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Stabilization of Image Classification Accuracy in Hybrid Quantum-Classical Convolutional Neural Network with Ensemble Learning

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ABSTRACT

Stabilization of Image Classification Accuracy in Hybrid Quantum-Classical Convolutional Neural Network Model with Ensemble Learning. Image classification plays a significant role in various technological applications, such as object recognition, autonomous vehicles, and medical image processing. Higher accuracy in image classification implies better capabilities in recognizing and understanding visual information. To enhance image classification accuracy, a Hybrid Quantum-Classical Convolutional Neural Network (HQ-CNN) model is developed by integrating quantum and classical computing elements with ensemble learning techniques. Compared to conventional neural networks, HQ-CNN enriches feature mapping in image classification predictions. The research results with HQ-CNN using ensemble learning demonstrate impressive and stable accuracy, with the lowest deviation being 1.1037.

1. INTRODUCTION

With the ability to recognize and understand visual information, image classification plays a central role in various applications, including medical image processing [1], autonomous vehicles [2], as well as object recognition [3]. The Convolutional Neural Networks (CNN) method is a deep learning method that is often used in image classification [4]. CNN has one or more convolution layers, fully interconnected layers [5] and pooling layers [6]. This structure allows CNN to utilize 2D image input [7]. However, the implementation still uses an ordinary computer system which has large resources.

With rapid advances in quantum computing hardware. Currently technology is entering an era of development in quantum software to carry out various computing tasks using noisy intermediate scale quantum (NISQ) [8]. Quantum computing can output wave functions with a polynomial number of quantum gate operations, which in turn can produce statistical distributions that are very difficult to produce by classical computing [9] [10] [11]. Apart from that, because the output of the quantum convolutional layer is a classical array [12]. Therefore, HQ-CNN can exploit all the features of classical CNNs, and at the same time, it is able to take advantage of current NISQ computers [13]. As well as the framework automatically calculating the gradient of an arbitrary quantum-classical loss function using a hybrid quantum-classical computer. A representative function of the CNN is created to classify the synthetic Tetris dataset and compare the learning accuracy with a classical CNN that has the same architecture.

HQ-CNN has been used to predict coronavirus disease 2019 (COVID-19) from patient chest X-ray images. This previous research successfully used HQ-CNN with a data set consisting of 5445 chest X-ray images, including 1350 COVID-19 images, 1350 normal images, 1345 viral pneumonia images, and 1400 bacterial pneumonia images. The results of this study show that the proposed HQ-CNN model achieves higher performance with an accuracy of 98.6% and a recall rate of 99% in the first experiment (COVID-19 and normal cases). In addition, this model managed to achieve an accuracy of 98.2% and a recall rate of 99.5% in the second experiment (cases of COVID-19 and viral pneumonia). This model also achieved an accuracy of 98% and a recall rate of 98.8% on the third dataset (COVID-19 cases and bacterial pneumonia). Finally, this model achieved accuracy and recall of 88.2% and 88.6%, respectively, in the case of multiclass datasets [14]. The accuracy of HQ-CNN is quite high, but the weakness of HQ-CNN is the instability of accuracy which will continue to decrease after several trials. This research will increase the accuracy of HQ-CNN to become more stable.

By combining several image classification models from ensemble learning, such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbours (KNN), in an ensemble, you can take advantage of the combination of models to increase accuracy [15]. Ensemble learning allows combining several different classification models into one, which often results in higher accuracy than a single model. Apart from that, ensemble learning can reduce variance, carry out collaborative decision making, and have robustness [16].

In this research, we are looking for a combination of HQ-CNN with several ensemble learning, namely Random Forest, SVM, and KNN, which is more suitable for increasing and stabilizing accuracy. The HQ-CNN model uses elements of quantum computing, which can produce highly variable results due to the probability nature of quantum computing. Using ensemble learning can even out these uncertainties and produce more stable and reliable results.

2. RELATED WORK

The current research aims to explore the potential of Hybrid Quantum-Classical Convolutional Neural Network (HQ-CNN) in overcoming limitations in accuracy instability using ensemble learning methods. The exponential growth of data sizes as system sizes increase has become a significant obstacle in utilizing classical computing methods to solve quantum physics problems. HQ-CNN addresses these challenges by leveraging qubits to represent data in a quantum environment and applying the CNN structure to quantum computers. By adding an algorithm from one of the ensemble learning, it can be a solution to overcome the problem of unstable accuracy.

