Application of quantum technology Variational Quantum Classifier in agriculture for classification of wheat varieties

D T Mukhamedieva[1*], and *R A* Sobirov[1]

[1]Tashkent Institute of Irrigation and Agricultural Mechanization Engineers National Research University, 39, Kari Niyaziy street, Tashkent, 100000, Uzbekistan

Abstract. This study proposes the use of Variational Quantum Classifier for automated classification of wheat varieties. A model trained on a large data set will be able to identify unique patterns and relationships between seed characteristics and cultivar membership. This will allow farmers and researchers to more accurately identify wheat varieties, which in turn can improve growing and crop management processes. This approach is justified not only by the need to optimize agricultural production, but also in the context of the use of advanced technologies to achieve precision and efficiency in the agricultural sector. As a result of this research, it is expected that the quality and sustainability of wheat production will improve, which is important for food security and sustainable agricultural development. The goal of the problem is to classify wheat varieties based on seed characteristics. VQC is trained on the training dataset and then evaluated on the test dataset. To evaluate the performance of the model, various metrics are used, such as accuracy, precision, recall, F1-score and Confusion Matrix.

1 Introduction

Agriculture is one of the key sectors of the world economy, ensuring food security and economic development. One important aspect in this area is the cultivation of crops such as wheat, which is the main source of food for millions of people around the world. Wheat varieties vary in their characteristics such as size, shape and other seed attributes. Understanding and classifying these varieties becomes important tasks for optimizing agricultural production processes. In agriculture, it is important to have reliable methods for identifying crop varieties. Classification of wheat varieties can be useful for breeders and farmers in choosing the optimal seeds for sowing. Different varieties of wheat may have different characteristics that affect the yield and quality of the crop. By classifying seeds according to their characteristics, the optimal conditions for growth and maximum yield can be determined. Knowing the variety of wheat can be of economic importance for agricultural enterprises. Different varieties may have different market prices, affecting farmers' incomes. Classification of wheat varieties can be an important part of scientific

* Corresponding author: dilnoz134@rambler.ru

research in agriculture, biology and genetics. This may contribute to a better understanding of the diversity of varieties and their adaptation to different conditions. Taking into account modern trends in agriculture, where machine learning and artificial intelligence technologies are being introduced, classification tasks are becoming more relevant for automating processes and improving efficiency. Thus, the task of classifying wheat varieties based on seed characteristics has a wide range of applications and can provide practical benefits in agriculture, scientific research and agricultural decision making.

In this context, the application of machine learning methods, in particular VQC (Variational Quantum Classifier), provides unique opportunities for the efficient classification of wheat varieties based on their seed characteristics. VQC (Variational Quantum Classifier) is a quantum classifier designed to solve machine learning problems. It is based on the idea of a variational quantum approach that uses a parameterized quantum schematic ansatz to represent the input data and a parameterized classical algorithm to train these parameters [1-3].

Variational quantum algorithms, including VQC, are hybrid models that combine classical and quantum computing resources. They use a quantum circuit to represent information and a classical circuit to learn the parameters of that quantum circuit. This allows quantum hardware to be used to solve specific problems within a machine learning application. A quantum circuit that represents input data in quantum space. The input data is first mapped into quantum states, which are then subjected to evolution on a quantum computer. A parameterized quantum circuit block that represents parameterized quantum ansatz gates provides flexibility in choosing the form of quantum state representation. A classic optimizer that updates ansatz parameters based on feedback from the training data. Various optimizers can be used to find optimal parameters. Once the model is trained, VQC is used to classify new data. The input data is first subjected to the same process of feature map and ansatz evolution, and then classification is made based on the results. Benefits of VQC include the ability to use quantum computational acceleration to solve certain classification problems, especially where quantum effects can provide performance benefits over classical methods. VQC is currently applied predominantly in the context of hybrid computing, using quantum and classical resources together [4-7].

