Variational Quantum Classifier with Enhanced Feature Mapping

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***Abstract*—Quantum Computing uses the principles of quantum physics to process information faster and solve difficult problems. Quantum Machine Learning combines quantum computing principles with machine learning to improve data processing capabilities and more efficient analysis, with the potential to solve complex problems with greater accuracy. Variational Quantum Classifier with Enhanced Feature Mapping (VQCEFM) is introduced as an approach to enhance quantum classifiers. The enhanced feature mapping integrates classical machine learning techniques to transform data into a high-dimensional quantum feature space. The objective of VQCEFM is to enhance quantum classifiers, allowing them to rival classical machine learning methods. Experimental results demonstrate that VQCEFM achieves comparable performance to classical methods. This research contributes to the advancement of quantum machine learning by harnessing quantum properties and highlights the potential of VQCEFM as a powerful tool for classification in quantum systems. This research used 8 feature mappings on the Wisconsin breast cancer dataset. The feature mappings used are ZZFeatureMap, ZFeatureMap, PauliFeatureMap and five encoding functions equation 8 to equation 12 adopted from the paper by Suzuki et. al., which is a study of the pioneering paper Supervised learning with quantum enhanced feature spaces by Havlíček et. al.**

***Index Terms*—Quantum Computing, QML, VQC, Feature Mapping, CML, Breast Cancer, Encoding Functions.**

I. Introduction

In recent years, there have been significant advancements in the affordability and efficiency of computers, accompanied by improved computational techniques. These developments have created numerous opportunities for the extensive utilization of machine learning across diverse fields, encompassing education, healthcare, gaming, finance, transportation, energy, business, science, and engineering [1]. As time progresses, the evolution of intelligent machines will lead to a gradual transformation and augmentation of human capabilities across diverse domains [2]. Machine Learning is a field within Artificial Intelligence (AI) that employs principles from computer science and statistics to develop powerful models capable of capturing and representing complex patterns present in data [3].

Quantum computing introduces a fresh perspective to artificial intelligence. In a research comparing the performance of a quantum learning algorithm to a classical in data categorization, it was observed that the quantum approach exhibited faster processing capabilities [4]. A new field of research and research from quantum computing and starting to emerge is called Quantum Machine Learning (QML). Quantum machine learning offers several advantages, including its ability to conduct computations at a considerably accelerated rate compared to classical machine learning, due to the increased speed of quantum computers. Additionally, quantum machine learning demonstrates the capability to generate outputs with a higher degree of precision [5]. QML is a growing interdisciplinary field of research that merges quantum physics and machine learning [6].

Machine learning has gained significant popularity in the field of technology. It encompasses two distinct approaches: classical machine learning and quantum machine learning. Under the classical machine learning paradigm, Support Vector Machines (SVM) algorithms, specifically Support Vector Classification (SVC), are widely adopted and continuously evolving. SVC is a powerful and popular algorithm used for classification tasks across various domains. On the other hand, in the domain of quantum machine learning, the Variational Quantum Classifier (VQC) algorithm is currently being developed to perform classification.

VQC is a hybrid classical-quantum machine learning algorithm developed to tackle classification tasks using quantum computers, similar to classical machine learning in classification. VQC aims to map classical data into quantum inputs to be processed by a quantum computer. The mapped data is referred to as a feature map [6], which serves as the quantum representation of classical data in a high-dimensional space. VQC is a classification algorithm that utilizes quantum circuits to process data and generate predictive models. The resulting predictive model is a trained quantum circuit using both quantum data and classical algorithms. VQC leverages the properties of quantum systems to generate better predictive models compared to classical algorithms. Currently, VQC is a key algorithm in Quantum Machine Learning (QML) for classifying interesting physics events from background events. [7].

Feature Mapping has an important role in machine learning, as they map any type of input data into a space with well-defined metrics. This space usually has much higher dimensions [6]. Feature mapping is one of the key components in the

VQC algorithm used to process data in quantum computing. In VQC, Feature Mapping is the component responsible for transforming classical input data into a quantum representation in quantum feature space that can then be further processed using quantum circuits. Feature Mapping that can be used in the VQC algorithm, such as ZZFeatureMap, ZFeatureMap, PauliFeatureMap, or other types of Feature Mapping.

