Quantum AI for Engineering Education: Assessment of Students' Problem-Solving Performance in Electric Circuits

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Wade Goodridge is a tenured Associate Professor in the Department of Engineering Education at Utah State University. His research often has a focus on what drives us to learn, how we learn and how well we do it, and what can improve that learning. This work is often directed with a spatial thinking emphasis. Dr. Goodridge has investigated different learning modalities (fully online, hybrid, blended courses), cognitive and metacognitive learning processes (self-regulation, engineering problems solving, neural efficiency in engineering problem solving) learning motivators (engineering self-efficacy), and effective and personalized engineering education interventions (tactile engineering curriculum, physical teaching models, XR environments and AI informed systems of delivering and monitoring engineering learning). Dr. Goodridge has created a valid and reliable instrument to assess spatial ability in blind and low vision (BLV) learners thus opening new areas of research centered on tactile spatial ability. He has created tactile and visual learning tools and has offered professional development experiences on how to improve the education of tomorrows engineers.

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Zain ul Abideen holds a Ph.D. in Engineering Education from Utah State University, where he also served as a Graduate Researcher. He is a computer engineer and earned his bachelor's degree in computer engineering and master's degree in engineering, and brings over a decade of experience in teaching and research with undergraduate engineering students. He actively contributes to several technical committees and serves as a reviewer for leading journals and international conferences. His doctoral research focused on cognitive engagement, AI in education and engineering design, self-regulated learning, and mobile learning. His work seeks to deepen our understanding of how these elements influence learning and success in engineering education. With a strong commitment to educational advancement and a robust academic background, Zain is recognized as a dedicated and emerging scholar in the field of engineering education.

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Sehrish Jabeen is currently a Ph.D. student and Graduate Research/Teaching Assistant. She brings over five years of teaching experience across K–12 and undergraduate educational settings, along with seven years of professional experience in the field of information technology, where she worked in the banking sector. Her research interests include mathematical well-being, mathematical modeling and problem-solving, and the application of Cognitively Guided Instruction (CGI) in mathematics and engineering education. Through her work, Sehrish aims to explore how instructional practices and learning environments can support students' mathematical thinking and their engagement with engineering and mathematics problem-solving.

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Abstract

Quantum computing marks a transformative shift in information processing by leveraging the fundamental principles of quantum mechanics—entanglement, superposition, and interference—to achieve computational capabilities beyond those of classical systems. As Noisy Intermediate-Scale Quantum (NISQ) devices continue to mature, researchers are actively developing quantum algorithms and exploring their applications across a range of disciplines. Prior studies highlighted mathematical parallels between Support Vector Machine (SVM) and quantum classifier, suggesting that quantum models may offer comparable classification performance.

This exploratory study investigates the effectiveness of a Variational Quantum Classifier (VQC) in evaluating student performance within engineering education, specifically in problem-solving contexts. The dataset comprises 363 solution events collected from a "Fundamental Electronics for Engineers" course at a mid-sized Carnegie R1 university in the western United States. These events are categorized into three cognitive task types based on the PPST framework. A hybrid SMOTEN resampling method was applied to further increase the sample size for this study setting.

Each student response was evaluated by two independent raters using Docktor et al.'s (2016) five process-oriented constructs adapted from their rubric: Useful Description, Engineering Approach, Specific Application of Engineering Principles, Mathematical Procedures, and Logical Progression. Based on expert judgment, responses were classified into three performance levels or classes: High, Medium, and Low.

Quantum machine learning models were developed and tested using IBM's gate-based quantum computing simulator. Multiple configurations were explored, including variations in encoding circuits, Ansatz structures, circuit depths, and optimization algorithms such as ADAM, COBYLA, TNC, and SLSQP. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, F1-score, and specificity. Results from the simulated environments were analyzed and compared in this study.

The findings offer preliminary insights into the feasibility of quantum machine learning (QML) for educational assessment and point toward promising directions for the integration of quantum AI-driven tools in engineering education for the future.

Keywords: *Quantum Computing, Quantum Machine Learning, Variational Quantum Classifier, Quantum AI, Problem-Solving, Learning Management System, Assessment Technology*

1. Introduction

Quantum computation utilizes the law of quantum mechanics to perform computation [1] – [3]. While the fundamental representations of any information in classical computers are binary digits or bits (0 or 1), quantum computers operate on qubits or quantum bits. The quantum bits can stay in $|0\rangle$, $|1\rangle$ and any linear combination of $|0\rangle$, and $|1\rangle$ states [1] – [3]. The fundamental difference between classical and quantum bits are the underlying governing laws [1]. Classical bits follow the laws of Newtonian mechanics, whereas qubits leverage the principles of quantum mechanics, such as superposition, entanglement, and interference [1], [3]. Traditionally, qubits are represented as state vector $|\psi\rangle$ in mathematical notation, a 3-dimensional Bloch sphere for visualization. Their geometry, and the relationships can be modeled as [1] – [3]:

$$|\psi\rangle = Cos\left(\frac{\theta}{2}\right)|0\rangle + e^{i\phi}Sin\left(\frac{\theta}{2}\right)|1\rangle, \text{ where } 0 \leq \theta \leq \pi \text{ } and \text{ } 0 \leq \phi \leq 2\pi \quad (1)$$

In essence, the classical computer can represent information with bipolar and discrete values. However, the qubit (as the geometric representation demonstrates) can utilize the entire surface of the Bloch sphere or any combination of $|0\rangle$ and $|1\rangle$ for encoding and processing information [1], [3]. Therefore, the computation in quantum computers is inherently parallel, allowing it to process information exponentially faster than any classical computer [1]. This provides theoretical groundwork to ponder upon when performing any classical equivalent computation in any quantum system.

Modern artificial intelligence (AI) driven tools, including statistical learning, and neural network (NN) systems, perform enormous amount of data processing and computations [2]. Moreover, multimodal AI (or current generative AI) tools are combining multiple knowledge structures as well as using Linkers, resulting in an incremental need of computation power, and speed. Therefore, future computation may require computing systems that are governed by the law of quantum mechanics, which is inherently parallel.

Prominent Quantum Physicist John Preskill defined this quantum era as the age of NISQ (Noisy Intermediate-Scale Quantum) devices [4]. This era is often compared to the pre-semiconductor period for classical computational devices. However, the current lack of ability to produce required physical systems does not prohibit us from developing mathematical formulation or testing algorithms for future practices. For example, Lov Grover developed a search algorithm that theoretically works in $O(\sqrt{N})$ times. Additionally, MIT mathematician Peter Shor has created an algorithm that can efficiently find prime factors of a large number [1]. IBM, Google, and Xanadu have also developed some quantum machine learning (QML) algorithms for future real-world applications. This study explores if Variational Quantum Classifiers (VQC) can be implemented in educational psychology or in engineering education, especially in the applications of the problem-solving assessment. This study is an extension of the existing work to understand how to leverage quantum information processing systems to assess human cognition associated with problem-solving on the future learning management systems (LMS) platform.

