The Role of Connectivity and Scale in Variational Quantum Classifiers (VQC): An Empirical Analysis of ZFeatureMap-EfficientSU2 on Standard Classification Datasets

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Abstract

This study presents a comparative empirical evaluation of Variational Quantum Classifier (VQC) performance within the Quantum Machine Learning (QML) framework, focusing on VQC architectural analysis under NISQ-era qubit constraints. The VQC was designed utilizing ZFeatureMap for data encoding and EfficientSU2 as the ansatz. A systematic test was performed to evaluate the impact of three entanglement topologies (default, circular, pairwise) and two qubit scales (4 and 8) with four classical optimizers on standard classification datasets: Iris, Wine, and Breast Cancer. The results demonstrated that no single configuration is universally optimal. The default topology achieved the highest peak accuracy on multi-class datasets (Iris: 97% with P-BFGS), suggesting its efficiency in simpler parameter landscapes. Conversely, the pairwise and circular topologies showed superior stability and competitive accuracy (up to 92%) on the high-dimensional Breast Cancer dataset, confirming that richer qubit connectivity is essential for effective feature separation in more complex classification problems. Increasing the scale from 4 to 8 qubits was found to be crucial for improving the overall stability and consistency of performance rather than merely increasing peak accuracy. These findings provide essential empirical guidance for designing optimal and trainable VQC architectures under current quantum device limitations.

Keywords : Quantum Machine Learning, Variational Quantum Circuit (VQC), Entanglement Topology, Quantum Classification

1. INTRODUCTION

This research explores the utilization of Variational Quantum Circuits (VQC) as an approach for data classification problems, a crucial domain in machine learning. VQCs have attracted significant attention within the Quantum Machine Learning (QML) community as they offer the potential for quantum computational acceleration in ML tasks (Singh & Pokhrel). The essence of VQCs lies in the integration of parametric quantum circuits which function as an ansatz or a feature map with classical optimization (Yin et al.). In this experiment, we specifically test the performance of Variational Quantum Classifiers (VQCs) on three standard classification datasets from the sklearn library: Iris, Wine, and Breast Cancer. The choice of these datasets, which vary in the number of samples, attributes, and classes, allows for a comprehensive evaluation of the adaptability and effectiveness of the proposed VQC architecture (Hwang et al.) (Regadío).

The advancement in quantum computing technology has paved the way for a new paradigm in artificial intelligence, particularly through Quantum Machine Learning (QML). Quantum-based classification algorithms, such as VQC, promise a computational advantage (quantum advantage) over their classical counterparts, especially in processing high-dimensional data and uncovering complex patterns within the Hilbert space. However, the design of effective and efficient quantum circuits specifically the optimal selection of the feature map and ansatz remains a central challenge. In this study, the utilize the ZFeatureMap for data encoding and EfficientSU2 as the ansatz or variational circuit. Furthermore, the current limitations of quantum hardware in terms of qubit count and connectivity necessitate restricting the experiments to circuits of 4 qubits and 8 qubits. This constraint forces an adjustment where the number of input qubits is matched to the number of relevant attributes, highlighting the importance of dimensionality reduction or feature selection in QML (Yogaraj et al.). The core problem to be addressed is how the variation in entanglement topologies within the ansatz (i.e., default, circular, and pairwise) and the choice of classical optimizer affect classification accuracy across diverse dataset characteristics, and to what extent this VQC can handle the complexity of real-world data.

Based on the outlined background, the research questions for this study are:

1) How does the classification accuracy performance of VQC, using the ZFeatureMap feature map and EfficientSU2 ansatz, compare across variations in entanglement topology (default, circular, pairwise) and qubit count (4 and 8) on the Iris, Wine, and Breast Cancer datasets?
2) Which classical optimizer (COBYLA, SLSQP, L-BFGS-B, P-BFGS) provides the highest classification accuracy performance for each combination of VQC architecture (topology and qubit count) and dataset used?

To ensure the research remains focused and can be implemented with available computational resources, the following scopes and limitations are established:

1) Datasets are limited to three classification datasets from the sklearn library: Iris, Wine, and Breast Cancer.
2) Data preprocessing is restricted to the use of MinMaxScaler.
3) Data splitting is fixed at 80% for training samples and 20% for testing samples.
4) The VQC architecture is limited to the combination of ZFeatureMap for data encoding and EfficientSU2 as the ansatz.
5) The number of input qubits is limited to 4 qubits and 8 qubits , adjusted to the number of dataset attributes and the constraint of the processing unit's memory and speed.
6) The entanglement topologies tested are limited to the default, circular, and pairwise modes.
7) The classical optimizer algorithms used are limited to COBYLA, SLSQP, L-BFGS-B, and P-BFGS.

