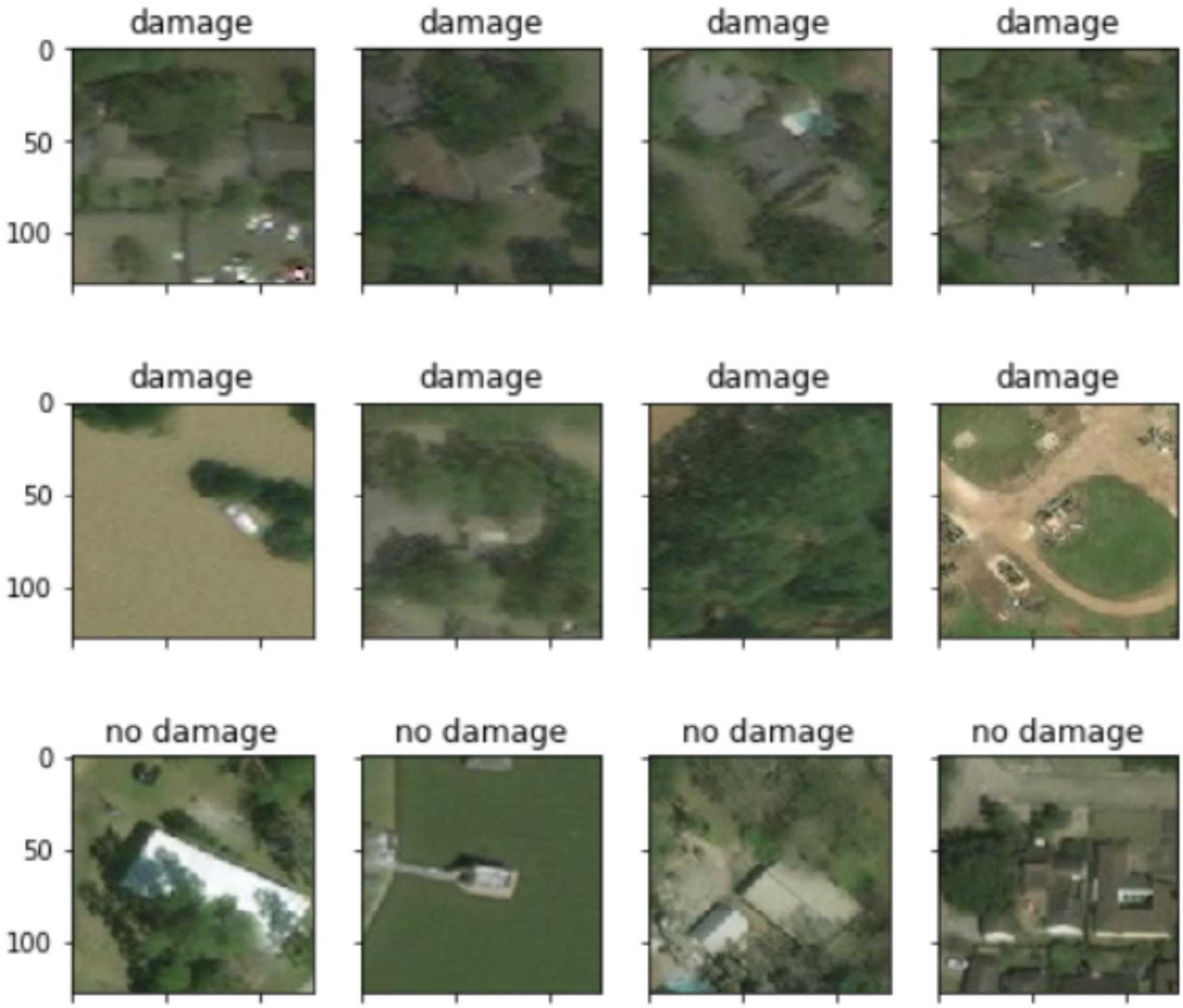

Fig. 3. Sample of "Satellite Images of Hurricane Damage" dataset.