In recent research, the application of quantum machine learning techniques has gained attention and has been evaluated against conventional approaches. Research utilizing the Machine Learning Quantum algorithm was conducted using VQC for binary classification on real and synthetic dataset [8]. A subsequent research conducted focused on the Performance Analysis of Quantum Machine Learning Classifiers [9]. Another research conducted focused on applying Quantum Machine Learning to the classification of diabetes [10]. The latest research is comparing Classic Machine Learning with Quantum Machine Learning on breast cancer dataset. [11].

The contribution of this research is to develop a variational quantum classifier algorithm that utilizes enhanced feature mapping. Enhanced feature mapping is designed to transform the input feature representation into a more informative representation and enable more accurate classification. So that the feature mapping technique used can make VQC algorithm can compete with the classic algorithm SVC in classification.

This research specifically focuses on the Feature Mapping techniques used in the Variational Quantum Classifier (VQC) algorithm. This research utilizes a total of eight Feature Mapping methods, including ZZFeatureMap, ZFeatureMap, PauliFeatureMap, and five encoding functions adopted from research by Suzuki et al [12], which is a study of the pioneering paper Supervised learning with quantum-enhanced feature space by Havlíček et al [7].

II. Methods

A. DATASET

This research using Breast Cancer Wisconsin dataset. The Breast Cancer Wisconsin dataset, also known as the ”WDBC” dataset, contains 569 samples of breast tumors. It was collected by Dr. William H. Wolberg and aims to predict whether tumors are benign or malignant. The dataset consists of 30 numerical features extracted from digital images of fine needle aspiration (FNA) of the tumors. These features include measurements and shapes of the tumors. Each sample is labeled as ”benign” or ”malignant” based on histopathology test results. The objective is to develop models that accurately predict tumor malignancy based on these features. This dataset has a data size of 569 rows and 32 columns. Out of these 32 columns, 31 columns represent the features, while 1 column is dedicated to the target variable, which is the diagnosis column. After preprocessing, the dataset is reduced to 31 columns, excluding the diagnosis column. The features in the dataset provide valuable information for analyzing and predicting the diagnosis of breast tumors.

This dataset has a high dimensionality so to reduce the computational burden, feature selection is performed. This process involves selecting the most relevant features based on their correlation with the target variable, which in this case is the diagnosis. By selecting the important features that are highly correlated with the target, the dataset can be streamlined to contain only the most informative attributes, improving the efficiency and effectiveness of subsequent analyses and modeling tasks. From the feature selection based on the correlation between variables and the target diagnosis data, it can be considered, as can be shown in Table I.

TABLE I
FEATURES SELECTION

Features	Correlation with Target
concave points_worst	0.793566017
perimeter_worst	0.782914137
concave points_mean	0.77661384
radius_worst	0.776453779
perimeter_mean	0.74263553
area_worst	0.733825035
radius_mean	0.730028511
area_mean	0.708983837
concavity_mean	0.696359707
concavity_worst	0.65961021
compactness_mean	0.596533678
compactness_worst	0.590998238
radius_se	0.567133821
perimeter_se	0.556140703
area_se	0.54823594
texture_worst	0.456902821
smoothness_worst	0.421464861
symmetry_worst	0.416294311
texture_mean	0.4151853
concave points_se	0.408042333
smoothness_mean	0.358559965
symmetry_mean	0.330498554
fractal_dimension_worst	0.323872189
compactness_se	0.292999244
concavity_se	0.253729766
fractal_dimension_se	0.077972417
symmetry_se	-0.006521756
texture_se	-0.008303333
fractal_dimension_mean	-0.012837603
smoothness_se	-0.067016011

The table above presents the results of correlation analysis between variable features and diagnosis target data. The correlation value reflects the strength of the linear relationship between each feature and the target. Among the features, ”concave point_worst”, ”perimeter_worst”, ”concave point_average”, and ”radius_worst” show the highest correlation values with the target. These four features will be used in building the model.