The main objectives of this research are:

1) To analyze and compare the VQC classification accuracy performance based on the variations in entanglement topology (default, circular, pairwise) and qubit count (4 and 8) for the Iris, Wine, and Breast Cancer datasets.
2) To identify the optimal configuration of the VQC architecture (topology and qubit count) and classical optimizer that yields the highest classification accuracy for each dataset tested.

2. REVIEW OF LITERATURE

2.1 Quantum Machine Learning (QML)

Quantum Machine Learning (QML) represents a rapidly evolving interdisciplinary field at the intersection of quantum physics and classical machine learning. It seeks to leverage the unique principles of quantum mechanics, such as superposition, entanglement, and interference, to develop novel algorithms capable of processing data and performing computational tasks with potential advantages over classical methods (Ding et al.). The promise of QML is to enhance various machine learning tasks, including classification, regression, and clustering, by encoding information into quantum states and utilizing quantum circuits for computation. The current focus within QML is predominantly on implementing these algorithms on Noisy Intermediate-Scale Quantum (NISQ) devices, where the development of hybrid quantum-classical algorithms is crucial.

2.2 Variational Quantum Circuits (VQC)

Variational Quantum Circuits (VQC) are a key family of hybrid quantum-classical algorithms designed to run on NISQ hardware. VQCs operate by defining a quantum circuit with tunable parameters (θ). This circuit, often called an ansatz or variational form, prepares a quantum state. The output of the quantum circuit is measured to calculate a classical cost function (or loss function). A classical optimizer then iteratively adjusts the circuit parameters (θ) to minimize the cost function, effectively training the quantum model.

A fundamental component of VQC for classification is the use of a Feature Map (*U(x)*), which encodes classical input data (*U(x)*) into a quantum state. This encoding process is critical for achieving a quantum advantage, as it aims to map data into a high-dimensional quantum Hilbert space where classification boundaries may be more easily separable (Souza et al.) (Regadío). In this study, the ZFeatureMap is specifically employed as the data encoding technique.

The other primary component is the Ansatz (variational form), which consists of layers of parameterized single-qubit rotations (like Ry, Rz) and fixed two-qubit gates (like CNOT, CZ) to generate entanglement. The choice of ansatz directly impacts the circuit's expressibility (its ability to explore the Hilbert space) and entangling capability (Biswas), (Singh & Pokhrel). This research utilizes the EfficientSU2 ansatz, which is known for its high expressibility and relatively shallow depth, making it suitable for NISQ devices.

The performance of VQC is significantly influenced by the entanglement topology within the ansatz (Yogaraj et al.), (Regadío). The current study investigates three specific topologies for the EfficientSU2 ansatz on both 4-qubit and 8-qubit circuits:

1) Default: A standard entanglement structure.
2) Circular: Entanglement between adjacent qubits in a ring formation.
3) Pairwise: Entanglement between specific, non-adjacent pairs of qubits.

The architectures for the 4-qubit VQC with ZFeatureMap and EfficientSU2 are explicitly designed for the default, circular, and pairwise modes (Souza et al.), (Regadío). Similarly, the architectures for the 8-qubit VQC are designed for the default and circular modes.

2.3 Qiskit as a Framework

The implementation of VQC algorithms relies on robust software frameworks that bridge the gap between theoretical quantum circuits and physical quantum hardware or simulators. Qiskit (Javadi-Abhari et al), developed by IBM, is one of the leading open-source quantum computing frameworks. It provides comprehensive tools for creating, manipulating, and executing quantum circuits, including modules for developing VQC, such as qiskit.circuit.library for various feature maps (like ZFeatureMap) and variational forms (like EfficientSU2). Qiskit enables researchers to design the precise quantum gate sequences, specify the entanglement patterns, and integrate with classical optimizers for the hybrid training process. The experiments in this research are inherently dependent on such a framework for the construction and simulation of the VQC architectures presented.