From the samples shown, it can be seen that the images from both datasets are quite diverse. While the CIFAR10 contain diverse pictures of 10 different classes in low resolution, the Hurricane Damage dataset contains higher-resolution images of only 2 classes, featuring different buildings in a similar setting.

4.3. Quantum circuit as a hidden layer of HNN

The first approach to building HNNs investigated in this research is using a quantum device as part of a HNN that acts as one of the hidden layers of a neural network. This approach is based on the assumption that encapsulating part of the required computations within a quantum circuit will enable making the classical part of the network less deep and perform a portion of the necessary computations on the quantum device with a significant acceleration, compared to the unmodified classical part of the network.

A high-level architecture diagram of the approach is demonstrated in Figure 4.

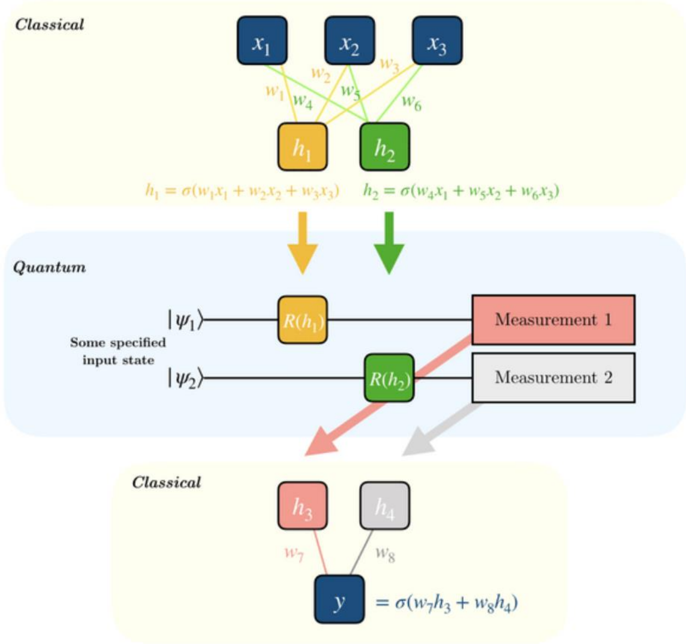

Fig. 4. Diagram of HNN that use a quantum device as one of the hidden layers [12].

The investigated HNN architecture is based on the backbone architecture [12] that consists of three convolutional layers, two linear layers and a quantum Ry circuit with four qubits. Convolutional layers transform the image into a flat vector of elements. Three linear layers reduce the dimensionality of the data to the number of qubits in a quantum layer. All layers apart from the last one use ReLU [13] activation function, while the last one utilizes tanh activation function. The tanh activation function is used because it transforms the value of parameters to the interval (-1; 1). Before entering the quantum circuit, all values are multiplied by π because the quantum circuit operates on qubit shifts, which are measured with their rotation angles. Moreover, the final operation consists of the usage of sigmoid [14] activation function on the outputs of the quantum layer.

4.4. Quantum-convolutional HNN

The second approach of building HNNs investigated in the research is based on using a quantum device that acts as the first quantum convolutional layer of HNN. The structure of the quantum convolutional layer corresponds to a single quanvolutional operation proposed by Maxwell Henderson [15]. A detailed description of this concept can be found in its founding paper. In order to avoid confusion, this approach will be referenced as a quanvolutional neural network (QNN).

A high-level architecture diagram of the approach is demonstrated in Figure 5. This research used the VGG-16 model architecture as a classical part of HNN.