2. Literature Review

This section of the study discusses the foundational idea of the Variational Quantum Classifier (VQC) architecture for classification problems as well as some existing endeavors in utilizing the mathematical framework to solve those problems. It is important to note that there was almost no attempt being made to classify the cognitive processes associated with the problem-solving activities except the researchers' current investigations [5], because the thinking related to the problem-solving activities was never ordinarily measured (like UCI car dataset) as independent variables to train machine learning models. Therefore, the VQC has also never been utilized in this context. However, VQC has been implemented for many other purposes.

2.1 Variational Quantum Classifier (VQC) as Quantum Machine Learning (QML) Model

The mathematical formulation found in the previous study suggests that the Variational Quantum Classifier (VQC) mathematically functions as a linear classifier or decision function as similar as a classification algorithm [2], [6], [7]. There is also other quantum machine learning (QML) architecture available, such as, QuClassi, Hybrid Quantum Neural Network (QNN), QSVM [6] – [8]. This study only focuses on the application of VQC architecture for engineering education context. The mathematical proof of VQC as linear classification model has also been shown with similar findings with verifiable data (100% success in classification accuracy) conducted in the United States in 2019 and in Daffodil International University, Dhaka, Bangladesh throughout 2021-2022 [6], [7]. The verifiable dataset (i.e. iris, MNIST, Boston Housing Price, Wine quality dataset) is authentic and thoroughly investigated data, often utilized to develop trustworthy, high-quality, and suitable algorithms, or mathematical models.

In supervised settings, this multiclass classification problem for quantum computation can be defined as the minimization of the cost function to optimize the tunable gate parameters, θ, of the parametric unitary quantum circuit (also known as Ansatz) with the given input data, $x \in \mathbb{R}^d$ for d-dimensional features, and for output k classes, $y \in [0,1]^k$ [9]. To solve this problem with a quantum computer, the input data, x, is transformed by encoder or the feature map circuit into the quantum state vectors that represent the initial qubit states [9], [10]. The initial encoding process of transforming classical information into quantum states is also called the state preparation stage. This initial transformation (or state preparation) of the input data, x, takes the data to the higher dimensional Hilber space, enabling exploitation of quantum mechanical properties (i.e., superposition, entanglement, and interference) for detecting more nuanced boundaries in a multiclass problem [11]. The encoder circuit is followed by a tunable parametric unitary circuit (or, Ansatz) [10]. The tunable parametric circuits are the foundation in the optimization processes [7], [10], like how backpropagation works in any neural network. After initial tuning of the parametric quantum circuit, the measurement is performed that then collapses the quantum states [1], [9], [10], and a probability distribution of the classes of each data point is calculated [2], [7], [10]. The highest probability distribution is associated with a predicted class of a data point. VQC then compares the predicted class with the actual class labels for all cases [7], [10]. Then, VQC calculates the mean-square-error to calculate the overall cost of the initial VQC model. After that step, the classical optimizers are used to tune the parameters of the quantum gates and minimize the cost function mathematically defined by the researchers [7], [9], [10]. The lowest cost function then represents the configuration of the optimized VQC. In all cases the VQC algorithms compute, $y = f_\theta(x) = sign\ (tr[w\emptyset(x)] + b)$ and assign correct labels, $y \in [0,1]^k$, for unknown data [6], [7]. The overall foundational working process diagram of the VQC engaged in this process is shown in **Figure 1**.

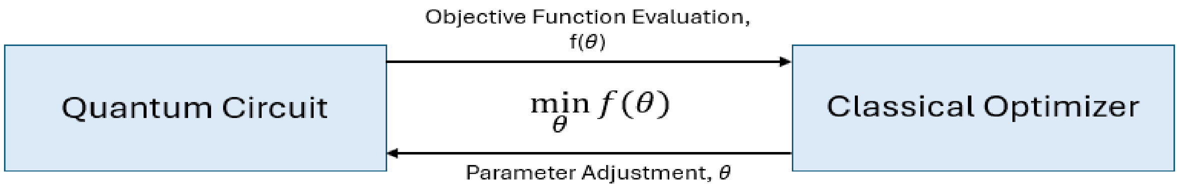

Figure 1: Foundational Working Process of VQC (Hybrid Quantum-Classical) Algorithm

2.2 Related Work

Quantum machine learning (QML) is comparatively new and growing research field and is mostly in the stages of foundational research, development of simulators and new algorithms that function like or better than classical models. Some QML models are still applied for testing, validation, applications, and benchmarking, laying foundational ground for future Quantum AI ecosystems [6] – [8], [12] – [18].

Stein et. al. (2022) developed a Quclassi architecture and tested on IRIS and MNIST dataset and found QuClassi to be performing comparatively better in binary and multiclass problems. When they implemented the QuClassi algorithm on IRIS dataset, they found Quclassi to be performing around 94% accuracy with lesser epoch [8]. In classifying three classes using MNIST dataset, the Quclassi architecture achieved around 94% of accuracy [8]. The classifier has its performance is about 78.69% accuracy, when tested for 10 classes [8]. Saxena et. al. (2022) implemented the angle encoded VQC model with 4 qubits on the IRIS dataset with the IBM's Qiskit 0.36.1 simulator, and found their algorithm works with 82.10% and 76.76% of accuracy for training and testing dataset respectively [17]. Maheswari et. al. (2022) conducted a study with VQC and QSVM (quantum support vector machine) for binary classification problems with synthetic, sonar, and diabetes dataset and identified that the data encoding or state preparation techniques affected the classifiers' outcomes [14]. They also found that VQC using angle encoding technique had accuracy of 75%, 71.4% and 74.19% in synthetic, sonar and diabetes dataset, whereas the amplitude encoding technique improved the VQC performance for synthetic dataset (98.40%) and diabetes dataset (74.50%) [14]. However, the amplitude encoding was related to the decrease of the VQC performance to 67.30% accuracy [14]. Kakız et. al. (2023) designed a variational part of the quantum classifying circuit with Rot and CNOT gate and compared with Ry and CNOT gate on Xanadu's PennyLane simulator [18]. They utilized the maternal health risk dataset containing 200 samples [18]. Kakız et. al. (2023) implemented the amplitude encoding state preparation techniques and found that the changes of Rot to Ry gate do not change the classifiers' overall performance [18]. However, the depth of the variational aspect of quantum circuit or ansatz has an impact of classifiers' performance [18]. Similar findings were also observed in Haque, Himel, and their colleagues' study, where IBM's built-in state preparation techniques, ansatz, and the quantum circuit depth resulted in the changes of VQC's performance [8]. They determined a VQC model with 2 layers of both encoder and ansatz depth that provides the optimum performance [8]. Findings of this study aligns with seminal work conducted by Havlíček et. al. (2019) [6]. Havlíček et. al. (2019) also suggested that the increase of quantum circuits' depth results in the higher performance [7], [8]. In fact, Havlíček et. al. (2019) demonstrated quantum circuit depth (l=4) having superior performance [7]. All these findings provide a theoretical grounding for the exploration, and application of the VQC in this study context.