2.4 Data Processing and Optimization

The necessity of data preprocessing in QML is widely acknowledged, as quantum circuits often require input data to be normalized or mapped within a specific range, such as [0, 2π] for rotation angles. This study uses MinMaxScaler to normalize the dataset attributes before they are fed into the ZFeatureMap. The datasets used Iris (150 samples, 4 attributes, 3 classes), Wine (178 samples, 13 attributes, 3 classes), and Breast Cancer (569 samples, 30 attributes, 2 classes) are standard benchmarks from the sklearn library for classification tasks. Finally, the success of VQC relies heavily on the choice of the classical optimizer used to minimize the cost function. The optimization landscape of VQCs can be plagued by issues like Barren Plateaus, making the choice of optimizer critical. This research evaluates four common gradient-based and gradient-free optimizers: COBYLA, SLSQP, L-BFGS-B, and P-BFGS (likely referring to the Powell method, or a variant of BFGS). The results presented show a direct comparison of these optimizers across different VQC configurations.

3. METHOD

3.1 Type of Research and Research Environment

This study employs a comparative experimental research design, focusing on the performance evaluation of the Variational Quantum Circuit (VQC) algorithm for data classification tasks. The experiment aims to systematically investigate how variations in architectural components and optimization strategies impact classification accuracy across different benchmark datasets. The experiments were conducted within a simulated quantum computing environment. Specifically, the implementation leverages the Qiskit Machine Learning application module (Sahin et al) to construct and train the hybrid quantum-classical classifiers. Quantum Computing Framework: Qiskit (IBM Quantum) served as the primary open-source framework for designing, simulating, and executing the Variational Quantum Circuits. The Qiskit Machine Learning module was instrumental in defining the VQC models, handling the integration of the feature maps, and managing the training loop. Classical Computing Libraries: Standard Python libraries, including Scikit-learn for data handling and performance metrics, and NumPy for numerical operations, were used to manage the hybrid quantum-classical workflow.

The core materials used are three standard classification datasets sourced from the Scikit-learn (sklearn) library, representing varying complexities in terms of features and classes:

1) Iris Dataset: 150 samples, 4 attributes, 3 classes.
2) Wine Dataset: 178 samples, 13 attributes, 3 classes.
3) Breast Cancer Dataset: 569 samples, 30 attributes, 2 classes.

3.2 Data Preprocessing

Standard data preprocessing steps were uniformly applied to all three datasets:

1) Normalization: All feature attributes in each dataset were scaled using MinMaxScaler to transform the data values into a standardized range, typically [0, 1], a requirement for efficient encoding into quantum states.
2) Data Splitting: Each dataset was partitioned into two distinct sets: 80% for training and 20% for testing, ensuring an unbiased evaluation of the model's generalization capability.

3.3 Variational Quantum Circuit (VQC) Design

The VQC architecture was constructed as a hybrid model comprising two fundamental components:

1) Feature Map: The ZFeatureMap was employed as the data encoding method, which maps the classical input data (x) into a quantum state via rotations (Rz) and entanglement gates.
2) Ansatz (Variational Form): The EfficientSU2 circuit was selected as the parameterized variational form, consisting of layers of single-qubit rotations and CNOT gates for entanglement.

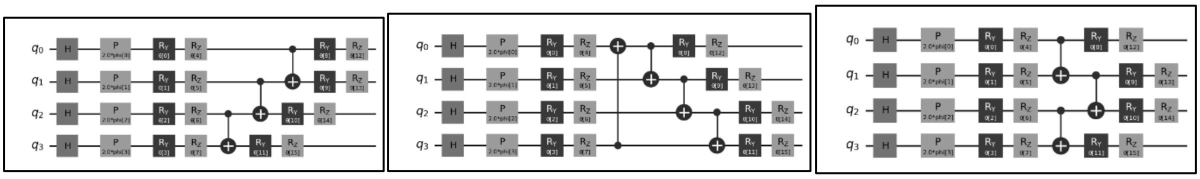
3.4 Qubit Configuration and Topology Variations

The circuit design was constrained to two specific scales, reflecting current NISQ limitations (Aravinda et al.):

1) 4 Qubits: Used for the Iris dataset and as a reduced-feature study case for the Wine and Breast Cancer datasets.
2) 8 Qubits: Used for the Wine and Breast Cancer datasets, where a larger number of attributes necessitates higher dimensionality encoding.