B. FEATURE MAPPING

This research focuses on developing feature mappings that will be used in the VQC quantum machine learning algorithm. VQC (Variational Quantum Classifier) is an algorithm used to perform data classification using quantum computers. In the Variational Quantum Classifier (VQC) algorithm, there are feature map parameters that play an important role in building a quantum classification model. This feature map parameter is filled with feature mapping generated by the classical input data entered. One of the key components of the

VQC algorithm is feature mapping, which is responsible for converting classical data into a quantum representation suitable for processing inside a quantum computer.

Feature mapping in VQC serves as a bridge between the classical and quantum worlds. The data to be classified is usually given in the form of a numerical vector or matrix. Feature mapping is responsible for converting the vector or matrix into a quantum circuit that can be understood by a quantum computer.

Feature Mapping is used on the breast cancer wisconsin dataset so that it converts classical input data into a quantum representation in quantum feature space. Mapping any type of input data into a space with well-defined metrics.

In this research, eight feature mapping techniques were utilized, namely ZZFeatureMap, ZFeatureMap, PauliFeatureMap, and five encoding functions derived from Suzuki's journal [12], specifically equations 8 to 12. For the purpose of this research, equations 8 to 12 are notated as equations 1 to 5. The following are the results of feature mapping on the Wisconsin breast cancer dataset using ZZFeatureMap, ZFeatureMap and PauliFeatureMap :

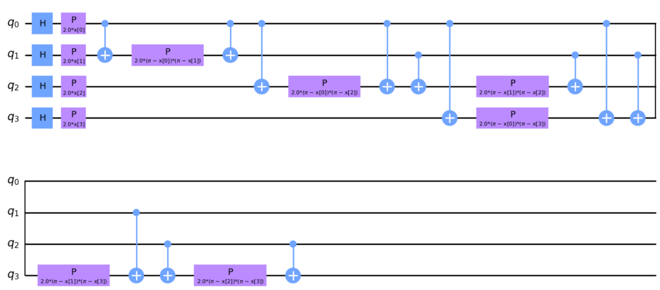

Fig. 1. ZZFeatureMap

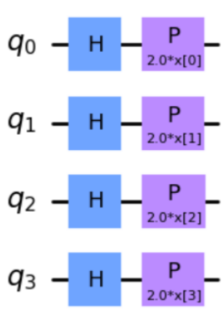

Fig. 2. ZFeatureMap

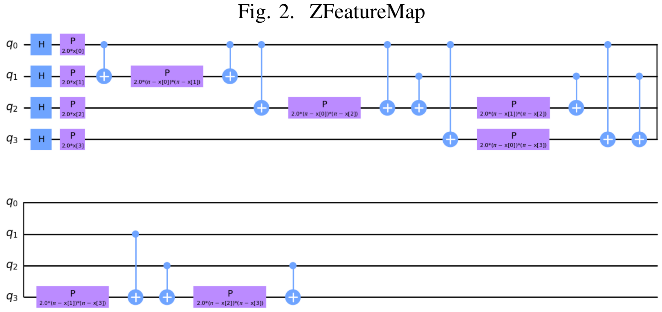

Fig. 3. PauliFeatureMap

After that, this research uses feature mapping adopted from the five encoding functions in Suzuki's journal with the notation of equations 1 to 5. The following are the equations :

$$\phi_1(\boldsymbol{x}) = x_1, \phi_2(\boldsymbol{x}) = x_2, \phi_{1,2}(\boldsymbol{x}) = \pi x_1 x_2 \quad (1)$$

$$\phi_1(\boldsymbol{x}) = x_1, \phi_2(\boldsymbol{x}) = x_2, \phi_{1,2}(\boldsymbol{x}) = \frac{\pi}{2}(1 - x_1)(1 - x_2) \quad (2)$$

$$\phi_1(\boldsymbol{x}) = x_1, \phi_2(\boldsymbol{x}) = x_2, \phi_{1,2}(\boldsymbol{x}) = \exp\left(\frac{|x_1 - x_2|^2}{8/\ln(\pi)}\right) \quad (3)$$

$$\phi_1(\boldsymbol{x}) = x_1, \phi_2(\boldsymbol{x}) = x_2, \phi_{1,2}(\boldsymbol{x}) = \frac{\pi}{3\cos(x_1)\cos(x_2)} \quad (4)$$

$$\phi_1(\boldsymbol{x}) = x_1, \phi_2(\boldsymbol{x}) = x_2, \phi_{1,2}(\boldsymbol{x}) = \pi\cos(x_1)\cos(x_2) \quad (5)$$