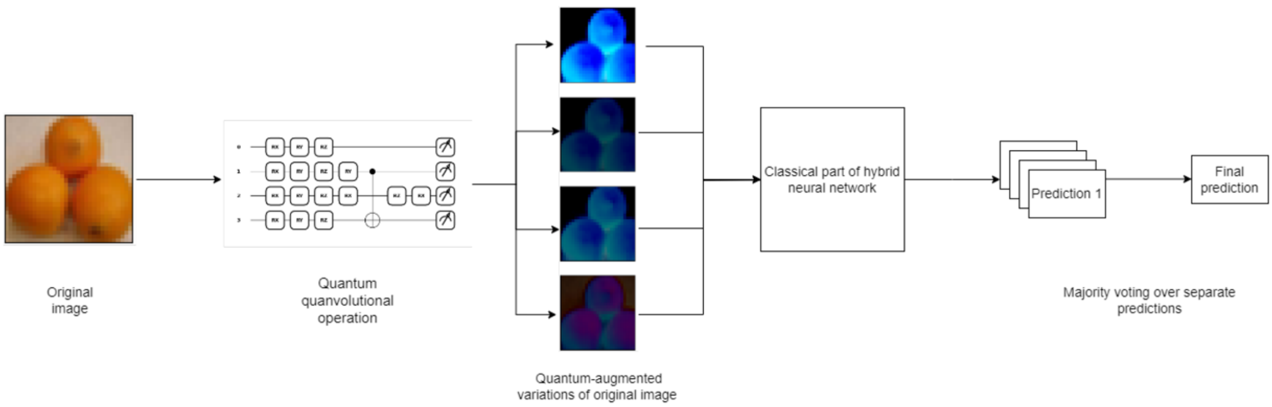

Fig. 5. Architecture diagram of HNN that uses quanvolutional layer [16].

This approach was initially proposed in our previous research [16]. The main distinguishing feature of the approach is that the result of the quanvolutional operation is used as multiple variations of the same image. The process of preparing the model can be described by the following algorithm:

1. Quantum processing of the original dataset using quanvolutional operation.
2. The results of the quantum processing are transformed into a new training dataset, which contains n times more images than the original dataset, where n equals the number of channels produced by the quanvolutional operation.
3. The new training dataset is then used to train the classical part of the model.

Thus, as a result of performing preliminary quantum data processing, a new training dataset is created, consisting of n variations of each input image. As mentioned, the value of n corresponds to the number of channels in the output of the quanvolutional operation, which depends on the number of qubits in the quantum circuit used for the quantum preprocessing of the images. The algorithm for training the classical part of the hybrid model does not differ significantly from the training process of any conventional artificial intelligence model. However, the use of the trained model has a key difference: since the quanvolutional layer of the hybrid neural network (unlike a classical convolutional operation) produces multiple images, the classical part of the hybrid model must process and classify all produced images. Therefore, to obtain the final prediction from the hybrid quantum-classical neural network, the last step involves aggregating the predictions for each variation of the processed image. Many different approaches and algorithms can be used for this aggregation step, depending on the context of the specific task. One such method is the majority voting algorithm. This introduces a certain level of flexibility into the process of determining the final prediction of the hybrid network, which can be helpful in many practical applications.

A more in-depth description of the approach and the reasoning behind it can be found in its founding paper, which is our previous piece of research [16].

5. Experimental results

Two sets of experiments were conducted. Additional research based on our previous work [16, 17] yielded new and better results, described in the current article as a result of miscellaneous improvements and enhancements. Figure 6 and Figure 7 demonstrate charts of models' accuracy during the training process until they reach their max values of accuracy on CIFAR10 and Hurricane Damage datasets, respectively. On both charts, the results of HNN are indicated in blue, the results of QNN are indicated in red, and the results of the reference model are in brown.