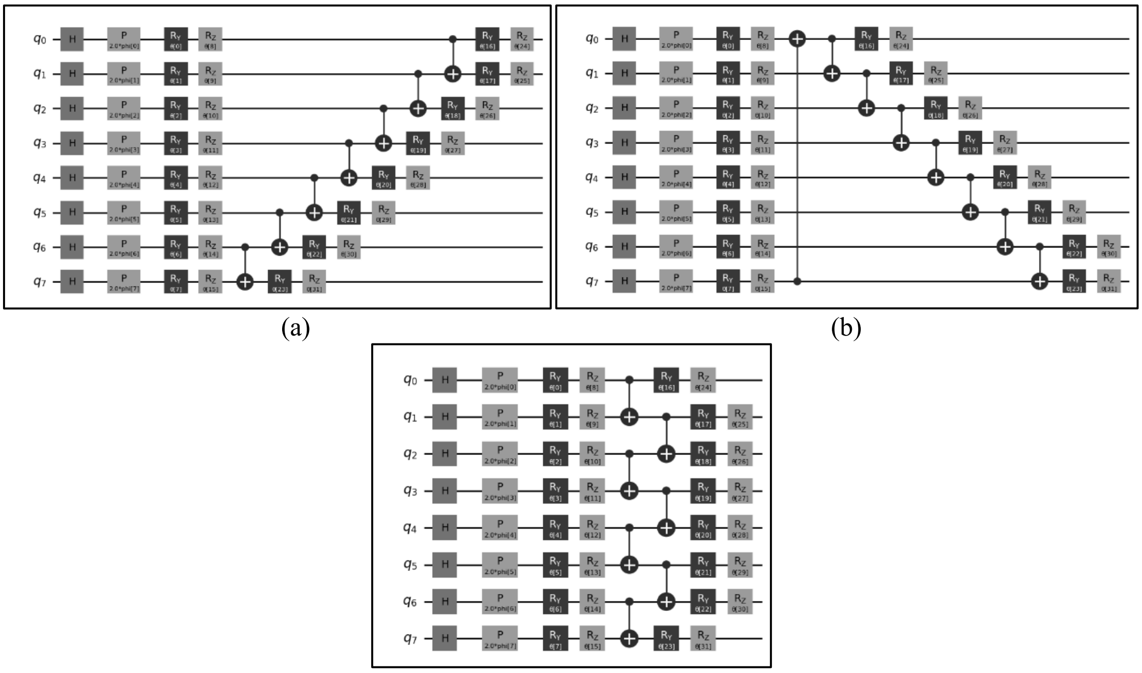
The models using 4 and 8 PCA components were compared based on their performance (Hwang et al.). The critical variable under investigation was the entanglement topology of the EfficientSU2 ansatz, with three modes being tested for each configuration:

1) Default: Standard gate connectivity as defined by the Qiskit library.
2) Circular: Qubits are connected in a cyclic, nearest-neighbor manner.
3) Pairwise: Entanglement is established between specific non-adjacent pairs of qubits, optimizing connectivity for the given qubit count.



(a) (b) (c)

Fig. 1. VQC Architecture (4 Qubits) using ZFeatureMap-EfficientSU2 with: (a) Default, (b) Circular, and (c) Pairwise Entanglement Topology).



(a) (b)

(c)

Fig. 2. VQC Architecture (8 Qubits) using ZFeatureMap-EfficientSU2 with: (a) Default, (b) Circular, and (c) Pairwise Entanglement Topology).

3.5 Model Training and Optimization (Hybrid Quantum-Classical)

The VQC models were trained using a hybrid quantum-classical loop to minimize a defined cost function:

1) Cost Function: The training objective was to minimize a suitable loss function (Cross-Entropy), calculated from the measurement outcomes (expectation values) of the final quantum state.
2) Classical Optimizers (Biswas): The following four classical optimization algorithms were used to iteratively update the circuit parameters (θ) based on the calculated loss: COBYLA, SLSQP, L-BFGS-B, P-BFGS (referencing the classical Powell method or a related BFGS variant optimized for boundaries).

4. RESULT & DISCUSSION

This section presents the results of the comparative experiment on various Variational Quantum Circuit (VQC) configurations, which utilized the ZFeatureMap as the feature encoder and EfficientSU2 as the ansatz. Performance is evaluated based on the Test Accuracy across three standard datasets, by varying the entanglement topology (default, circular, pairwise), the qubit count (4 and 8), and the classical optimizer (COBYLA, SLSQP, L-BFGS-B, P-BFGS).

