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Machine Learning in the Quantum Age: Classical vs. Quantum Algorithms Using Iris Data for Accuracy Analysis

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Abstract: - Quantum-enhanced techniques are widely employed to address machine learning difficulties. This work compares Support Vector Classifier (SVC) with Variational Quantum Classifier (VQC) on the Iris dataset, a typical machine learning benchmark. This study compares the performance, accuracy, and efficiency of two approaches: classical computing and quantum computing. The paper emphasizes the positive and negative aspects of each method, as well as practical data demonstrating quantum computing's potential for bettering machine learning tasks. This comparison offers helpful perspectives into the practical applications of quantum algorithms, providing an enhanced awareness of quantum machine learning's abilities and possibilities.

Keywords*:* Quantum computing, Machine Learning, Support Vector Classifier, Variational Quantum Classifier, Artificial Intelligence.

1. Introduction

Machine learning (ML) [1] is frequently utilized in artificial intelligence applications such as computer vision, image recognition, natural language processing, and healthcare. Quantum computing (QC) [2] has recently grown rapidly. Despite the limitations of Noise Intermediate Scale Quantum (NISQ) devices, QC has the potential to outperform conventional computers in several ML applications. The significance of quantum computing in defining the limits of conventional machine learning capabilities is widely acknowledged [3]. Simplifying the complexity of quantum algorithms is crucial for producing consistent results. Quantum Machine Learning (QML) [4] is made up of four methods based on data and processing devices, including both conventional and quantum techniques. Support Vector Machines (SVM) [5] have been extensively studied as a supervised learning method onvarious datasets, but kernel-based algorithms have been found to work better. VQC [6] is commonly uti- lized for classification tasks on NISQ devices. There are several classifications for well-known supervised QML algorithms, such as QSVM and VQC. Quantum-inspired classifiers have been used to improve clas- sification performance (giuntini2023quantum), as well as hybrid low-depth VQC classification approaches using simple error mitigation measures [8]. State preparation is a critical step in QML since it converts classical data into quantum states. This strategy reduces experimental complexity and addresses data nonlinearities, thereby improving the performance of linear classifiers and kernel-based prediction tech- niques [9]. It also makes it easier to use near-term quantum processors, potentially leading to exponentialspeedups in methods such as VQC [8]. Feng et al. [10] say that quantum algorithms can greatly simplify queries in nearest neighbor classification compared to traditional methods. Data encoding is required forstate preparation, while feature map encoding converts traditional data into a higher-dimensional space.

The purpose of this work is to assess the performance of classical machine learning (CML) and quan- tum machine learning (QML) approaches on the publicly accessible Iris dataset. The study employs theIBM Qiskit framework to enhance the previously mentioned data encoding methods. Encoding featuremaps improves the performance of the VQC model. Our VQC studies use the same features and param-eters as before, including feature-based VQC. We divide the article into four major sections. Section Iconducts a literature review. Section II describes the materials and methods used. Section III presents the experimental results and discussion. The conclusion section summarizes the study's findings.

2. Related Work

Power and Guha (2024) [11] examine the problem with black-box models in machine learning, which lack flexibility in their predictions. It emphasizes the importance of features and their explainability, particularly in critical industries like healthcare and finance. The article introduces quantum machine learning (QML), a hybrid of quantum computing and machine learning approaches that may improve transparency. Using the Iris dataset, it compares traditional ML methods (SVM and Random Forest) to hybrid quantum models (VQC and QSVC) built on IBM's Qiskit. The comparison is mostly about the information that permutation, leave-one-out feature significance, ALE (Accumulated Local Effects), and SHAP (Shapley Additive Explanations) give.SIMÕES *et al.* (2023) [12] compares kernel-based quantum support vector machines and quantum neural networks on iris and four other datasets, concluding that quantum algorithms outperform classical ones, with quantum neural networks demonstrating the greatest accuracy improvement. SINGH *et.al* [13], the Iris dataset is used to explore quantum learningapproaches for huge data. The study introduces a new machine learning methodology based on quan- tum computing. It solves the difficulty of quantum image identification by employing a global quantum feature extraction technique based on Schmidt decomposition. We also propose a new quantum learn- ing technique that utilizes the Hamming distance for classification. The enhanced quantum classifier, QeSVM, QPSO-TWSVM, and other Q-CNN models can get an average accuracy of 98% on a numberof very large data sets, as shown in experiments on the Caltech 101 database.