3. The Study

This study is conducted with engineering students' as participants and who submitted homework on a learning management system (LMS) platform for a sophomore-level engineering course, *Fundamental Electronics for Engineers*. The homework on this course is generally domain-specific, closed-ended, and focused on engineering problem-solving activities [19]. Their homework solutions represent their cognitive efforts utilized during solving problems [5]. The researchers of this study have already proposed a Human-Machine Dual Problem-Solving Assessment (HHMDPSA) solution for LMS platform based on a classical computation system [5]. Researchers discussed how the judgment from human and classical AI algorithms can be orchestrated together to design the HHMDPSA system to understand the cognitive quality of solutions developed by students in generating solutions [5]. As the HHMDPSA solution's discussion is beyond the scope of this study, the researcher will only discuss the computational or AI section involved within it [5]. In the HHMDPSA solution, there is a machine-driven section that is run by classical AI algorithm [5]. This study is an exploration of using VQC as a replacement for that classical AI algorithm.

4. Research Questions and Objectives

This study is guided by two major research questions: (1) Can variational quantum classifiers (VQC) algorithm be implemented to classify problem-solving categories? and (2) Which VQC configurations perform comparatively superior among others within this study constraint? The major objective of this study is to explore if any variations of VQC can be implemented for assessing problem-solving performance; and to find comparatively better performing VQC configurations in problem-solving assessment.

5. Data Collection and Analysis

To conduct this study, the researchers collected problem-solving data from the homework solutions submitted in a foundational engineering class. The foundational engineering class is called *Fundamental Electronics for Engineers* and is typically taken by sophomores, and juniors in Mechanical, Civil, Environmental, and Biological Engineering programs at the institution the study was conducted at. According to Family Education Rights and Privacy

Act (FERPA) and Institutional Review Board (IRB), the submitted problem-solving data (students' work) cannot be directly downloaded for research purposes because the data contains identifiable information. Therefore, the researcher requested the data governing body at the University to provide the selected deidentified data for this study.

The researchers initially collected a total of 396 problem-solving data for this study. Then, they qualitatively filtered the data and reduced the collected samples down to 363, as 33 problem-solving data sets were either unintelligible, blank, or griffonage. The filtered 363 problem-solving data sets are used to conduct the data analysis in the steps shown in **Figure 2**.

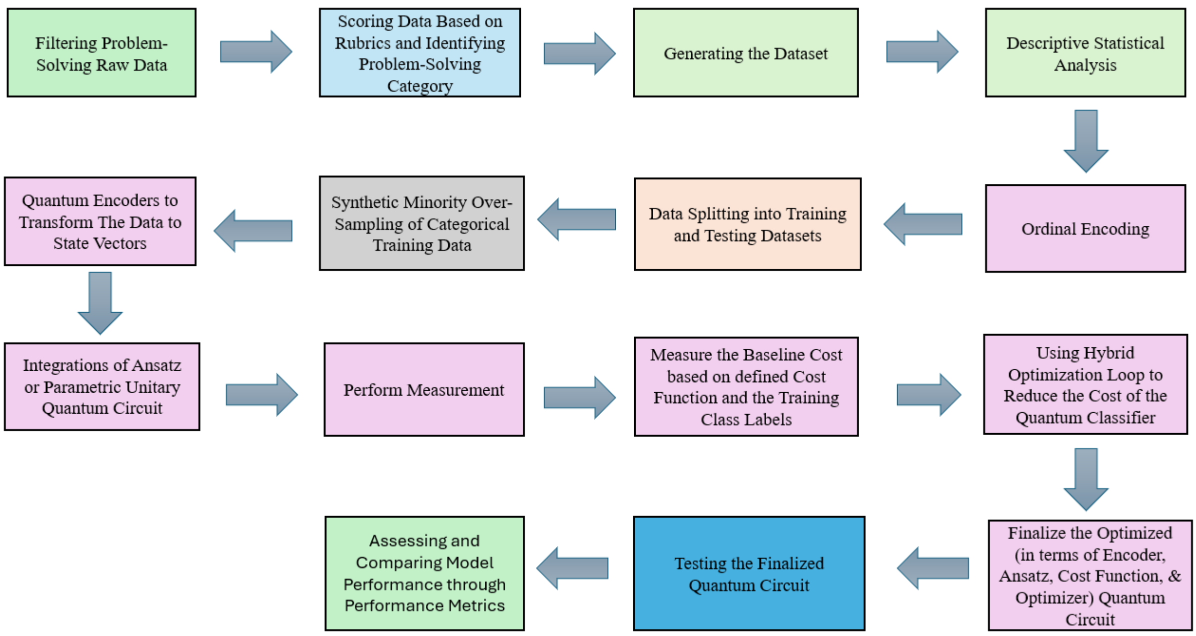

Figure 2: Data Analysis Workflow Diagram

Two independent researchers, having similar experience and expertise, independently studied, and scored individual problem-solving data sets based on a slight modification to Docktor et. al.'s (2016) rubrics [20]. The dimensions of the rubrics are: Useful Description (UD), Engineering Approach (EA), Specific Application of Engineering (SAE), Mathematical Procedures (MP) and Logical Progression (LP) [5], [20]. These dimensions will be a multiplier to a scoring system. The definition of each measure (used as independent variables) is provided in **Table 1** [5], [20]. Then, the researchers discussed their scoring processing together, came to consensus on their disagreements resulting in 100% agreement for scoring [21]. The researchers scored each solution on 0-5 Likert scale (0 is almost no to minimum manifestation of cognitive effort, and 5 as a maximum cognitive effort) for each measure [5], [20]. After that, the researcher calculated the total scores of each problem-solving event by adding 6 distinct scores (0-5 Likert scale) from five measures [5], [20]. The total score for each problem solution, therefore, can lie between 0 to 25. The researchers also gave each solution a pseudonym or unique identifier (such as, event001, event002, event003, etc.). Finally, the researchers stored all the information, including the unique identifier of each solution, the scores of five dimensions, and the total score of those five dimensions in a separate Excel file, and prepared the dataset of this study. The detailed modified rubrics are included in the **Appendix** section in this paper.

Table 1: Scoring Dimensions, and their Definitions (Problem-Solving Rubrics)

Dimension	Definition
UD	Useful Description or UD are the written illustrations of the problem analysis in the form of written text, diagrams, labeling or notations.
EA	Engineering Approach or EA is the application or the utilization of the underlying engineering concepts for solving a problem.
SAE	Specific Application of Engineering or SAE refers to the usage of engineering concepts for a specific purpose in a solution. SAE occurs in the sub-processing labels during problem-solving activities.
MP	Mathematical Procedures or MP are the applications of mathematical axioms or principles in solving a problem.
LP	Logical Progression or LP is organized thought processes, and consistent reasoning mechanisms during the problem-solving process.