Table 1. Iris dataset with 4 qubits

No.	Dataset	default		circular		pairwise	
		Training (%)	Test (%)	Training (%)	Test (%)	Training (%)	Test (%)
1	COBYLA	86	83	82	87	**86**	**93**
2	SLSQP	88	87	80	87	75	70
3	L_BFGS_B	84	87	64	83	82	80
4	P_BFGS	**93**	**97**	**92**	**90**	83	87

Table 2. Wine dataset with 4 qubits

No.	Dataset	default		circular		pairwise	
		Training (%)	Test (%)	Training (%)	Test (%)	Training (%)	Test (%)
1	COBYLA	88	83	70	58	**88**	**78**
2	SLSQP	**92**	**92**	83	64	87	72
3	L_BFGS_B	87	81	82	61	84	72
4	P_BFGS	92	89	**83**	**69**	85	69

Table 3. Wine dataset with 8 qubits

No.	Dataset	default		circular		pairwise	
		Training (%)	Test (%)	Training (%)	Test (%)	Training (%)	Test (%)
1	COBYLA	93	89	**89**	**89**	78	53
2	SLSQP	92	92	70	81	89	86
3	L_BFGS_B	80	67	84	72	89	83
4	P_BFGS	**93**	**92**	82	61	73	75

Table 4. Breast Cancer dataset with 4 qubits

No.	Dataset	default		circular		pairwise	
		Training (%)	Test (%)	Training (%)	Test (%)	Training (%)	Test (%)
1	COBYLA	89	89	**90**	**90**	91	91
2	SLSQP	**91**	**90**	90	89	**91**	**92**
3	L_BFGS_B	**91**	**90**	**90**	**90**	91	91
4	P_BFGS	**91**	**90**	**90**	**90**	91	91

Table 5. Breast Cancer dataset with 8 qubits

No.	Dataset	default		circular		pairwise	
		Training (%)	Test (%)	Training (%)	Test (%)	Training (%)	Test (%)
1	COBYLA	88	86	90	90	**91**	**91**
2	SLSQP	71	74	**91**	**91**	**91**	**91**
3	L_BFGS_B	91	89	90	90	90	91
4	P_BFGS	**90**	**90**	90	90	**91**	**91**

The following summary table highlights the highest Test Accuracy achieved for each dataset and qubit configuration, pinpointing the optimal combination of topology and optimizer:

Table 6. The optimal combination of topology and optimizer

No.	Dataset	Qubit	Highest Test Accuracy	Optimal Topology	Optimal Optimizer
1	Iris	4	97%	*Default*	P-BFGS
2	Wine	4	92%	*Default*	SLSQP
3	Wine	8	92%	*Default*	SLSQP & P-BFGS
4	Breast Cancer	4	92%	*Pairwise*	SLSQP
5	Breast Cancer	8	91%	*Circular & Pairwise*	SLSQP, COBYLA, L-BFGS-B, P-BFGS