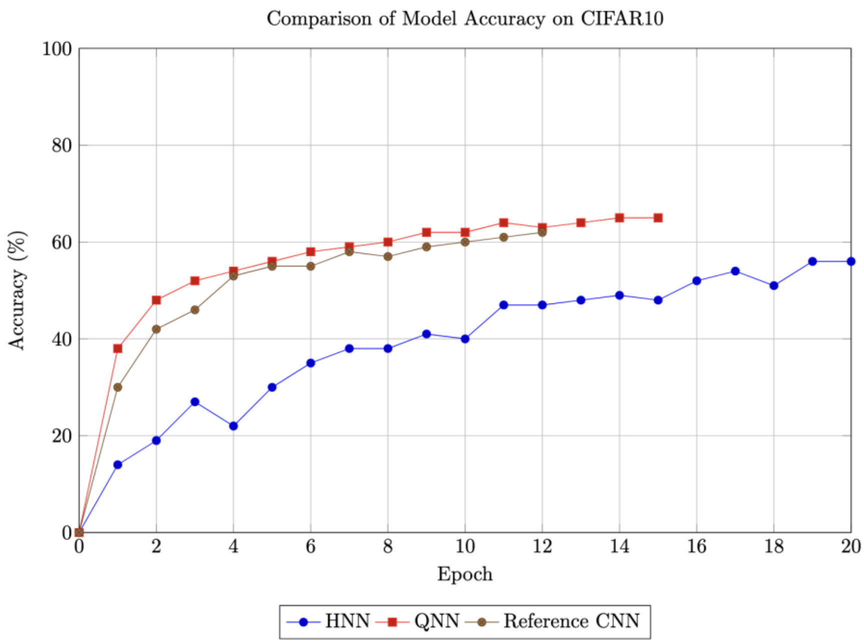

Fig. 6. Models accuracy on CIFAR10 dataset.

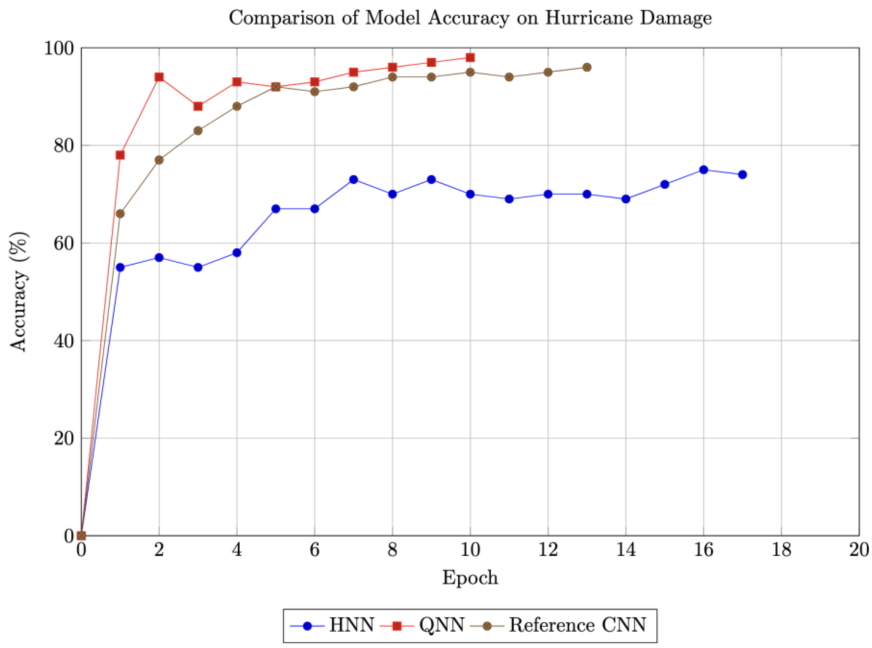

Fig. 7. Models accuracy on Hurricane Damage dataset.

Number of quantum operations needed for HNN model preparation can be described using the following formula:

$$N_{QC} = epoch * N_{train} \tag{1}$$

where,

N_{QC} – number of quantum operations for model training;

epoch – number of epochs needed for model training;

N_{train} – number of elements in training dataset.

This comes to 20 * 3000 = 60000 quantum operations for HNN preparation on the CIFAR10 dataset. And to 17 * 2000 = 34000 quantum operations for HNN preparation on the Hurricane Damage dataset.

For producing a single prediction, HNN needs just 1 quantum operation.

For QNN, number of quantum operations needed for model preparation does not depend on number of epochs needed for training and can be described using the following formula:

$$N_{QC} = image_h * image_w * (qubits * 3 + 1) * N_{train} \tag{2}$$

where,

N_{QC} – number of quantum operations for model training;

$image_h$ – heights of images in dataset;

$image_w$ – wight of images in dataset;

qubits – number of qubits in quantum circuit;

N_{train} – number of elements in training dataset.