In the next phase of data analysis, the researchers defined three classes, k, as mentioned in **Table 2**. The problem solutions are then analyzed, and categorized into three categories (i.e., high, medium, and low). These categorizations of the problems were included in the Excel sheet. These classes are ordered (a subsection of categorical variables) variables or categories and have equal intervals.

Table 2: Definition of Problem-Solving Classes

Class (k = 3)	Definition
High (~ 100%)	The solution is considered '**High**' when there were only minimum mistakes that happened in the solution. The solution followed all necessary cognitive processes associated with the solution.
Medium (~ 50%)	The problem solution is '**Medium**' when it demonstrates both problem-relevant consistent and inconsistent components in the solution. This manifests partially correct cognitive processing in solution generation.
Low (~ 0%)	The solution is considered '**Low**' when it illustrates problem-solving components containing flawed cognitive processing.

Then, the researchers identified that 37% of the total solution found in the data sets as belonging to the **'High'** class, 21% in **'Medium'** class, and '42%' is in **'Low'** class. **Figure 3** illustrates the distribution of the problem-solving data in multiple solution categories.

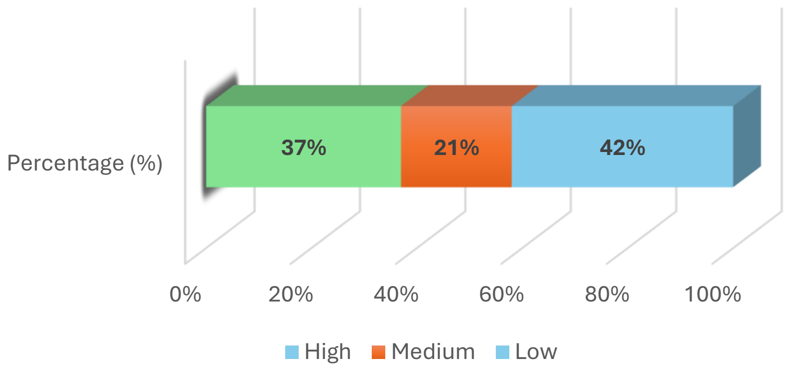

Figure 3: Data Distribution Across Multiple Classes

As this data is manually prepared, the researchers did not conduct deep initial explorations in the data preparation, and the analyses phase of this study. For larger datasets (i.e., customer data for industries, churn analysis, any d-by-d pixel image data etc.), the analysis does require a considerable amount of time in the preparation phase. In this study, the researchers only conducted a descriptive analysis to facilitate the study of the basic data distributions (average and standard deviation) for whole set as well as for each problem-solving class. The average of the total dataset is 13.66 with a standard deviation of 6.94. A descriptive analysis (**Table 3**) shows that the average of **'High'**, **'Medium'**, and **'Low'** varies across all problem-solving measures as described by the modified Docktor et. al.'s (2016) rubrics [20]. The **'High'** solutions are found to have greater detail and logistical flow in Engineering Approach (EA), Specific Application of Engineering (SAE), and Mathematical Procedures (MP) compared to the other two categories. **'High'** rated solution typically performed well in the broader usages of engineering and mathematical axioms and concepts. The EA and MP scores are of **'High'** solutions are 4.69 and 4.67 on average. **'Medium'** and **'Low'** solutions' values of the engineering approach were found to be 3.00 and 1.69, respectively. The '**High**' solution also performed comparatively better in the category of 'Specific Application of Engineering (SAE)', demonstrating superior expertise in domain-specific contextual or specific usage of engineering concepts in solving problems [22], [23]. The average scores for the SAE in **'High'**, **'Medium',** and **'Low'** are 4.51, 2.49, and 0.94, respectively, thus illustrating the considerable differences in SAE for **'High'**, '**Medium'** and **'Low'** cases. This descriptive statistical analysis also demonstrates the rigor and scoring procedures followed by the researchers in the scoring procedures, as the random value assignment would not separate the performance and associated problem-solving classes (i.e., **'High'**, **'Medium'**, **'Low'**) appropriately.

Table 3: Descriptive Analysis of Problem-Solving Samples Based on Rubrics

Measures	Overall Problem-Solving Sample (n=363, *M*=13.66, *SD*=6.94)					
	High (~ 100%)		Medium (~ 50%)		Low (~ 0%)	
	M	*SD*	*M*	*SD*	*M*	*SD*
UD	2.37	1.56	2.25	1.47	1.88	1.50
EA	4.69	0.83	3.00	1.15	1.69	1.14
SAE	4.51	1.01	2.49	1.16	0.94	1.13
MP	4.67	0.74	3.25	1.14	2.09	1.22
LP	4.07	0.87	2.58	1.15	1.28	1.17

n: Sample Size*; M:* Mean or Average*; SD:* Standard Deviation

The data prepared for this study is ordinal (a subcategory of categorical data) in nature. Both dependent and independent variables, therefore, need to be sent to the ordinal encoder to transform the categorical features into numerical ranks while preserving the data order [24] – [26]. The converted data was divided into 70% training, and 30% testing data. To ensure the preservation of class proportionality in both train and test set data, the stratify method was implemented. The 70:30 proportional data distribution ensures availability of enough testing data to test the optimized VQC models. Then, a standard oversampling technique, SMOTEN (Synthetic Minority Over-Sampling for Categorical Data) was applied, resulting in the generation of nearly 25% additional and similar synthetic datasets for training purposes [27]. Therefore, the researchers have a total of 430 samples to study in the engineering educational context. Previous studies on QML used only 150 IRIS, 768 diabetes, 560 breast cancer data, 200 Maternal Health Risk data, 208 sonar, and 891 titanic data in their analysis [12] – [18].

The researchers then proceeded to implement a variational quantum classifier (VQC) for analyzing and classifying the problem-solving data. For developing VQC, the researchers used IBM's Qiskit simulator version 2.3.0 [10]. Qiskit has built-in quantum encoders, and parametric circuits or Ansatz [10]. Qiskit also facilitates uses of optimizers (ADAM, COBYLA, TNC, and SLSQP) for developing quantum-classical hybrid loops in tuning quantum parameters [10]. The problem-solving dataset generated for this study is initially transformed into state vectors by the Encoder or Feature Map circuit [10], [14]. The researchers introduced 5 qubits for encoding 5 features. The parametric unitary quantum circuit or Ansatz, containing R_x, R_y, R_z and CNOT gates, is also integrated with the quantum encoder [10]. Researchers then defined the classes or categories (i.e., High, Medium and Low) based on the probability distribution derived from the ratio of the measured qubit strings. For example, if a data point is sent to the quantum circuit (with encoder and ansatz) and the measurement of quantum circuit gives a qubit string of 10011, then, the ratio is 60% and the datapoint predicted as the medium or within a class 1 category. This predicted category then compares actual data labels (Y_i) with predicted labels ($\widehat{Y_i}$) by using the following equation (cost function) [28]:

$$MSE = \frac{1}{n}\sum\left(Y_i - \widehat{Y_i}\right)^2 \tag{2}$$

A total baseline cost is calculated initially by combining all MSEs for an individual data point. The researchers then implemented the optimizers (ADAM, COBYLA, TNC, and SLSQP) to optimize the VQC model performance. The researchers opted for only 100 iterations (maxiter=100) in this process of the study, as the objective of this study was to explore these of the VQCs for the problem and not to find a highly optimal solution.