In VQC, the quantum ansatz circuit block is a parameterized model, similar to parameterized layers in neural networks. These parameters are subject to training to adapt the model to a specific task. Like neural networks, backpropagation is used to train VQC parameters. During training, the classical optimizer updates the parameters of the ansatz to minimize the error between the predicted and actual values. Like neural networks, VQC uses a loss function to measure the difference between predicted and actual values. The optimizer is used to tune the model parameters to minimize the loss function. Once training is complete, VQC is used to classify new data. The results obtained during the evolution of the quantum state are used to determine the class to which the input image belongs. Unlike traditional neural networks, where data is represented by numeric vectors, VQC uses quantum circuitry to represent data in quantum space. This makes it possible to take advantage of quantum computing advantages in solving certain classification problems. Thus, VQC is a hybrid model in which the quantum part is responsible for the representation and evolution of data in quantum space, and the classical part is responsible for learning the parameters of this representation [8-13].

2 Materials and methods

The "Seeds" dataset is a set of data describing the various characteristics of the seeds of three different varieties of wheat. This dataset is used in classification tasks to identify wheat varieties based on their characteristics.

Each record in the dataset contains the following attributes:

- Seed area.
- Seed perimeter.
- Seed length.
- Seed width.
- Seed compactness coefficient.
- Seed trough length.
- Seed trough area.
- Seed circle length.
- Class (real value).

The classification focuses on three wheat varieties: Kama, Rosa and Canadian. The dataset contains information about 210 seeds, 70 seeds for each of the three wheat varieties. The task is to predict their variety based on the characteristics of the seeds. It is important to perform data preprocessing, such as standardization or normalization, before training a machine learning model on this dataset. This dataset provides the opportunity to solve the classification problem in the context of machine learning and study the influence of various characteristics on wheat varieties.

V1 V2 V3 V4 V5 V6 V7
15.26, 14.84, 0.871, 5.763, 3.312, 2.221, 5.22.1
14.88, 14.57, 0.8811, 5.554, 3.333, 1.018, 4.956.1
...
11.26, 13.01, 0.8355, 5.186, 3.308, 2.356, 5.096.3

The data was pre-processed, including standardization of seed characteristics using methods such as StandardScaler from the scikit-learn library. Class labels were also encoded for use in VQC. Feature scaling is performed using MinMaxScaler from the sklearn.preprocessing library. A graph is constructed in pairs to visualize the interaction of features. The data is divided into training and test sets.

A quantum circuit is built using various quantum features (feature map) and ansatz (Figures 1 and 2). First, we import the required ZZFeatureMap class from the Qiskit library, which provides tools for creating quantum feature maps. We then determine the number of features in our data. This number will be used to create the quantum feature map. We create a ZZFeatureMap object, which represents a specific kind of quantum feature map. We specify feature_dimension equal to the number of features in the data, and reps (number of repetitions) equal to 1.

After creating a quantum feature map, we can decompose it (if necessary) and visualize the quantum circuit that corresponds to it. Visualizations of a quantum feature map that can be used in quantum machine learning algorithms to represent classical data in quantum form.

Then the model weights are optimized using the VQC quantum classifier. The learning process is visualized using a callback function. The accuracy of the quantum model is assessed on the training and test data sets. The results of the classical and quantum models on different sets of features and different ansatz are compared. A table comparing the results is displayed.

The developed program is an example of a hybrid machine learning model that uses both classical and quantum methods to solve a classification problem. A statistical analysis of the results obtained was carried out to assess the degree of reliability of the classification and the significance of the identified patterns.

This approach creates an efficient model for classifying wheat varieties based on their seed characteristics using deep learning techniques and neural networks.