The following are the results of feature mapping using five encoding functions :

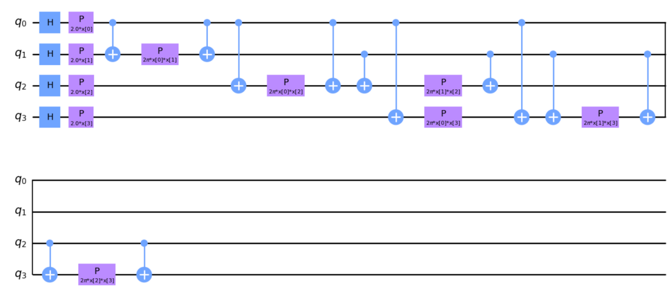

Fig. 4. Equation 1

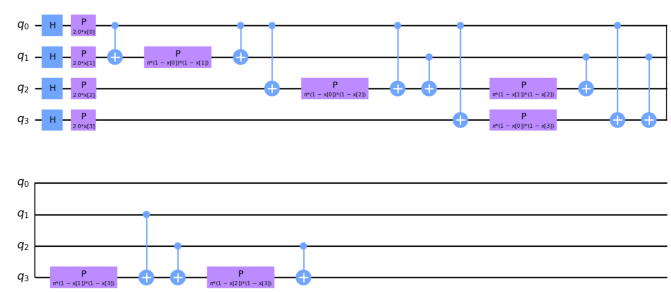

Fig. 5. Equation 2

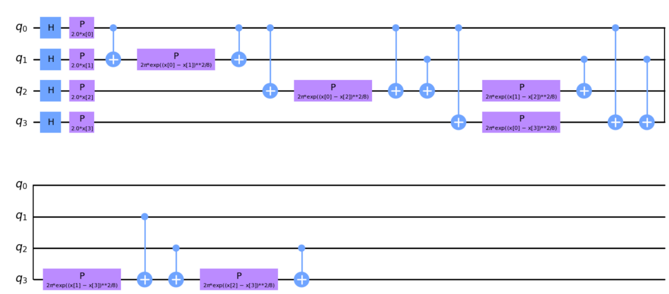

Fig. 6. Equation 3

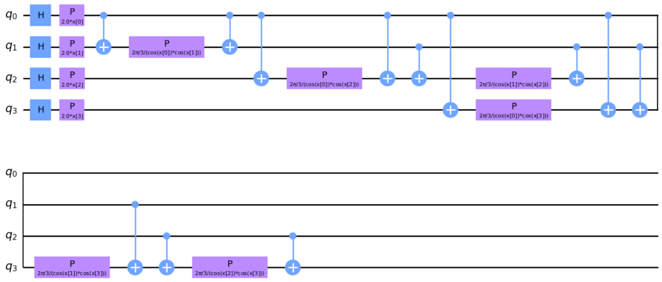

Fig. 7. Equation 4

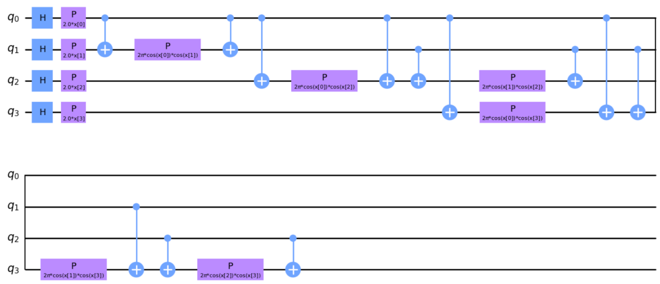

Fig. 8. Equation 5

Based on Fig. 1 to Fig. 8, it can be seen that each feature mapping used has a different shape, which affects the quantum representation and the resulting probability equation. In the context of feature normalization, it is important to choose a feature map that allows the data to be stored in qubits with the right precision to produce an effective quantum model. In the figure, feature mapping using ZZFeatureMap and PauliFeatureMap produces the same quantum representation and probability equation. In other feature mapping results produce different quantum representations and probability equations. This is because the feature mapping parameters used will adjust to the data map function entered so that the results are different. However, the ZFeatureMap feature mapping shows that after the qubit initiation, it continues with the H (Hadamard) gate and then ends only until the P (Probability) gate with the same initial equation as the other feature mappings. The feature mapping used in VQC has a significant influence on the quantum representation and the probability equations involved. The selection of the right feature mapping is crucial in the effort to build an effective quantum model for classification.