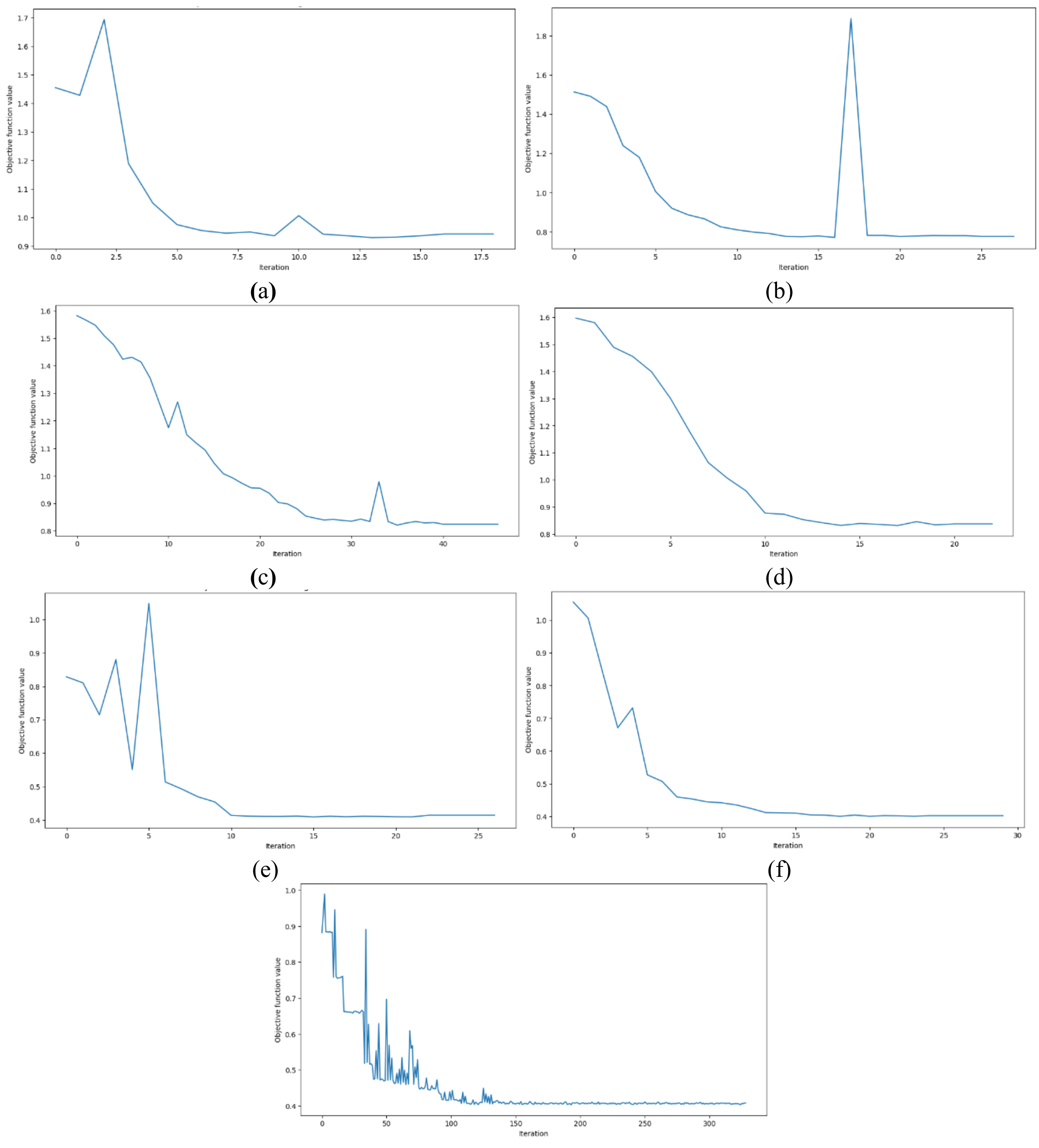


Fig. 3. Objective Function Value vs Optimization Steps/Iterations: (a) table 6 No.1, (b) table 6 No.2, (c) table 6 No.3 SLSQP, (d) table 6 No.3 P-BFGS, (e) table 6 No.4, (f) table 6 No.5 circular – SLSQP and (g) table 6 No.5 pairwise - COBYLA

The Iris dataset, characterized by its low dimensionality (4 attributes) and 3 classes, demonstrates a superior and highly stable VQC performance. The highest test accuracy achieved was 97%, using the VQC with the default topology and the P-BFGS optimizer. This result approaches the theoretical upper bound of classical classification algorithms on this dataset. The pairwise (93% with COBYLA) and circular (87% with COBYLA/SLSQP) topologies also yielded strong results. This suggests that for shallow 4-qubit circuits, increased connectivity complexity can lead to competitive performance, although the default topology provided the peak score. P-BFGS proved superior, achieving a 93% training accuracy and 97% test accuracy, indicating its effectiveness in navigating the relatively simpler parameter space of the 4-qubit Iris circuit.

The Wine dataset is higher dimensional (13 attributes) with 3 classes, requiring qubit scaling adjustments (4-qubit with feature reduction, 8-qubit for higher dimensionality). The peak accuracy was 92%, achieved with the default topology and the SLSQP optimizer. However, performance with the circular and pairwise topologies was substantially lower, with test accuracy ranging between 58% and 78%. The significant discrepancy between training accuracy (up to 92%) and test accuracy (as low as 58%) in the circular and pairwise configurations points toward overfitting or trapping in shallow local minima, indicating architectural instability under high-dimensional data with limited (4-qubit) entanglement. Scaling the circuit from 4 to 8 qubits did not increase the peak test accuracy (remaining at 92% with default topology). Nonetheless, the accuracy of the pairwise (86% with SLSQP) and circular topologies (89% with COBYLA) showed a significant improvement in stability. This stability suggests that the 8-qubit ansatz provides better entanglement capacity for the 13-attribute dataset, even if the peak performance is constrained, possibly due to the onset of the Barren Plateau phenomenon.