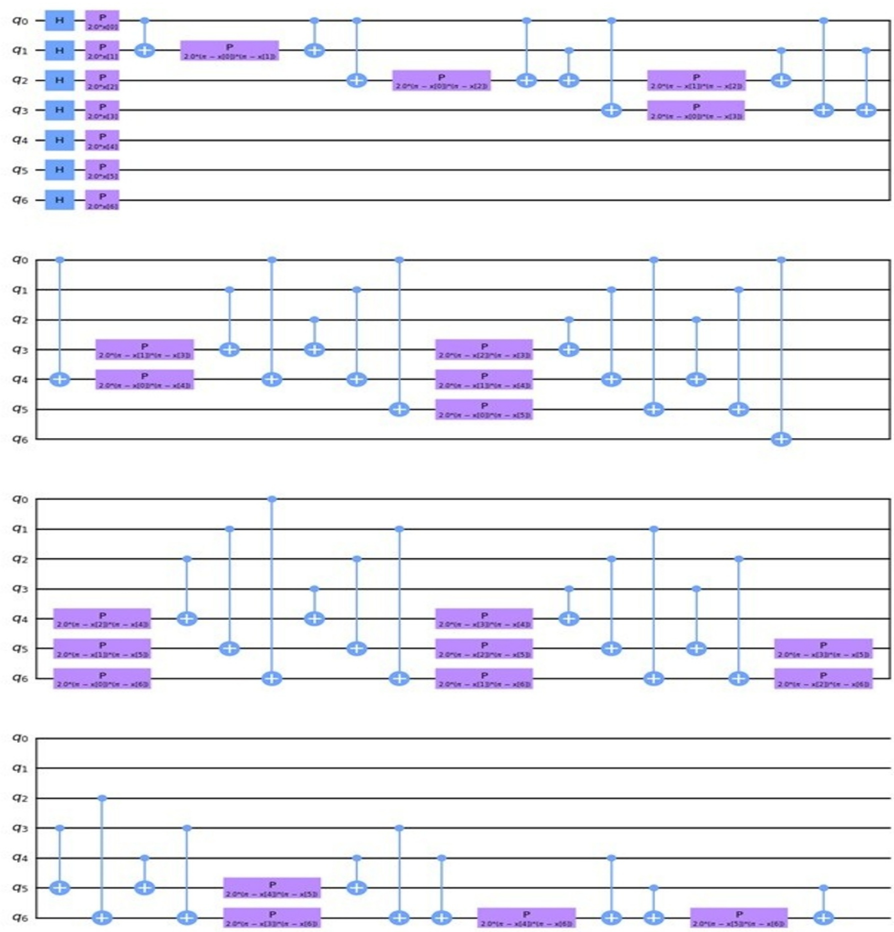

Fig. 1. Quantum circuit using various quantum features (feature map) and ansatz..

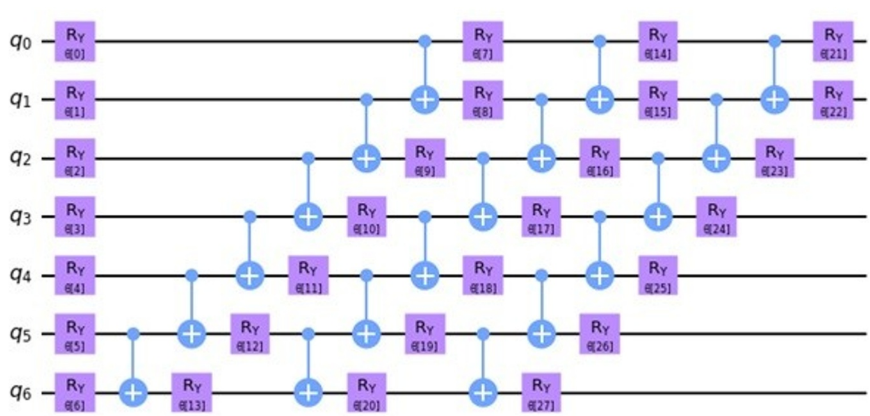

Fig. 2. Quantum circuit using various quantum features (feature map) and ansatz.

 https://doi.org/10.1051/e3sconf/202449404024

3 Results

During training of the VQC network on the training data set, an improvement in the values of the loss function was observed with an increase in the number of epochs. This indicates that the model successfully adapts to the training data. In the presented program, graphs are used to visualize data. In this case, we create a scatter plot for each pair of features from the data set. Each point on the graph represents a data instance with corresponding values of two features. Different colors of dots correspond to different classes (species). Thus, the plots allow us to visually assess how different species are distributed in feature space. Red crosses (x) in the graphs represent data instances that were incorrectly classified by our VQC. Thus, they represent the errors of the model (Figure 3).