Acampora et al. [14] use an iris dataset to discuss the variational quantum classifiers, which are com- mon in supervised learning and face a design difficulty known as "barren plateau landscapes," in which optimization is difficult due to vanishing gradients. This study investigates the potential application of gradient-independent evolutionary optimization techniques to address this challenge. We carry out a comparative analysis of various evolutionary algorithms to determine their usefulness as optimizers for variational quantum classifiers.Piatrenka and Rusek [15], using the Iris dataset, discuss recent break- throughs in quantum machine learning that are the result of two fundamental discoveries: translating features into exponentially huge Hilbert spaces for linear separability and applying the parameter-shift algorithm to easily compute gradients. These enable the creation of binary variational quantum classi- fiers. This study broadens the technique to multi-class classification and applies it to real-world data, doing in-depth analysis with multiple feature maps, classical optimizers, and circuit repeats. We validate the soundness of the model in both simulated and real-world scenarios, including on an IBM quantum computer.

The Iris dataset is used by Nguyen and Chen [16] to introduce QES, an automated search method for finding the best entangling layouts in supervised quantum machine learning. It connects entanglement structures to directed multigraphs using CNOT gates, resulting in a well-defined search space. By storing quantum entanglement as genotype vectors, the program efficiently explores this domain. It decreases the size of the search space by using entanglement levels and surrogate models to reduce assessment costs. Tests on simulated and benchmark datasets (Iris, Wine, and Breast Cancer) demonstrate that QES-made quantum embeddings beat manually built ones in terms of prediction performance. Table I includes detailed information on the iris dataset used in the above-mentioned studies.

2.1 Contribution of this Study

This paper discusses a comparative study between support vector classifiers (SVC) and variational quantum classification (VQC) using the well-known Iris dataset. It analyzes the performance, accuracy, sensitivity, and specificity of classical and quantum techniques for categorizing iris species. The paper focuses on the potential benefits of VQC in taking advantage of quantum computing for complicated pattern recognition tasks, as well as the current limitations and obstacles. This work contributes to the emerging topic of quantum machine learning and its practical applications in real-world datasets by presenting actual results and insights.

Table 1 Characteristics of the Iris dataset.

Reference	Dataset	#Features	#Records	Classes
Power And Guha (2024) [11]	Iris	4	150	3
SIMO˜ES Et Al. [12]	Iris	4	100	2
SINGH Et .Al [13]	Iris	4	150	3
Acampora Et Al. [14]	Iris	4	150	3
Piatrenka And Rusek [15]	Iris	4	150	3
NGUYEN And CHEN [16]	Iris	4	150	3

3. Materials and methods

3.1 Dataset Description

This study is based on the Iris dataset, which is freely available. The Iris dataset, created by Ronald Fisher in 1936, is a basic dataset for statistics and machine learning. The study includes 150 samples of three Iris flower species, each with four characteristics: sepal length, width, petal length, and width. The dataset is a popular teaching tool because of its simplicity and capacity to show the efficiency of various methods.

3.2 ML and QML Models Used

Support Vector classifier: Scikit-learn is a widely used Python machine learning package that includes methods for classification, regression, clustering, and dimensionality reduction. It includes sev- eral approaches for developing and assessing machine learning models. The SVM classification, whichis available via the SVC class in the sklearn.svm module, classifies data points in a high-dimensional feature space even when they are not linearly separable. The system maps the data to a hyperplane after determining a dividing line between classes, enabling the classification of new data based on its attributes. A classification SVM model not only draws the dividing line, but it also uses margin lines to define the separation between two groups, with data points on the edges known as support vectors.This common SVM approach supports a wide range of kernel functions and regularization parame-ters. In machine learning, the SVC class is a popular method for SVM classification because adjustingits parameters improves classification accuracy and robustness while avoiding overfitting. Increasingthe difference between the two categories enhances the model's prediction accuracy. Permitting somemisclassifications can improve an overfitted model with a limited margin, thereby increasing the mar- gin. The goal is to achieve the best balance with the fewest number of misclassified points. In this experiment, we set the hyperparameters to their default values.