The Breast Cancer dataset is the highest-dimensional (30 attributes) but is a binary classification problem (2 classes). High Stability The VQC demonstrated highly consistent performance across this dataset. Nearly all 4-qubit and 8-qubit configurations consistently yielded Test Accuracy around 89%-92%. Topological and Scale Influence: At 4 qubits, the pairwise topology reached the peak of 92% with SLSQP. At 8 qubits, both circular and pairwise topologies dominated at 91%. This stability confirms that for binary classification tasks, even with high-dimensional input, VQCs (especially those with richer entanglement like circular and pairwise) are highly effective at separating the quantum feature space. Scaling to 8 qubits successfully maintained the high accuracy and notably increased stability across all optimizers.

The results demonstrate that entanglement topology is highly dependent on the dataset characteristics and qubit scale. It was the most reliable, often achieving peak scores on both multi-class datasets (Iris and Wine). This suggests that the linear, direct connection architecture may be the best starting point for VQCs, offering a good balance between expressibility and avoiding complex optimization landscapes. Pairwise and Circular Topologies: These topologies showed the best performance for the Breast Cancer dataset (binary classification). This confirms the hypothesis that richer connectivity (leveraging wider entanglement) is beneficial for complex or higher-dimensional classification problems. However, these topologies also exhibited the largest performance variance (e.g., Wine 4-qubit), underscoring the challenge in balancing expressibility with trainability.

Restricting the experiments to 4 and 8 qubits provides insight into VQC scaling. In the Wine dataset, scaling from 4 to 8 qubits did not increase the maximum test accuracy (remaining at 92%). This suggests that increasing the qubit count without proper optimization of depth and topology can lead to stagnated results, possibly due to the rapid increase in parameter space complexity overwhelming the classical optimizer. The increase to 8 qubits in both the Wine and Breast Cancer datasets demonstrably improved the consistency of performance, especially for the circular and pairwise topologies. This indicates that VQC scaling is more effective at enhancing stability and generalization rather than simply boosting peak performance on more complex data.

No single optimizer was universally superior, highlighting a strong dependence on the VQC's optimization landscape. SLSQP, Emerged as the most versatile optimizer, achieving peak scores across Wine (4Q and 8Q) and Breast Cancer (4Q and 8Q). SLSQP, as a sequential least squares programming method, appears effective in handling the non-smooth parameter landscapes of VQCs. P-BFGS, Demonstrated peak performance on the Iris Dataset (97%), emphasizing the importance of quasi-Newton methods in VQC optimization. In conclusion, these results provide clear empirical guidance on the most effective VQC configurations under NISQ constraints. The study suggests that careful design of the entanglement topology is often more critical than merely increasing the qubit count to achieve optimal accuracy and stability.

5. CONCLUSION

This empirical analysis successfully evaluated the impact of entanglement topology, qubit scale, and classical optimization on the performance of the ZFeatureMap-EfficientSU2 Variational Quantum Classifier (VQC), thereby addressing the core research questions. The comparative experiments demonstrated that no single architecture is universally optimal, underscoring the critical dependency of VQC performance on dataset characteristics. Entanglement Topology: The default entanglement topology achieved the highest peak accuracy for multi-class datasets like Iris and Wine, suggesting its efficiency in simpler parameter landscapes. Conversely, the pairwise and circular topologies exhibited superior stability and competitive accuracy on the complex, high-dimensional Breast Cancer dataset, confirming that richer qubit connectivity is essential for effective feature separation in more challenging classification problems. Increasing the qubit count from 4 to 8 did not necessarily elevate the maximum accuracy but was crucial for improving the general stability and consistency of the more complex topologies across different optimizers. The SLSQP optimizer proved to be the most robust choice, achieving peak performance across the Wine and Breast Cancer datasets, while P-BFGS secured the highest overall score.

These findings provide essential empirical guidance for designing future VQC architectures, particularly under Noisy Intermediate-Scale Quantum (NISQ) device constraints. Future research should focus on developing adaptive VQC structures where the entanglement topology can be dynamically selected based on dataset complexity. For quantum hardware development, the observation that increasing qubit count primarily enhances stability and consistency rather than peak performance highlights the critical need to prioritize connectivity and qubit fidelity over mere scaling. This result emphasizes that optimizing the geometry of qubit interactions is paramount for creating reliable and trainable variational quantum algorithms.

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