Another parameters in the VQC algorithm that also contribute to building the quantum classification model are the ansatz and the optimizer. The parameters that help in constructing circuit-based quantum machine learning models are variation circuits (parameters) called ansatz (plural ansaetze). The ansatz construction is formed by stacking multiple identical sub-layers, similar to the construction of a cell-based neural architecture design [13]. The ansatz used in this research are RealAmplitudes and EfficientSU2. The parameter optimizer COBYLA iteratively updates the parameter values to minimize the cost function and improve the performance of the quantum machine learning model. The iterations used in the optimizer are one hundred.

Ansatz is used as a quantum model representation that is used to model the relationship between input data and the desired classification output. Ansatz plays an important role in modeling and optimizing quantum representations that are able to capture patterns and features in data for classification purposes. The following are the results of mapping using the RealAmplitudes and EfficientSU2 ansatz :

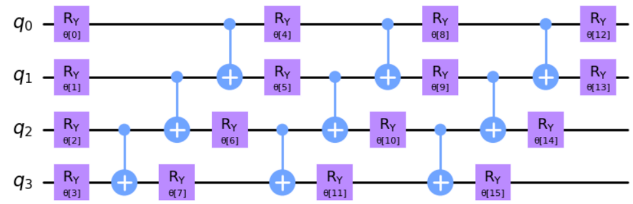

Fig. 9. ansatz RealAmplitudes

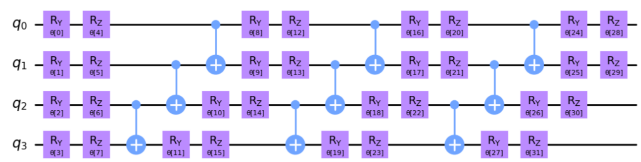

Fig. 10. ansatz EfficientSU2

Furthermore, after doing feature mapping, then optimize using ansatz and optimizer and get the results of training accuracy and test accuracy using 4 features. Then the dimensionality reduction using PCA is carried out to 2 features.

Dimension reduction, also known as principal component analysis (PCA), is a data processing technique used to reduce the dimensionality of a data set. PCA is based on the idea of finding a set of principal components that explain most of the variability in the data [14].

C. CLASSIC MACHINE LEARNING

Classic Machine Learning refers to the traditional approach of developing algorithms and models that rely on statistical techniques and mathematical frameworks to analyze and extract patterns from data, enabling tasks such as classification, regression, and clustering.

SVM (Support Vector Machine) is a popular machine learning algorithm that aims to find an optimal hyperplane in a high-dimensional space to classify data points into different classes, maximizing the margin between the classes and minimizing the classification errors.

SVC (Support Vector Classifier) is a variant of SVM specifically designed for classification tasks, where it learns from labeled data to build a decision boundary that effectively separates different classes by maximizing the margin and generalizing well to unseen data. In this research, standard hyperparameters are used in the SVC algorithm.

D. QUANTUM MACHINE LEARNING

Quantum Machine Learning (QML) is a field that combines concepts from quantum computing with classical machine learning. Its main goal is to use the power of quantum computing to accelerate the machine learning process and solve difficult problems in the machine learning domain. Quantum Machine Learning (QML) is a field that combines concepts from quantum computing with classical machine learning. The main goal is to use the power of quantum computing to accelerate the machine learning process and solve difficult problems in the machine learning domain. Variational Quantum Classifier (VQC) is one of the algorithms in Quantum Machine Learning used for classification. VQC uses a variational approach to learn the optimal quantum model to separate data in different categories. The VQC training process involves optimizing the parameters in the quantum model to achieve high classification accuracy. VQC uses feature mapping to transform the input data into a quantum representation.