For developing highly optimized solutions, the researchers may need to test the other customized parameterized quantum circuits and implement other optimizers with many iterations. With a highly optimized solution development lying out-of-scope of this study, the optimized (including Encoder, Ansatz, Cost Function and Optimizer) quantum circuit found within this configuration and iteration is implemented to test our classifier and assess the performance metrics of the variational quantum classifiers (VQC) model.

5.1 Performance Evaluation Metrics

The performance of the VQC model developed for this study was evaluated based on the calculations of the performance metrics: True Positive Rate (TPR) or Recall, a True Negative Rate (TNR) or specificity, a False Positive Rate (FPR) or Type I Error, a False Negative Rate (FNR) or Type II Error, and classification accuracy from the confusion matrix found as outcomes for individual VQC model [29] – [31]. A N × N confusion matrix can be represented by $C_{i,j}$ for representing and comparing actual and predicted k labels. The row, i, is the actual category, and j is the predicted one. For a confusion matrix, $C_{i,j}$, the row and column will always be the same.

TPR for confusion matrix, $C_{i,j}$, is the proportion of '**True**' class that is also predicted as '**True**' by a VQC model, whereas TNR is the ratio of '**Not True**' class to total '**Not True**' class [29] – [31]. FPR and FNR are the errors and can be defined as the proportion of false classifications as of '**Not True**' and '**True**' classes respectively [29] – [31]. The performance metrics for each VQC model are calculated based on the following equations (where, i and j are the rows and columns of the confusion matrix respectively) [29] – [31]:

$$TPR_k = \frac{C_{k,k}}{\sum_{j=0}^{N-1} C_{k,j}} \quad (3)$$

$$TNR_k = \frac{\sum_{i=0,i\neq k}^{N-1} \sum_{j=0,j\neq k}^{N-1} C_{i,j}}{\sum_{i=0,i\neq k}^{N-1} \sum_{j=0,j\neq k}^{N-1} C_{i,j} + \sum_{i=0,i\neq k}^{N-1} C_{i,k}} \quad (4)$$

$$FPR_k = 1 - TNR_k \quad (5)$$

$$FNR_k = 1 - TPR_k \quad (6)$$

To calculate the accuracy of models, the researchers used the same N × N confusion matrix mentioned above and calculated the classification accuracy (ACC_k) for individual classes (i.e. High, Medium, and Low) by using the following equations [29] – [31]:

$$ACC_k = \frac{\sum_{i=0}^{N-1} C_{k,k}}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C_{i,j}} \quad (7)$$

6. Results

As discussed in the analysis section, the researchers built Variational Quantum Classifier (VQC) models using IBM's quantum simulators, Qiskit (version 2.3.0) [10] for this study. They created the VQC models based on built-in encoders, and tunable parameterized unitary circuits (Ansatz). Primarily, the researchers compared the VQC models for individual categories or classes (i.e., High, Medium and Low).

After calculating these metrics, the researchers plotted TPR, FPR, TNR, and FNR values for all three classes. Figure 4 contains the line plots for all four measures (TPR, FPR, TNR, and FNR) of the performance metric for all VQC models. The blue color represents a 'High' class, the orange is a 'Medium' class, and the green color represents a 'Low' problem-solving class. As FNR and FPR are complementary to TPR and TNR respectively, the following discussion will be only based on TPR and TNR to avoid any redundancy.

Overall, the last VQC models, containing the COBYLA and the SLSQP optimizers, performed comparatively better than any other model developed (Figure 4 and Appendix). All implemented quantum circuits for VQC models are illustrated in the **Appendix** section. The high performing VQC model contains a Z feature map circuit with depth 2 and in-built ansatz depth 2. This quantum classifier appeared to classify High classes comparatively better than others as shown in TPR and FNR curve in Figure 4. The last VQC model containing COBYLA has a TPR score of 0.83, and the VQC with the SLSQP's TPR performance is 0.85 for the High class. With all other models' the TPRs for High classes were less than 0.7. For categorizing the Low class, the VQC models containing the TNC and the COBYLA perform comparatively better than every other model, however, their TPRs are still very low. With the TNC optimizer, TPR for the low class was found to be only 0.24 and for the SLSQP optimizer, it was found to be only 0.2.

From the TPR and TNR graph shown in Figure 4, it is also noticed that the VQC model with the Pauli Feature Map, encoder depth 1, and Ansatz depth 1 comparatively perform better in classifying 'Medium' solutions. Three of the four VQC models with the above configurations performed better than almost every other model with two exceptions (Z Feature Map, encoder depth 1, ansatz depth 2, and the ADAM and the TNC optimizers). The TPR score for all these three models and the two other exceptional models for medium solutions was 1.00.

Interestingly, TNR scores for High and Low classes are very high (> 0.85) in almost all VQC models. This argues that VQC can effectively categorize 'Not High' and 'Not Low' classes. However, TPR and TNR analyses indicate that there are many Type-I, and Type-II errors (shown in FPR and FNR in Figure 4). The bottom-right line graph shows that there is higher rate of false negative (or, Type II error). This is, especially true for High class classifications, and on many occasions for Low classes. The Type II error for the Low classes for all models is greater than 0.75. Moreover, seven VQC models (out of 20) have greater than or equal to 0.9 Type II errors for the High class. The last VQC model, containing the SLSQP optimizer, has shown a comparatively better TNR rate (0.61) than others for the 'Medium' category.