- **Variational quantum classifier:** The VQC, a pioneering model in Quantum Machine Learning (QML), performs similarly to a linear classifier in quantum physics. The ZZFeatureMap transforms classical data for quantum computing. To improve the model's efficiency, we tried several combinationsof ansatz and classical optimizers.

– **RealAmplitudes:** Chemistry and machine learning categorization can both use the RealAmplitudes circuit, a trial wave function. "RealAmplitudes" refers to quantum states with solely real amplitudes, where the imaginary part is zero. The circuit uses alternating CX entanglements and Y rotations,allowing users to construct their own entanglement patterns or select from a list of existing options.

– **EfficientSU2:** This approach uses a heuristic technique to generate trial wave functions that are suited for a variety of quantum algorithms and machine learning classification problems. There are many layers of single-qubit operations in the EfficientSU2 circuit, which are linked by SU (2) and CX entanglement gates. The SU (2) group has 2×2 unitary matrices with one determinant, which correspond to Pauli rotation gates.

3.3 Methodology

- **Data Pre-Processing:** After obtaining the dataset, the following preprocessing steps were performed: *Principal Component Analysis (PCA):* Due to the restricted amount of qubits in practical quantum computers, dimensionality reduction is essential before mapping features to the quantum space. The purpose of PCA is to identify the principal components, which are new orthogonal axes representing the directions of largest variance in the data. Keeping the data variance ensures that the key patternsin the data are kept even when the dimensionality is (dramatically) reduced. PCA use methods suchas singular value decomposition to identify a linear transformation to a new set of coordinate axes (a new vector space basis) that maximizes variance along each of the new axes. In this investigation, the principal components of the dataset must match the number of qubits in our circuit. *Normalization:* Data normalization, particularly in quantum machine learning, allows data to be reliably converted into quantum states, increasing the efficiency of quantum algorithms. This study aims to employ the Min-Max normalizing approach. Min-Max normalization is a technique for scaling data characteristicsto a given range while maintaining their original distributions. This approach limits data features toa specific minimum and maximum range. Min-Max normalization is often applied using the following formula:

$$x_{normalize} = \frac{(x - min(x))}{max(x) - min(x)}$$

In here, $x_{normalize}$ represents the normalized value x , represents the original value $\min(x)$, is the minimum value and $\max(x)$ is the maximum value of the data feature.

- **State Prepration:** State preparation is critical in Quantum Machine Learning (QML). Traditional machine learning kernel approaches are the inspiration for quantum feature mappings, which transfer adataset non-linearly into a higher-dimensional space in order to discover a hyperplane for categorizing non-linear data.

$$U_{\phi(x)} = \prod_{d} U_{\phi(x)} H^{\otimes n} U_{\phi(x)} = H^{\otimes n}$$

A feature map with quantum properties $\phi(\vec{x})$ converts the classical feature vector $|\phi(\vec{x})\rangle, \langle\phi(\vec{x})|$ quantum states, generating a Hilbert space vector. The unitary operation on the starting state increasesthe size of our feature space (Z_i), necessitating that the classifier finds a separating hyperplane in thisextended space. The equation explains a circuit that encodes classical data using a layer of Hadamard gates (H) interleaved with entangling blocks, as well as circuit depth (d).

$$U_{\phi(x)} = \exp(i \sum_{S \subseteq [n]} \Phi_S(x) \prod_{k \in S} Z_i)$$

The number of qubits required varies according on the dimension of the data. Unitary gates $U_{\Phi(x)}$ are used to encode data by adjusting angles to specific values. For categorization, we used a number of fea-ture maps, including FirstOrderExpansion, SecondOrderExpansion, and SecondOrderPauliExpansion. Encoding methods for these feature maps are as follows:

- **FirstOrderExpansion:** $\phi S: x \mapsto x_i$
- **SecondOrderExpansion:** $\phi S: x \mapsto (\pi - x_i)(\pi - x_i)$
- **SecondOrderPauliExpansion:** $\phi S: x \mapsto \sin(\pi - x_i)\sin(\pi - x_i)$

Using non-classical feature maps provides a quantum advantage over classically simulated feature maps.