This comes to 32 * 32 * (4 * 3 + 1) * 3000 = 39936000 quantum operations for QNN model preparation on the CIFAR10 dataset. And to 128 * 128 * (4 * 3 + 1) * 2000 = 425984000 quantum operations for QNN model preparation on the Hurricane Damage dataset (the size of the original images was scaled from 256x256 pixels to 128x128 pixels).

For producing a single prediction, QNN needs number of quantum operations that can be described using the following formula:

$$N_{QC} = image_h * image_w * (qubits * 3 + 1), \tag{3}$$

where,

N_{QC} – number of quantum operations for model training;

$image_h$ – heights of images in dataset;

$image_w$ – wight of images in dataset;

qubits – number of qubits in quantum circuit;

This comes to 32 * 32 * (4 * 3 + 1) = 13312 quantum operations for processing single image of the CIFAR10 dataset. And to 128 * 128 * (4 * 3 + 1) = 212992 quantum operations for processing single image of the Hurricane Damage dataset.

6. Discussion

6.1 Accuracy results analysis

According to the results shown in Figure 6 and Figure 7, the following observations can be made:

1. QNN demonstrated superior accuracy results for both datasets, with a result of 65.12% accuracy on the CIFAR10 dataset and 98.1% accuracy on the Hurricane Damage dataset. QNN outperformed HNN by a large margin in both experiments (23% higher accuracy on the Hurricane Damage dataset and 9% higher accuracy on the CIFAR10 dataset). QNN also outperformed the reference model by a smaller margin (1.6% higher accuracy on the Hurricane Damage dataset and 3% on the Hurricane Damage dataset).

2. HNN demonstrated significantly lower performance compared to a reference model and QNN on both datasets, with a resulting accuracy of 56.8% on the CIFAR10 dataset and 75% on the Hurricane Damage dataset.

3. HNN requires more epochs to finish the training process to reach the highest level of accuracy. On the other hand, the training process of QNN is the shortest (in terms of epochs required) for a less complex Hurricane Damage dataset and just slightly longer compared to a reference model.

6.2 Computation complexity analysis

According to the results of computing the number of quantum operations required for preparing and operating, the following observations can be made:

1. Despite the fact that QNN needs to process every image of the training dataset only once, it requires a significant number of quantum operations to prepare the model – 39.49 million operations for model training on the CIFAR10 dataset and 425.984 million operations for model training on the Hurricane Damage dataset.

2. The number of operations needed to produce a single prediction of the QNN model also requires a significant number of quantum operations – 13312 quantum operations for processing a single image of the CIFAR10 dataset and 212992 quantum operations for processing a single downscaled (to size of 128x128pixels) image of Hurricane Damage dataset.

3. The number of quantum operations required for preparing and operating the QNN model linearly depends on the number of pixels in the dataset's original images, which makes the application of QNN much more expensive for solving problems that require analysis of high-resolution images.

4. The number of quantum operations required for preparing HNN is several orders of magnitude lower compared to QNN – 60000 quantum operations for training a model on the CIFAR10 dataset and 34000 quantum operations for training a model on the Hurricane damage dataset. The number of quantum operations needed to produce a single prediction is constant and equal to 1 for all cases. This makes HNNs a lot (orders of magnitude) cheaper compared to QNNs in terms of quantum computing.

5. The complexity of the classical part of QNN is 4 times higher compared to a reference model and more than 4 times higher compared to the HNN model. This is because each image of a dataset requires the processing of 4 variations produced by a quantum layer, which directly translates to 4 times increased processing time by a classical part of a hybrid neural network.

6.3 General discussion

It should be noted that all experiments were conducted using the Qiskit quantum simulator [18] due to a very limited availability and very high cost of quantum hardware, which made it impossible to conduct experiments on actual quantum computer.

All source code and data are provided for open access on GitHub and Kaggle [19-22].