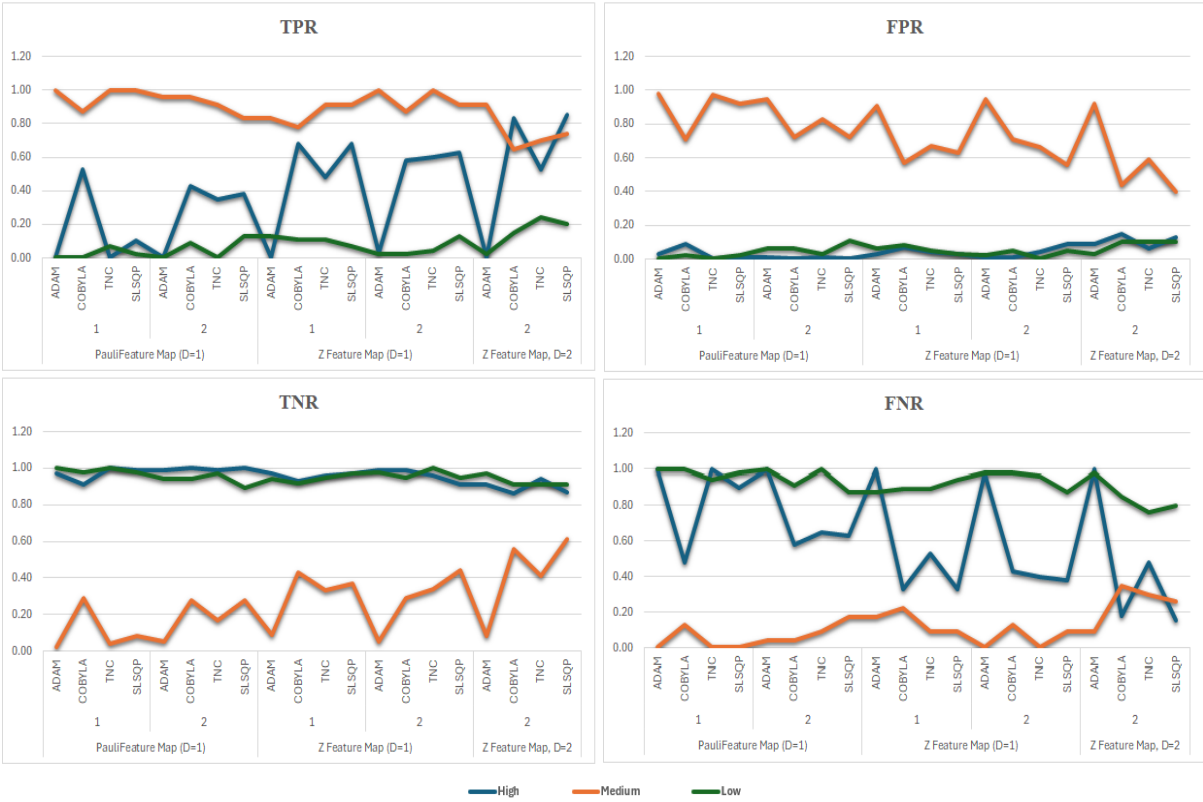

Figure 4: TPR/Recall (Top Left), TNR/Specificity (Top Right), FPR/Type I Error, (Bottom Left) and FNR/Type II Error (Bottom Right) of Variational Quantum Classifier (VQC) Models for Individual Classes

At this point, the researchers conducted further experiments with VQC models to find which had the highest accuracy among all the developed models. Researchers calculated precision and F1-score for overall categories (Tables 4, 5, and 6), but they did not calculate those measures for individual cases. The researchers will calculate precision and F1-score for individual cases in the future paper to provide more a nuanced set of details about the VQC study. After calculating the accuracy of VQC models, the researchers created a table for comparing the accuracy for individual classes. Table 4 illustrates the accuracy values for all classes. The values in a red background are comparatively lower in their accuracy score while those in the green background are comparatively higher in their accuracy score. This accuracy comparison table (Table 4) is systematically designed to illustrate the best and worst possible models through numbers and visualizations in colors. For instance, the last three VQC models are comparatively greener in accuracy than all other models. The respective accuracy scores also show that the last three models in **Table 4** are better models in terms of accuracy than others. The top models (containing PauliFeature Map and Ansatz) shown in **Table 4**, and the models with the ADAM classifiers are found to be more ‘red’ with accurate values confirming that these models are worse in performance.

Table 4: Accuracy Comparison for Individual Classes

Encoder	Ansatz Depth	Optimizers	Accuracy		
			High	Medium	Low
PauliFeature Map (D=1)	1	ADAM	0.62	0.23	0.58
		COBYLA	0.77	0.41	0.57
		TNC	0.63	0.24	0.61
		SLSQP	0.66	0.28	0.58
	2	ADAM	0.62	0.24	0.54
		COBYLA	0.79	0.42	0.58
		TNC	0.72	0.33	0.56
		SLSQP	0.77	0.39	0.57
Z Feature Map (D=1)	1	ADAM	0.62	0.25	0.60
		COBYLA	0.84	0.51	0.58
		TNC	0.78	0.45	0.60
		SLSQP	0.86	0.49	0.59
	2	ADAM	0.63	0.25	0.58
		COBYLA	0.84	0.41	0.56
		TNC	0.83	0.48	0.60
		SLSQP	0.81	0.54	0.61
Z Feature Map, D=2	2	ADAM	0.58	0.26	0.57
		COBYLA	0.84	0.58	0.59
		TNC	0.79	0.47	0.62
		SLSQP	0.86	0.63	0.61

After analyzing the individual classes, the researchers further investigated the performance of overall classes for all twenty VQC models' applications. In calculating the performance metrics for all VQC models, the researchers treated individual classes, or categories equally important irrespective of problem-solving sample size of individual category. The overall model performance is calculated based on model accuracy, precision, recall, F1-Score, and specificity. **Table 5**, **6**, and **7** illustrate all model performance. The quantum circuits for all VQC models are in the **Appendix** section.

Based on all analysis shown in **Table 5, 6,** and **7**, it was found that VQC models with encoder depth 2 and ansatz depth 2 perform comparatively superior, except for one with the ADAM optimizer. In fact, any VQC models with the ADAM optimizers are found to be low performing models. It is also observed that the Z Feature Map comparatively performs better than the Pauli feature maps. As the data for this study is relatively simple, they may not require Pauli feature mapping, or the quantum entanglement phenomenon in this case. However, when the data gets more complicated, there might be a need for utilizing the quantum entanglement phenomenon. Overall, the VQC containing the Z Feature Map, although not showing outstanding overall performance, are comparatively better for encoding this simple dataset. Further analysis illustrates that the increment of ansatz or tunable parametric quantum circuit layers enhances the VQC performance. So, the better VQC requires more layers of ansatz. Similar observation is also found for encoder circuit depth. When the researchers increased the encoder circuit depth of the Z Feature map from 1 to 2, the overall performance improved, specifically when the COBYLA and the SLSQP optimizers were applied. The best model in this study was found to be the Z Feature map circuit, encoder depth 2, ansatz depth 2, and SLSQP optimizers. The model accuracy of this VQC is 0.55, precision 0.57, recall 0.59, F1-score 0.52, and specifically 0.79. **Table 7** demonstrates that a combined quantum circuit depth (l=4) with encoder depth 2, and ansatz depth 2 performs comparatively better than any other configurations, which is similar to the findings of the previous study.