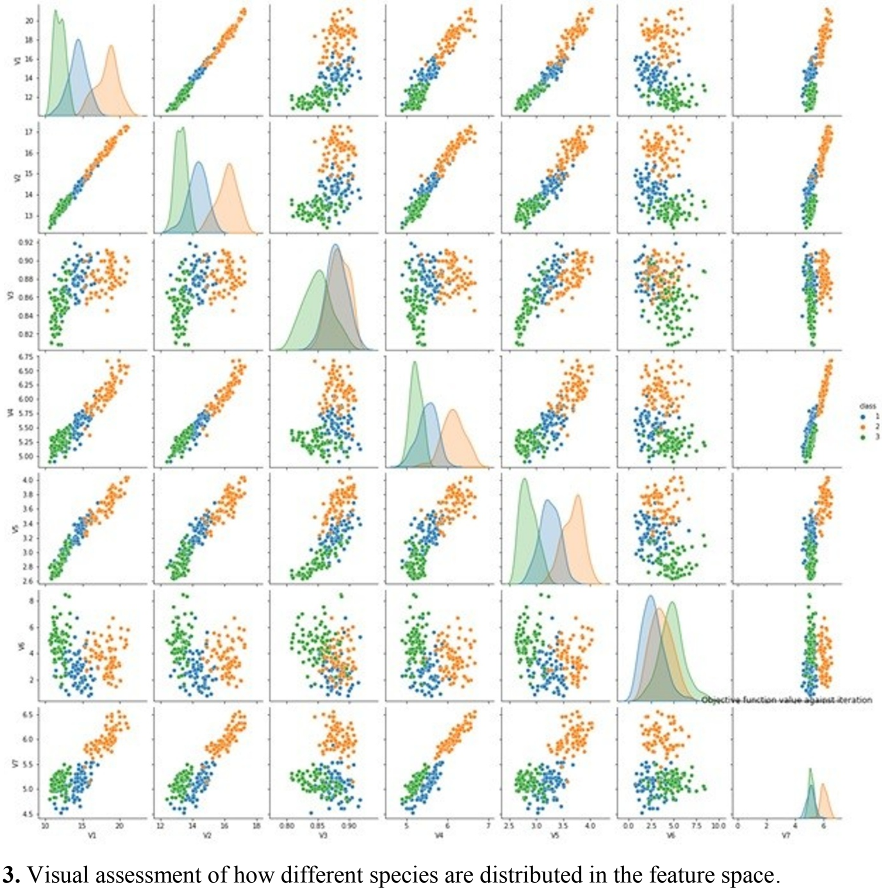

Fig. 3. Visual assessment of how different species are distributed in the feature space.

These plots provide a visual representation of how the classification model performs on the test dataset. Visualizing errors allows us to understand where exactly the model is making mistakes, which can be useful for analyzing its performance and improving training.

A statistical analysis of the obtained results was carried out to assess the degree of reliability of the classification and the significance of the identified patterns. This approach makes it possible to create an effective model for classifying wheat varieties based on their seed characteristics using deep learning methods and neural networks (Figure 4).

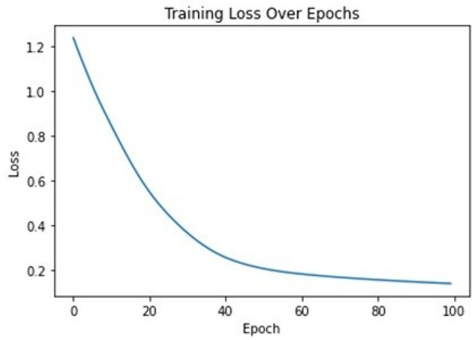

Fig. 4. Statistical analysis of the results obtained to assess the degree of reliability of the classification and the significance of the identified patterns.