7. Conclusion

Based on the results of the study, the following conclusions can be drawn:

1. The results of the experiments proved that hybrid neural networks based on quanvolutional operation are able to achieve a superior level of accuracy compared to a reference classical model. However, at the same time, QNNs require a very significant number of quantum operations for both preparation and operating a model and also require 4 times more compute time of classical hardware because it needs to process 4 times more data compared to alternative approaches discussed in this research. This renders the approach much more expensive compared to alternatives.

2. The results of the experiments also indicated that hybrid neural networks built upon a quantum device that acts as one of the hidden layers of the neural network may be a feasible approach, even though it demonstrates a significantly lower accuracy compared to alternative approaches. The feasibility of this approach is attributed to a relatively low cost in terms of quantum operations number and decreased complexity of the classical part of the neural network, which may be highly beneficial in terms of increasing the speed of computations of the model by making a classical part of the model less deep and utilizing quantum device instead of dropped layers of the neural network.

3. QNN architectures proved to be a feasible and effective solution for critical practical tasks that require higher levels of accuracy of the model and, at the same time, can tolerate higher processing time and significantly increased costs due to a high number of quantum operations required.

4. HNN architectures proved to be a feasible solution for time-critical practical tasks that require higher processing speed and can tolerate slightly decreased model accuracy.

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УДК 004.8

ЕФЕКТИВНІСТЬ ГІБРИДНИХ КВАНТОВИХ ТА КВАНТОВО-ЗГОРТКОВИХ НЕЙРОННИХ МЕРЕЖ ДЛЯ ЗАДАЧІ КЛАСИФІКАЦІЇ ЗОБРАЖЕНЬ

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Стаття присвячена дослідженню ефективності двох різних архітектур гібридних нейронних мереж (*HNN*) для вирішення практичних задач класифікації зображень. Перший підхід, що розглядається в дослідженні — це техніка гібридизації, яка дозволяє створювати гібридну нейронну мережу на основі класичної нейронної мережі шляхом заміни певної кількості прихованих шарів нейронної мережі на варіаційну квантову схему. Це дозволяє зменшити складність класичної частини нейронної мережі та перенести частину обчислень на квантовий пристрій, що забезпечує прискорення обчислень. Другий підхід ґрунтується на використанні кванволюційних операцій для обробки зображень як першого квантового згорткового шару гібридної нейронної мережі, створюючи таким чином кванволюційну нейронну мережу (*QNN*). *QNN* використовує квантові явища для поліпшення процесу вилучення ознак, що дозволяє моделі досягати вищих показників точності порівняно з її класичним аналогом.

Ефективність обох архітектур була перевірена на кількох задачах класифікації зображень. Перша задача — це класична задача класифікації зображень *CIFAR10*, яка широко використовується як еталон для різних завдань, пов'язаних із зображеннями. Друга задача, що використовувалась для дослідження ефективності, стосується аналізу гео-даних. Друга задача представляє реальний випадок використання, де застосування квантових обчислень може бути дуже перспективним у майбутньому. Для дослідження ефективності було створено кілька моделей: гібридну нейронну мережу з квантовим пристроєм, який замінює один із прихованих шарів нейронної мережі; кванволюційну нейронну мережу, засновану на кванволюційній операції з архітектурою *VGG*-16 як класичною частиною моделі; а також немодифіковану *VGG*-16 як референтну модель. Було проведено експерименти для вимірювання ключових метрик ефективності моделей: максимальної точності, складності квантової частини моделі та складності класичної частини моделі.

Результати дослідження підтвердили доцільність обох підходів для вирішення запропонованих задач класифікації зображень. Результати були проаналізовані для визначення переваг і недоліків кожного з підходів за обраними ключовими метриками. Експерименти показали, що архітектури *QNN* виявилися доцільним та ефективним рішенням для критично важливих практичних задач, які потребують високого рівня точності роботи та можуть допускати як збільшення часу обробки, так і значне зростання вартості через велику кількість необхідних квантових операцій. Також результати експериментів показали, що архітектури *HNN* є доцільним рішенням для практичних задач, де критичною є швидкість обробки, і допустиме незначне зниження точності моделі.

Ключові слова: нейронні мережі, квантові обчислення, гібридні квантово-класичні нейронні мережі, класифікація зображень.