Research from Essam. H., et al. [14] used random quantum circuits as a basis for detecting COVID-19 patients via chest X-ray images. The results of the proposed model have been shown to have a significant impact in the detection of COVID-19 using X-ray images. The proposed method can differentiate between COVID-19, viral pneumonia, bacterial pneumonia, as well as normal cases. Statistical analysis shows the reliability and validity of the HQ-CNN model and good classification performance.

Research conducted by Rishab Parthasarathy and Rohan Bhowmik [17] aims to investigate the potential of quantum computing in efficient image recognition by creating and evaluating a new machine learning algorithm, namely Quantum Optical Convolutional Neural Network (QOCNN). The QOCNN architecture combines the quantum computing paradigm with quantum photonics and has been compared with competing models, achieving comparable accuracy in terms of robustness. In addition, the proposed model has significant potential to improve computing speed. The results of this research demonstrate the significant potential of quantum computing in the development of artificial intelligence and machine learning.

Ji Guan et al. in their research [18] investigated formal robustness verification of quantum machine learning algorithms against unknown quantum perturbations. They found analytical bounds that can be calculated efficiently to provide robust accuracy estimates in real-world applications. Additionally, they developed a robustness verification algorithm that can precisely verify the robustness of ϵ-robustness of quantum machine learning algorithms and provide useful examples for detrimental models.

Tak Hur et al. [19] conducted a study where they simulated the MNIST and Fashion MNIST datasets with Pennylane and various factor combinations to test an 8-bit-based Quantum Convolutional Neural Network (QCNN) model for binary classification. The results of this study reveal that QCNN shows high classification accuracy, with the highest instances reaching 94% for Fashion MNIST and close to 99% for MNIST. Additionally, they compared the performance of QCNN with traditional convolutional neural networks (CNN) and found that, with the same training settings for both benchmark datasets, QCNN outperformed CNN by far.

Overall, the results of these studies show the great potential that quantum computing has in the development of artificial intelligence and machine learning, especially in terms of accuracy. QCNN models [19], [20] show promising results in terms of classification accuracy and outperform traditional CNN models. Additionally, a comparison of deep learning architectures on different types of computing platforms highlights the unique advantages of quantum computing in this field.

3. METHODOLOGY

In this research, there are several important stages, including data collection, design, development, and implementation. This approach was chosen to ensure that the development process takes place in a structured manner.

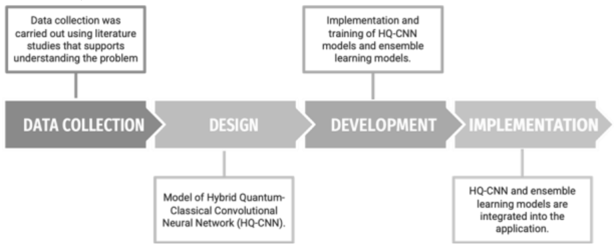

FIGURE 1. METHODOLOGY

In the initial stage, data was collected using literature studies with the aim of collecting information that supports understanding the problem. Literature studies include searching for relevant sources such as books and online sources related to the problem object [14]. Information obtained from these sources will be used as the main reference in developing the applications that we are developing. Several journals have also been collected as references, as we explained previously.

A Hybrid Quantum-Classical Convolutional Neural Network (HQ-CNN) model was designed. This includes selecting the appropriate network architecture, convolution layers, and parameters. Apart from that, the design of the ensemble learning model was also carried out, by selecting ensemble algorithms such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN).

Development includes implementation and training of the HQ-CNN model and ensemble learning model. This process involves training a model to understand the features in image data and make predictions. HQ-CNN and ensemble learning models are integrated into the application. Application testing is carried out with different test data to measure the accuracy and stability of the results. If necessary, optimizations and improvements are made to increase the efficiency and stability of the application.

The proposed method is ensemble learning with several different types including Random Forest, Support Vector Machine, and K-Nearest Neighbor. Then look for among the three methods the most stable test model (high accuracy and high recall) for each test. It will be explained in more detail in figure number 2.