Table 5: Comparative Performance Analysis of VQC Models (Encoder: Pauli Feature Map, Depth =1)

VQC Models			**Performance Metrics**				
Encoder	**Ansatz Depth**	**Optimizers**	***Accuracy***	***Precision***	***Recall***	***F1-score***	***Specificity***
Pauli Feature Map (Depth=1)	1	ADAM	0.21	0.07	0.33	0.12	0.67
		COBYLA	0.38	0.34	0.46	0.34	0.73
		TNC	0.24	0.41	0.36	0.16	0.68
		SLSQP	0.26	0.51	0.37	0.20	0.68
	2	ADAM	0.20	0.07	0.32	0.12	0.66
		COBYLA	0.40	0.59	0.49	0.39	0.74
		TNC	0.32	0.39	0.42	0.29	0.71
		SLSQP	0.37	0.57	0.44	0.37	0.72

Table 6: Comparative Performance Analysis of VQC Models (Encoder: Z Feature Map, Depth =1)

VQC Models			**Performance Metrics**				
Encoder	**Ansatz Depth**	**Optimizers**	***Accuracy***	***Precision***	***Recall***	***F1-score***	***Specificity***
Z Feature Map (Depth=1)	1	ADAM	0.22	0.27	0.32	0.18	0.67
		COBYLA	0.46	0.54	0.52	0.44	0.76
		TNC	0.41	0.58	0.50	0.40	0.75
		SLSQP	0.47	0.60	0.55	0.44	0.77
	2	ADAM	0.22	0.41	0.35	0.15	0.67
		COBYLA	0.40	0.49	0.49	0.38	0.74
		TNC	0.45	0.73	0.55	0.42	0.77
		SLSQP	0.47	0.59	0.56	0.46	0.77

Table 7: Comparative Performance Analysis of VQC Models (Encoder: Z Feature Map, Depth =2)

VQC Models			**Performance Metrics**				
Encoder	**Ansatz Depth**	**Optimizers**	***Accuracy***	***Precision***	***Recall***	***F1-score***	***Specificity***
Z Feature Map	2	ADAM	0.20	0.18	0.31	0.13	0.65
		COBYLA	0.51	0.53	0.54	0.48	0.77

(Depth=2)	TNC	0.44	0.58	0.49	0.45	0.75
	SLSQP	0.55	0.57	0.59	0.52	0.79

7. Conclusion

This study demonstrates that the VQC algorithms are implementable for the classification of the cognitive process associated with problem-solving activities. As this is an initial attempt to utilize the mathematical framework of quantum mechanics as an equivalent replacement for classical algorithms in the engineering education context, no customization with the quantum circuit was performed. Therefore, the algorithms developed with pre-defined quantum circuits by IBM (i.e., encoder, ansatz) are not performing as optimally as the classical one, a major limitation of using built-in circuits. Within this limitation, it is found that the Z features map (non-entangled quantum circuit) and predefined Ansatz (containing Ry and CNOT) with depth 2 for both cases performed superiorly in all classification cases. So, these findings state that the change of encoding technique results in study context also have the similar effect. Moreover, COBYLA, TNC and SLSQP, as found before, are better than ADAM optimizer. The AQGD optimizer was found to take more time than necessary for the comparatively simple calculation by the classifier. As a result, this AQGD optimizer is omitted from the analysis.

All the classifications performance across 20 VQC models were assessed based on five performance metrics, such as, accuracy, precision, recall, F1-score, and specificity. In almost all cases, SLSQP were able to optimize comparatively better in this study context regardless of the quantum circuit and their depth. Individually, the SLSQP classified High, Medium and Low cases with 0.86, 0.63 and 0.61 respectively. Its accuracy, precision, recall, F1-score, and specificity are also comparatively higher as shown in Table 7. TNC optimizers also showed better performance when the circuit depth was 3, where precision was 0.73, recall 0.55, and specificity 0.77 with accuracy and F1-score 0.45 and 0.42 respectively. This indicates that a lesser circuit depth with better design may also have chance to perform well and can reduce the calculation time and circuit implementation cost for larger computation. Finally, Pauli-Feature Map has shown low performance in this study as well as in the previous case, suggesting that the influence of data type in such computation. Simple data types may not require entanglement phenomena in data encoding processes.

8. Brief Discussion

From this study, it is found that variational quantum classifier (one architecture of quantum machine learning model) has potential to be useful for future quantum processing devices in engineering education context. The automatization of students' problem-solving process scoring is a ripe area that is ready for such work. Classical and quantum AI can assist in automatically observing students' cognitive efforts associated with problem-solving based on a instructors' chosen measures. However, the lack of current automatization should not prohibit educators from now combining human and machine judgment in assessing problem-solving performance. Moreover, there may be questions concerning the use of ordinal data (a subset of categorical data) in the classification problems in quantum computing settings. A previous study showed that VQC can be implemented for similar ordinal or categorical data (UCI car dataset). Therefore, this work adopted the machine and deep learning analytical approach of UCI car dataset and implemented appropriately with VQC as well, making the methodological pipeline developed for this study useful for similar future studies [32].

Even though this study focuses on exploring the VQCs for combining human and machine judgment to provide a futuristic quantum information processor-based solution, this study illustrates some mathematical insights as well. For example, the performance of classifiers is theoretically increasing when the number of quantum gates increases (whether it is encoder or ansatz). This performance improvement technique matches many popular neural network (NN) model-based AI systems, where the addition of layers increases the model performance on many occasions. Moreover, previous study supports these findings [6], [7]. Furthermore, many VQC or QML studies ignored the importance of using different optimizers which were major problems, as each optimizer had their own mathematical functions for optimization. Previous study conducted by Haque et. al. (2022) observed that problems and assess different optimizers performances for VQC cases [7]. Similar findings and consistent observations are also found in the analysis of this study.

This study is an initial investigation of using Quantum AI for engineering education and may encourage future engineering education researchers or communities to apply the existing quantum algorithms to develop new educational tools for NISQ, or future quantum devices, or build new QML algorithms for future use.

9. Limitations and Future Work

This study investigated the applicability of the VQC and found the best possible configurations within certain constraints (using existing quantum circuits). As this is an initial application of the VQC, the researchers only implemented the built-in encoders, and ansatz that may be found in IBM's Qiskit. Thus, researchers were limited in their exploration of multiple other variables within VQC configurations directed to better optimizations. Many customized encoders, ansatz, optimizers, or cost functions can be tested, and tuned to obtain a better VQC model. Moreover, the iterations to optimize the tunable parametric quantum unitary gates are limited to 100 and some optimizations may not be completed within this iteration range. Researchers will explore these configurations and iterations in their future work. Additionally, the researchers will run their optimized models on IBM's NISQ devices for analysis. Moreover, many previous studies found that verifiable or synthetic data were classifiable with 100% accuracy. However, real-life data also has its limitation found in the classical settings which contain noises, outliers, and many confounding factors result in lower performance than synthetic or verifiable dataset. The researchers also intend to work with multiple other real-life datasets, analyze and compare them in the future to observe the utility of VQC in engineering education settings. Additionally, the researchers will explore more mathematical grounding of the quantum framework to improve the QML models same as any seminal work on the classical algorithm design and development.