III. RESULTS AND DISCUSSIONS

A. Results

Feature Mapping	Model	Train Score	Test Score
ZZFeatureMap	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.88	0.90
	VQC, 4 features, EfficientSU2	0.87	0.87
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.72	0.81
	VQC, 2 features, EfficientSU2	0.94	0.98
ZFeatureMap	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.91	0.90
	VQC, 4 features, EfficientSU2	0.87	0.86
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.66	0.66
	VQC, 2 features, EfficientSU2	0.92	0.90
PauliFeatureMap	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.88	0.90
	VQC, 4 features, EfficientSU2	0.87	0.87
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.72	0.81
	VQC, 2 features, EfficientSU2	0.94	0.98
Equation 1	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.90	0.91
	VQC, 4 features, EfficientSU2	0.84	0.83
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.69	0.70
	VQC, 2 features, EfficientSU2	0.92	0.91
Equation 2	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.94	0.96
	VQC, 4 features, EfficientSU2	0.93	0.92
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.75	0.71
	VQC, 2 features, EfficientSU2	0.93	0.91
Equation 3	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.94	0.94
	VQC, 4 features, EfficientSU2	0.88	0.88
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.73	0.73
	VQC, 2 features, EfficientSU2	0.92	0.90
Equation 4	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.91	0.88
	VQC, 4 features, EfficientSU2	0.90	0.87
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.88	0.86
	VQC, 2 features, EfficientSU2	0.91	0.89
Equation 5	SVC, 4 features	0.95	0.96
	VQC, 4 features, RealAmplitudes	0.93	0.95
	VQC, 4 features, EfficientSU2	0.88	0.87
	SVC, 2 features	0.95	0.96
	VQC, 2 features, RealAmplitudes	0.80	0.76
	VQC, 2 features, EfficientSU2	0.92	0.91

B. Discussions

Based on results of the research conducted, it can be seen that there are differences in training and testing accuracy between the three feature mappings used: ZZFeatureMap, ZFeatureMap, and PauliFeatureMap. However, both ZZFeatureMap and PauliFeatureMap produce the same training and testing accuracy.

In ZFeatureMap feature mapping, there is a difference in accuracy depending on the number of features used. When using 4 features, the RealAmplitudes ansatz produces high accuracy, but after performing PCA reduction to 2 features, the accuracy drops. However, when using the EfficientSU2 ansatz, the accuracy remained high after PCA reduction to 2 features.

In the five encoding functions tested, there were differences in training and testing accuracy. The Equation 2 encoding function with 4 features and the RealAmplitudes ansatz produced the highest training and testing accuracy. However, after PCA reduction to 2 features, the encoding function with the EfficientSU2 ansatz provided higher training and testing accuracy.

Overall, ZZFeatureMap and PauliFeatureMap performed better than ZFeatureMap. In terms of encoding function, feature mapping using Equation 2 is better than the other equations.

IV. CONCLUSIONS

As seen in the research conducted, ZZFeatureMap and PauliFeatureMap perform similarly and better than ZFeatureMap in terms of training and testing accuracy. Both feature mappings produce consistent and better results in modeling the data compared to ZFeatureMap.

In ZFeatureMap feature mapping, there are differences in accuracy depending on the number of features used and the type of ansatz selected. The RealAmplitudes ansatz produced high accuracy when using 4 features, but the results decreased after PCA reduction to 2 features. However, the EfficientSU2 ansatz gives high accuracy both when using 4 features and after PCA reduction to 2 features.

In the five encoding functions tested, the Equation 2 encoding function with 4 features and the RealAmplitudes ansatz produced the highest training and testing accuracy. However, after PCA reduction to 2 features, the encoding function with the EfficientSU2 ansatz provided higher training and testing accuracy.

Thus, the feature mapping used in the feature map parameter of the quantum machine learning algorithm VQC is very influential in generating accuracy. So that it can make this VQC algorithm can compete with the classic machine learning algorithm, namely SVC, which has developed far and is already on the verge of being optimal in building classification models.

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