- **Variational Circuit:** We employed the VQC model with ansatzes such as Real Amplitude and Efficient SU2. Figure 1 illustrates VQC models with four features, whereas Figure 2 depicts a RealAmplitudes ansatz circuit with four features. Figure 3 illustrates a RealAmplitudes ansatz circuit with two features. Figure 4 depicts an EfficientSU2 ansatz circuit with two features.

$$|\psi(x:\theta)\rangle = U(\theta)|\phi(x)\rangle$$

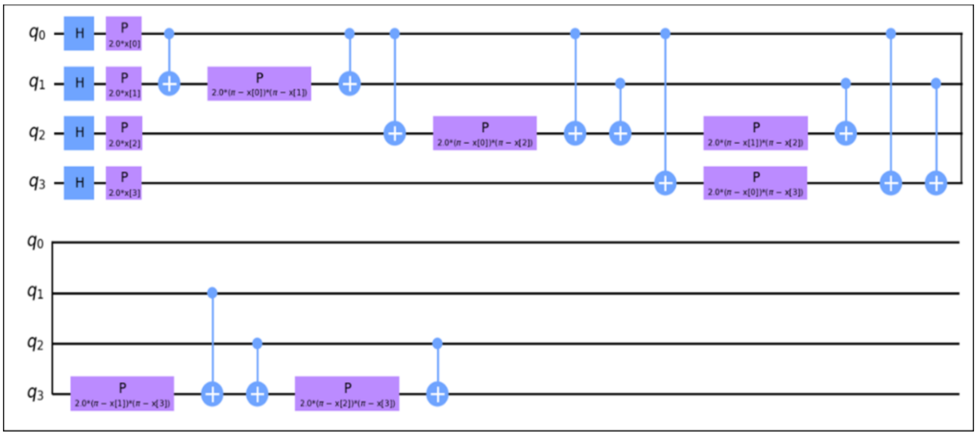

Figure. 1 Feature map with four features.

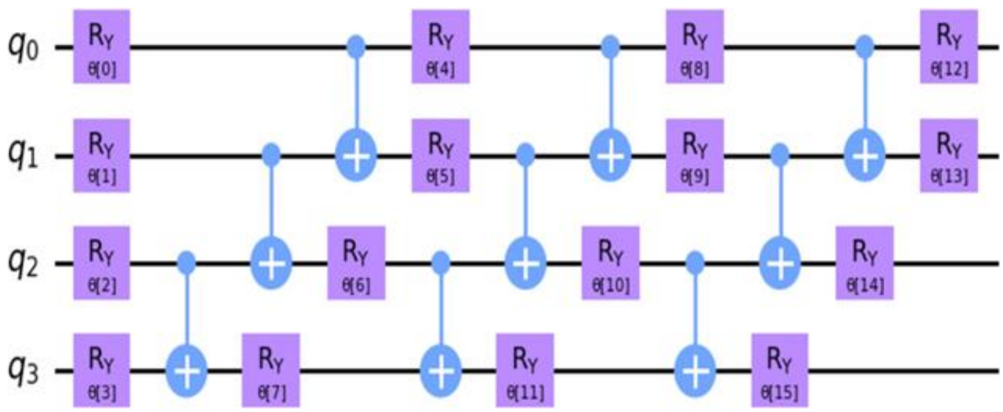

Figure. 2 RealAmplitudes ansatz circuit with four features.

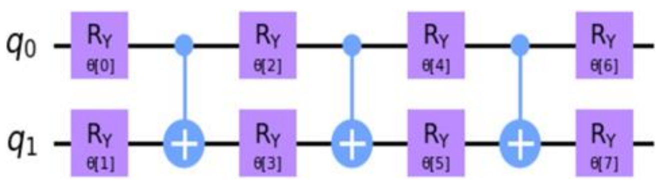

Figure. 3 RealAmplitudes ansatz circuit with two features.