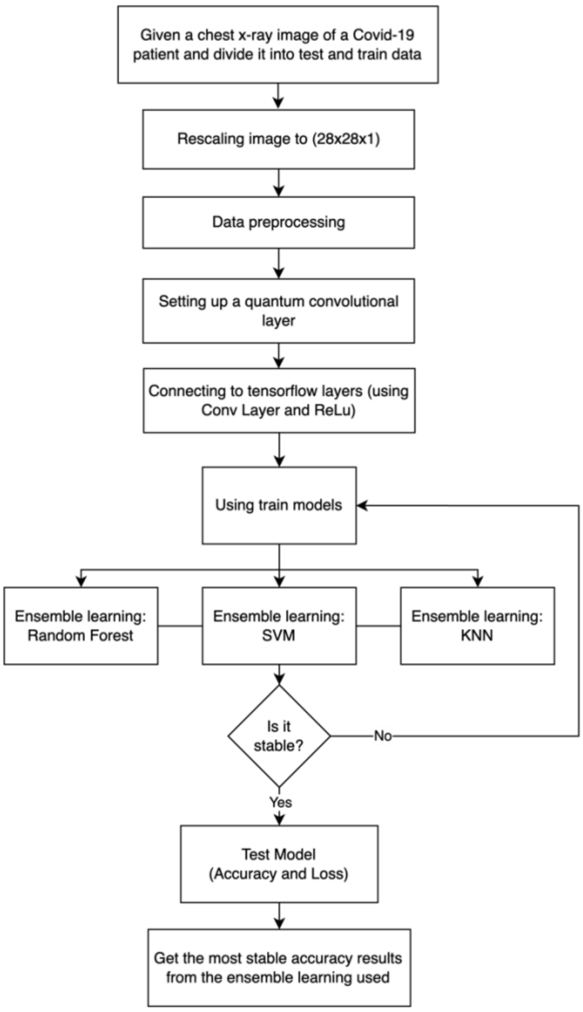

FIGURE 2. FLOW OF THE PROPOSED METHOD

4. RESULT AND DISCUSSION

The Hybrid Quantum-classical Convolutional Neural Network (HQ-CNN) model using quantum convolution was proposed and presented by the authors of [21]. The main idea of convolutional layers is to use them to process local fractions of an image rather than processing the entire original image. This concept is further developed in the context of quantum circuits. The main difference between quantum convolution and classical convolution is that quantum circuits can produce complex kernels whose processing may be classically difficult [21], [22]. Quantum convolution functions as a Random Quantum Circuits (RQC) circuit for computing convolution operations, using RQC to match near-range quantum devices and intermediate-scale quantum noisy devices.

Model training using the MNIST dataset. The MNIST dataset is a very frequently used dataset for training and testing image recognition algorithms. This dataset contains 60,000 training examples and 10,000 test examples of handwritten digits, each represented as a 28x28 pixel grayscale image, size-normalized to ensure consistency.

Quantum pre-processing in this study involves dividing the image resolution with an input size of $(28 \times 28 \times 1)$ to $(14 \times 14 \times 4)$, which is compatible with a classical convolution process using a kernel size of (2×2) and a stride value equal to 2. The input image is encoded into a quantum circuit by performing parametric rotation to the ground state of the qubit. In quantum devices, quantum computations associated with unit operators U are performed, which can be generated by RQC. Finally, the quantum system is measured to produce a classical expectation value. Each expectation value corresponds to one of the four channels in one output pixel. The same process is applied to the entire input image to build a multichannel output image. The classical convolution layer is added after the quantum convolution layer.

Testing of the HQ-CNN model without ensemble learning is shown in Figure 3.