4 Discussion

The results of testing VQC and a neural network on a dataset with wheat seeds indicate its high efficiency in the task of classifying varieties. Accuracy and other metrics validate the model's ability to correctly identify varieties based on seed characteristics. Confusion matrix analysis reveals where the model makes mistakes. Studying these errors can suggest ways to improve the model. Possible directions include further tuning of hyperparameters, increasing the amount of training data, or using more complex network architectures.

VQC testing results.
Test Accuracy: 92.86%
Precision: 0.93
Recall: 0.93
F1 Score: 0.93

Table 1. Confusion Matrix: Results of VQC testing on a dataset with wheat seeds.

	Confusion Matrix:	
9	0	2
0	14	0
1	0	16

Results of testing a neural network on a dataset with wheat seeds
Test Accuracy: 88.10%
Precision: 0.88
Recall: 0.88
F1 Score: 0.88

Table 2. Confusion Matrix: Results of testing a neural network on a dataset with wheat seeds.

	Confusion Matrix:	
9	0	2
0	14	0
3	0	14

We emphasize that the results of this study are limited by the available data. For a broader generalization, additional experiments should be conducted on different wheat seed datasets. The developed model can find application in agriculture and seed production, providing an automated tool for classifying wheat varieties. This can save time and resources by improving seed sorting and selection processes. For further research, it is proposed to expand the dataset and conduct additional experiments with different neural network and VQC architectures. It is also worth considering the influence of other factors, such as growing conditions, on classification results. In general, the developed neural network model is a promising tool for automated classification of wheat seeds, however, like any research, it requires additional research and testing in practice to confirm its usefulness in real conditions.

5 Conclusion

In this work, a Variational Quantum Classifier and a neural network were developed and tested to classify wheat varieties based on seed characteristics. The developed VQC and neural network successfully cope with the task of classifying wheat varieties, achieving high accuracy on the test data set. Research into the importance of seed characteristics identifies key factors influencing classification. This can be useful for optimizing data collection and analysis processes in agriculture. The developed model has potential for practical application in seed production and agriculture. An automated wheat seed classification process can save time and improve seed breeding efficiency. It is recommended to conduct additional research using more extensive datasets and different neural network architectures. Also, it is worth considering the influence of external factors on the classification of seeds. This work not only confirms the possibility of using neural networks for classifying wheat seeds, but also highlights the prospects for automating processes in agriculture using modern machine learning methods.

References

1. E. Biham, M. Boyer, G. Brassard, J. van de Graaf, T. Mor, Security of quantum key distribution against all collective attacks, arXive e-print quantph/9801022 (1998)
2. D. S. Bethune, W. P. Risk, An autocompensating quantum key distribution system using polarization splitting of light, In IQEC '98 Digest of Postdeadline Papers, pages QPD12–2, Optical Society of America, Washington, DC (1998)
3. M. Ettinger, P. Høyer, On quantum algorithms for noncommutative hidden subgroups, In Symposium on Theoretical Aspects in Computer Science. University of Trier, arXive e-print quant-ph/9807029 (1999)
4. C. Bernhardt, Quantum computing for everyone (2019)
5. A.Y. Kitaev, Quantum computations: algorithms and error correction, Russ. Math. Surv., **52**, **6**, 1191–1249 (1997)
6. M. Nielsen and I. Chuang, Quantum Computation and Quantum Information (2010)
7. N. D. Mermin, Quantum Computer Science(2007)
8. E. Strubell, An Intro to Quantum Algorithm (2011)
9. Liu, A rigorous and robust quantum speed-up in supervised machine learning
10. Havlicek, Supervised learning with quantum enhanced feature spaces
11. Glick, Covariant quantum kernels for data with group structure
12. D.T. Muhamediyeva, Model of estimation of success of geological exploration in perspective, International Journal of Mechanical and Production Engineering Research and Development, IJMPERDAPR201861, **8**, **2**, 527–538 (2018)
13. D. Sotvoldiev, D.T. Muhamediyeva, Z. Juraev, Deep learning neural networks in fuzzy modeling, Journal of Physics: Conference Series, **1441**, **1** (2020)