This variational circuit includes interlinking parameters R_y and R_z gates, as well as entanglementswith the CNOT gate.

– **Measurement:** Next, we make a final measurement to determine the class probabilities. This procedure entails sampling many times from a set of possible computational basis states and determining the average value. The final circuit consists of a PauliFeatureMap and a two-depth EfficientSU2 variational circuit. The training intent is to identify parameter values that minimize a given loss function. A quantum model, like a traditional neural network, is optimized by running it forwardto compute the loss function. Gradient-based optimization methods are then utilized to modifythe trainable parameters. This method calculates the loss function, which represents the difference between our forecasts and the actual results.

– **Optimization:** After the completion of the measurements, the parameters of the quantum variational circuit are modified using an optimization process. The classical training loop refines the parameters iteratively in order to minimize the cost function. The Constrained Optimization by Linear Approximations (COBYLA) optimizer generates consecutive linear approximations of the cost function and constraints using a simplex with $n + 1$ features. COBYLA is constantly refining these estimations within a trustworthy zone to increase accuracy. Furthermore, COBYLA han- dles constraint balancing by splitting them into two distinct versions, allowing for more effective optimization. The Figure 5 shows flow of the proposed methodology.

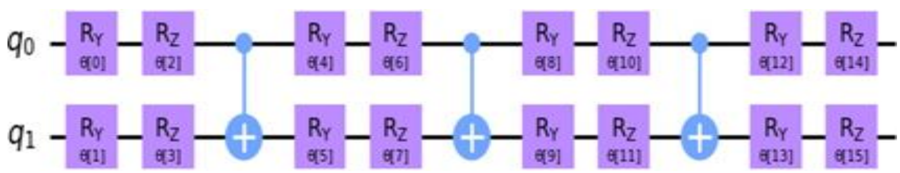

Figure. 4 EfficientSU2 ansatz circuit with two features.

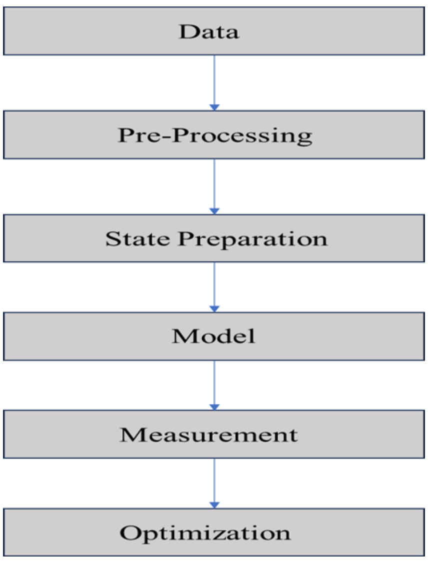

Figure. 5 Flow of the proposed methodology.

4. Performance Metrices

Several evaluation metrics were employed to assess the performance of the proposed scheme, including specificity, sensitivity, and accuracy. The results obtained from these analyses are presented in Table II. Furthermore, the proposed scheme was compared with other state-of-the-art techniques, demonstratingits superiority.

- **Accuracy:** It is the most frequent performance metric for classification models. It is calculated asthe percentage of correctly identified predictions. In mathematical terms, the expression is written as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

- **Sensitivity:** It refers to the proportion of accurately identified positive events that were appropriatelyidentified as positive. It is also known as the True Positive (TP). The mathematical representation of the expression is as follows:

$$Sensitivity = \frac{(TP)}{(TP + FN)}$$

- **Specificity:** It refers to the percentage of negative incidents that were accurately identified as negative.It is also known as the true negative (TN). Specificity is required for classification tasks in order to avoid false positives. The mathematical representation of the expression is as follows:

$$Specificity = \frac{(TN)}{(TN + FP)}$$

Table 2 Performance comparisons with some studies related to the dataset used in the article