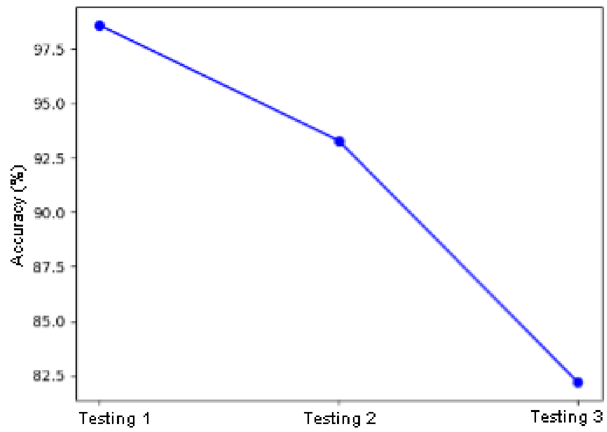

FIGURE 3. ACCURACY OF HQ-CNN MODEL WITHOUT ENSEMBLE LEARNING

Analysis of Hybrid Quantum-Classical Convolutional Neural Network (HQ-CNN) with Random Forest. Random Forest is an ensemble model consisting of many decision trees. Each tree decides on the output, and the results from multiple trees are combined for a final prediction. This is a relatively fast model and can handle many features. Random Forest does not involve the concept of epochs like in deep learning because it involves forming decision trees independently. This model is trained independently on a subset of the data with bootstrap sampling and random feature selection. Although different in concept to HQ-CNN, in experiments, Random Forest achieved high accuracy demonstrating the effectiveness of this model in classification tasks.

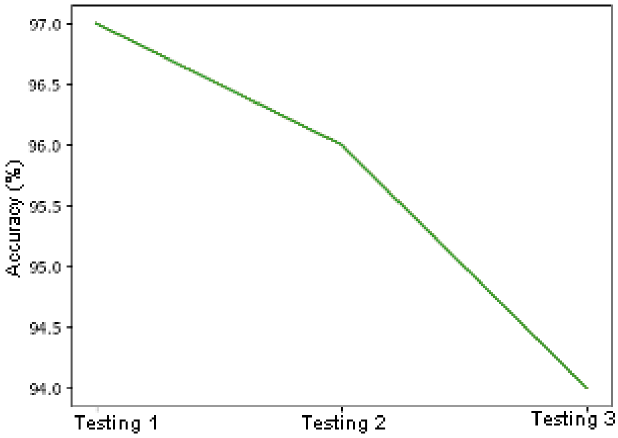

FIGURE 4. ACCURACY OF HQ-CNN MODEL WITH RANDOM FOREST

Analysis of Hybrid Quantum-Classical Convolutional Neural Network with Support Vector Machine (SVM). SVM is a machine learning model used for classification and regression. SVM tries to find the best hyperplane that separates the classes in the data. Epoch analysis in SVM is not like in deep learning, because SVM looks for hyperplanes that separate classes and does not involve iterative training. SVM involves mathematical optimization to find the best hyperplane, which is a relatively fast training process. However, the low accuracy results in the experiments may indicate that SVM is not effective enough for this classification task.

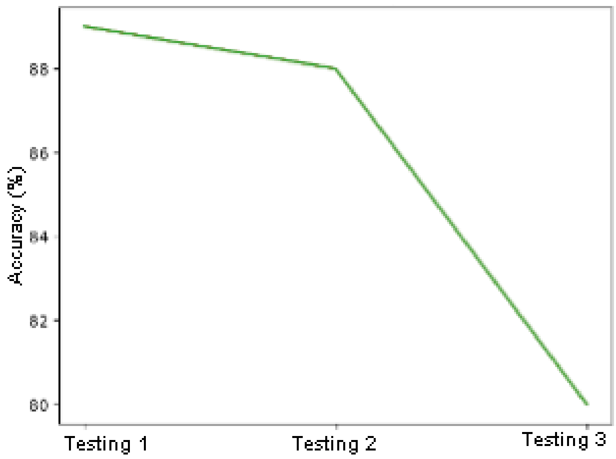

FIGURE 5. ACCURACY OF HQ-CNN MODEL WITH SVM

Analysis of Hybrid Quantum-Classical Convolutional Neural Network with K-Nearest Neighbour (KNN). KNN is a non-parametric model that operates by calculating nearest neighbours (training data) to classify a data point based on nearest neighbour classes. KNN is an instant model that only performs calculations when new data is classified, so it does not involve the concept of epochs or training. Even though it is simple, KNN can produce quite good accuracy results in some cases. However, this model does not have the ability to incorporate quantum computing like HQ-CNN.

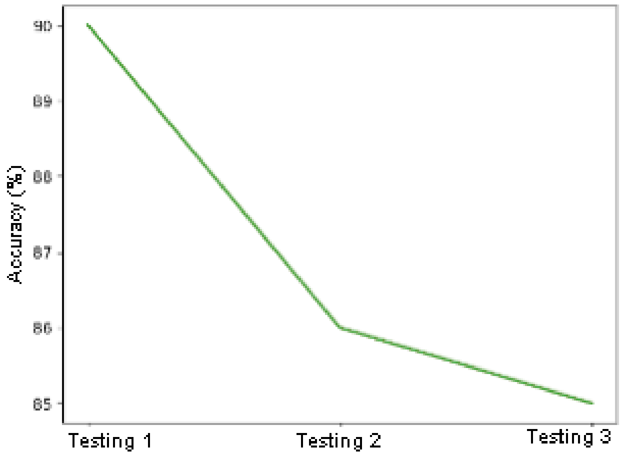

FIGURE 5. ACCURACY OF HQ-CNN MODEL WITH KNN

Overall comparison of the accuracy of the HQ-CNN model with the three-ensemble learning. The comparison is in table 2.

Random Forest is an ensemble learning algorithm based on decision trees and is known for its good performance and ability to overcome overfitting. This model shows high stability with a standard deviation of around 1.1037%. Meanwhile, SVM is a classification algorithm that looks for the best hyperplane to separate different data classes. Although SVM is known for its strong separation power, the model appears unstable with a standard deviation of around 4.0227%. Finally, KNN is a simple classification algorithm that works by considering the majority of classes of the nearest neighbours of a data point that you want to classify. The KNN model shows a moderate level of stability with a standard deviation of around 2.16%. Thus, Random Forest is the most stable, KNN has a medium level of stability, while SVM is the least stable among these three models.

In experiments, HQ-CNN achieved high accuracy, which shows the effectiveness of this model in image classification tasks. Epoch analysis and model training are not relevant for HQ-CNN because it is a quantum model that is fundamentally different from classical algorithms such as Random Forest, SVM, and KNN. HQ-CNN uses quantum computing to solve the classification problem, and the experimental results show good agreement in terms of accuracy. In table 2, “Standard Deviation” measures the extent to which accuracy varied across three experiments. The smaller the standard deviation, the more stable the model. In this case, Random Forest has a fairly low standard deviation, indicating that it is the most stable in the experiment.

5. CONCLUSIONS

In this research, the effectiveness of combining Hybrid Quantum-Classical Convolutional Neural Network (HQ-CNN) with ensemble learning methods has been successfully demonstrated in improving and stabilizing image classification accuracy. The HQ-CNN model achieved stable accuracy levels of 98.6%, 93.3%, and 82.2% in the three experiments conducted, although there were significant variations in accuracy between experiments. The standard deviation of Pure HQ-CNN accuracy is approximately 6.78, indicating a high degree of variability.

Apart from HQ-CNN, the accuracy results of ensemble learning models using the Random Forest, SVM and KNN methods have also been tested. Random Forest showed accuracy rates of about 97.2%, 96.4%, and 94.2%, with a standard deviation of about 1.1037, indicating better stability compared with HQ-CNN. SVM and KNN produce lower accuracy, namely around 89%, 88%, and 80% for SVM, and around 90.2%, 86.1%, and 85.5% for KNN, with standard deviations of 4.0227 and 2.16, respectively. Even though HQ-CNN has high variability, this model still performs better than SVM and KNN.

Future research needs to consider several aspects to improve the effectiveness and applicability of these models. In addition to maintaining a high level of accuracy, it is necessary to pay attention to its stability, especially when dealing with variations in real-world data. Computational efficiency needs to be improved to reduce additional computational costs that may be required. The development of more adaptive concept hierarchies and the ability of models to deal with data variability and noise are important steps in future research. Deeper integration between quantum and classical computing, as well as the interpretability of ensemble learning models, is also an interesting focus for future research. With efforts in these areas, it is hoped that future research will bring significant innovation in image classification combining quantum and classical elements.

TABLE 1. MODEL COMPARISON

Ensemble Learning	Accuracy of Experiment 1 (%)	Accuracy of Experiment 2 (%)	Accuracy of Experiment 3 (%)	Standard Deviation (%)
Only HQ-CNN	98.6	93.3	82.2	6.78
Random Forest	97.2	96.4	94.2	1.1037
SVM	89	88	80	4.0227
KNN	90.2	86.1	85.5	2.16

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