Researchers	Preprocessing	Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
Piryatinska *et al.* (2017) [17]	ϵ-complexity func-tion	SVM, RF	89.38, 85.30	88.6	82.6
Naira and Alamo (2019) [18]	Pearson Corre-lation Coefcient (PCC)	CNN	90.00	90.00	90.00
Bougou *et al.* (2019) [19]	Butterworth flter Connectivity Analysis	RF	82.36	-	-
Phang *et al.* (2020) [20]	Time-domain VAR coefcients, Frequency-domain PDC, Topological-based CN measures	MDC-CNN, SVM	93.06, 85.83	95.00, 87.50	91.11, 88.89
Singh *et al.* (2020) [21]	Butterworth band-pass Filter, Hjorth descriptors	CNN-SF, LSTM	94.08, 76.78	92.70, 80.72	95.31, 73.18

Phang *et al.* (2020) [20]	VAR, PDC, CN	SVM, CNN, RNN	90.37, 91.69, 77.50	91.11, 91.11, 86.67	89.64, 92.50, 66.79
Aslan and Akın (2020) [22]	Short-time Fourier Transform (STFT)	CNN (VGG-16)	95.00	95.00	95.00
Rajesh *et al.* (2021) [23]	Symmetrically Weighted Local Binary Pattern: SLBP	Logitboost	91.66	89.74	93.33
Khodabakhsh *et al.* (2021) [24]	Brain Functional Connectivity (FC)	MDC-CNN, FC-UNET	90.44, 94.11	97.78, 91.66	81.79, 100.0
Supakar *et al.* (2022) [25]	Random Projection (Dimensionality reduction)	RNNLSTM	98.00	98.00	98.00
Xin *et al.* (2022) [26]	Normal and Improved high-order functional connectivity matri-ces, Finite Impulse Response (FIR).	SVM	94.05	95.56	92.31
Sairamya *et al.* (2022) [27]	Discrete wavelet transform, Relaxed Local Neighbour Difference Pattern (RLNDiP).	YSA	100.0	100.0	100.0
Proposed Method	PVC, MinMaxScaler	SVC, VQC	97.47	94.53	93.23

5. Experimental Discussion

We have used Python for Simulation. We upload Iris dataset and SVC from Sci-kit learn and We upload

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VQC form qiskit library. We separated our database into 80% training and 20% testing samples. The study uses ML and QML methods, such as SVC and VQC, to address binary classification challenges onthe Iris dataset. In this work, the dataset is trained using both classical and quantum methods, with varied number of features. There were five experiments: two with four features and three with two. Table III displays the results obtained.

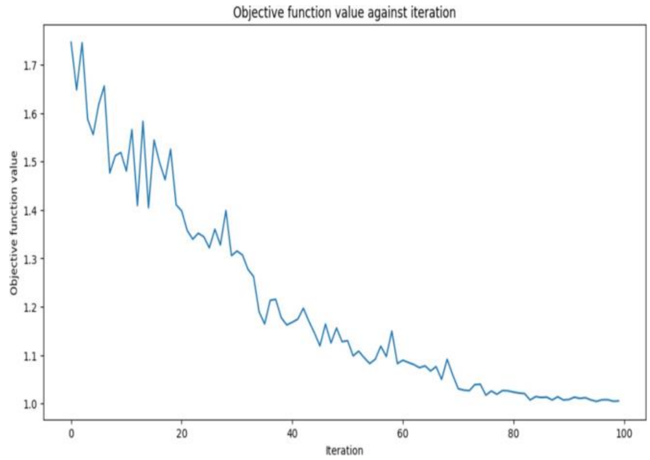

Figure. 6 Variational Quantum computing VQC objective function value vs iteration chart.

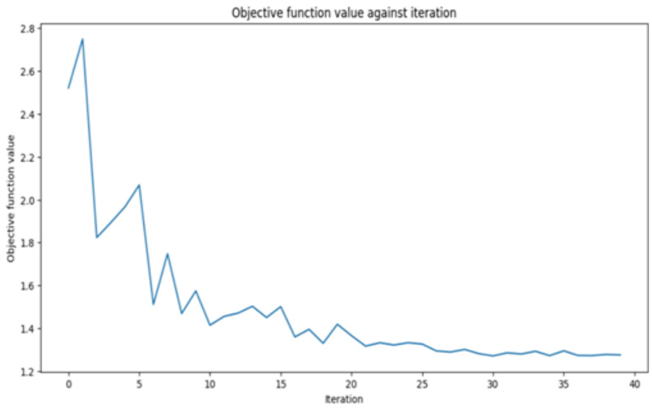

Figure. 7 Variational Quantum computing RealAmplitudes VQC objective function value vs iteration chart.

Table 3 Result obtained in ML and QML models.

Model	Train Score	Test Score
SVC, 4 features	0.99	0.97
SVC, 2 features	0.97	0.90
VQC, 4 features, RealAmplitudes	0.85	0.87
VQC, 2 features, RealAmplitudes	0.58	0.63
VQC, 2 features, EfficientSU2	0.71	0.67

The SVC technique has been used for classical training with four and two characteristics. Figure 5 depicts the variation in objective function value with iterations for VQC. For quantum training, two techniques were used: Real Amplitudes (for two partitions) and Effi-cientSU2 (two features). The goal of this research is to compare classical and quantum scores anddetermine how differing information influences the system's performance. Figure 6 depicts the variation of objective function value across iterations for VQC using the RealAm- plitudes ansatz. Figure 7 depicts the fluctuation of the objective function value across iterations for the VQC EfficentSU2 ansatz. Generally, test scores are little lower than train scores. The training was successful, and the model can accurately predict whether the growth is benign or malignant. Classical intelligence systems typically outperform quantum systems by an insignificant margin. How- ever, the distinction is not substantial. In the quantum case, the number of features is less important because less information has a lower impact on the model than it does in other data sets. Furthermore, there is no discernible difference between using RealAmplitudes and EfficientSU2 for feature partition- ing. Overall, the quantum technique outperforms studies on other real datasets in IBM's QML training course. Furthermore, the performance of the provided approach is assessed using evaluation matrices onthe Iris dataset. The obtained findings demonstrate an overall accuracy of 97.47 %, specificity of 93.23 %, and sensitivity of 94.53 %.

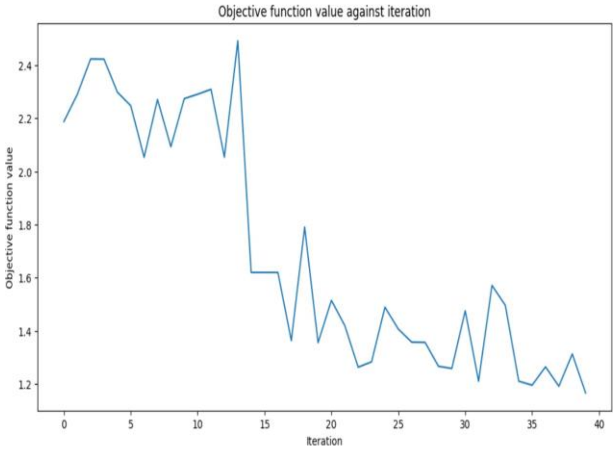

Fig. 8 Variational Quantum computing EfficientSU2 VQC objective function value vs iteration chart.

6. Conclusion

The present study investigated the VQC model implementation to improve the quantum framework through feature map encoding. Despite the advantages of feature map encoding, optimization should notsolely rely on it. Maximizing the potential of QML methods depends on good state preparation. Ourstudy indicates that QML has enormous promise even with the developments in conventional machine learning, which today beats quantum models because of their higher maturation. Investigating several data encoding methods, including angle encoding and repeated amplitude encoding, can help QMLmodels be much more scalable and performable.

The obtained data revealed that the traditional SVC produced the best results. Still, the quantum model developed based on four features showed really good performance. The performance drop in all models with a reduction in features caught attention and emphasizes the need to use whole datasets where practical. Developers have to be ready to weigh model performance, training time, and dataset size. Furthermore, we discovered that small changes in the ansatz could result in significant performance gains, as shown by the EfficientSU2 ansatz surpassing RealAmplitudes. Like in classical machine learning, choosing hyperparameters still remains a crucial and time-consuming procedure in QML. These findings pave the way for more research and development to fully use quantum computing in machine learning applications as QML develops.

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