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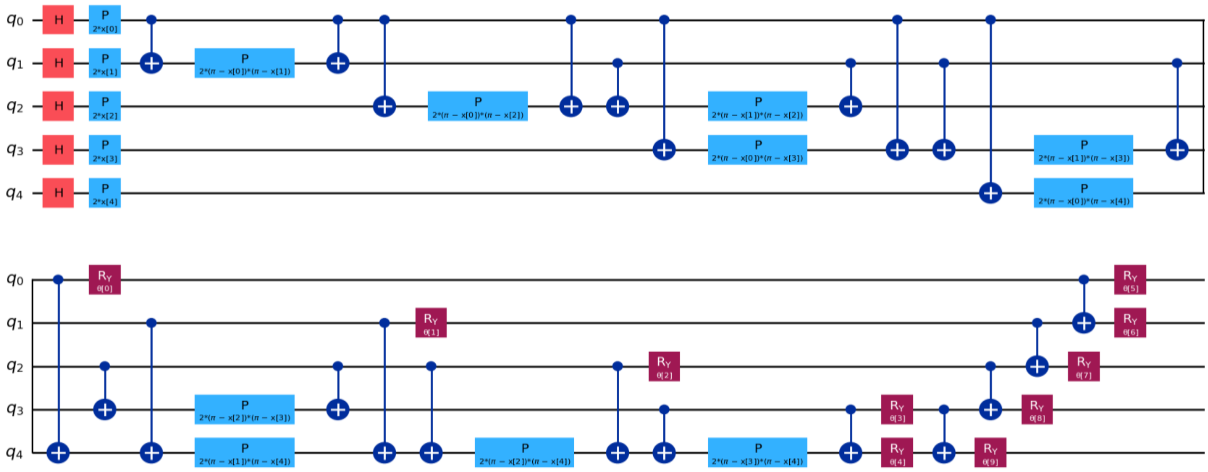
Appendix

MODIFIED RUBRIC FOR ENGINEERING PROBLEM-SOLVING

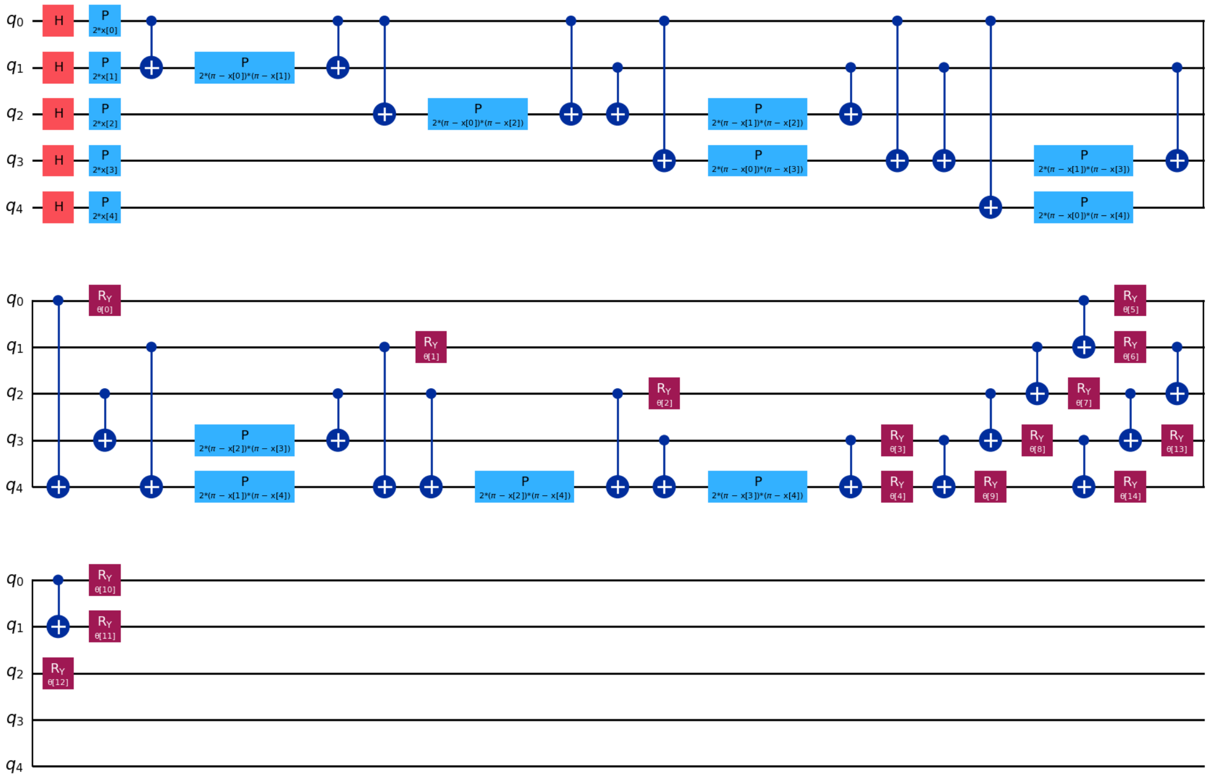
	5	4	3	2	1	0
USEFUL DESCRIPTION	The description is useful, appropriate, and complete.	The description is useful but contains minor omissions or errors.	Parts of the description are not useful, missing, and/or contain errors.	Most of the description is not useful, missing, and/or contains errors.	The entire description is not useful and/or contains errors.	The solution does not include a description and it is necessary for this problem /solver.
ENGINEEERING APPROACH	The engineering approach is appropriate and complete.	The engineering approach contains minor omissions or errors.	Some concepts and principles of the engineering approach are missing and/or inappropriate.	Most of the engineering approach is missing and/or inappropriate.	All of the chosen concepts and principles are inappropriate.	The solution does not indicate an approach, and it is necessary for this problem/ solver.
SPECIFIC APPLICATION OF ENGINEEERING	The specific application of engineering is appropriate and complete.	The specific application of engineering contains minor omissions or errors.	Parts of the specific application of engineering are missing and/or contain errors.	Most of the specific application of engineering is missing and/or contains errors.	The entire specific application is inappropriate and/or contains errors.	The solution does not indicate an application of engineering and it is necessary.
MATHEMATICAL PROCEDURES	The mathematical procedures are appropriate and complete.	Appropriate mathematical procedures are used with minor omissions or errors.	Parts of the mathematical procedures are missing and/or contain errors.	Most of the mathematical procedures are missing and/or contain errors.	All mathematical procedures are inappropriate and/or contain errors.	There is no evidence of mathematical procedures, and they are necessary.
LOGICAL PROGRESSION	The entire problem solution is clear, focused, and logically connected.	The solution is clear and focused with minor inconsistencies	Parts of the solution are unclear, unfocused, and/ or inconsistent.	Most of the solution parts are unclear, unfocused, and/ or inconsistent.	The entire solution is unclear, unfocused, and/ or inconsistent.	There is no evidence of logical progression, and it is necessary.

Implemented Quantum Circuits

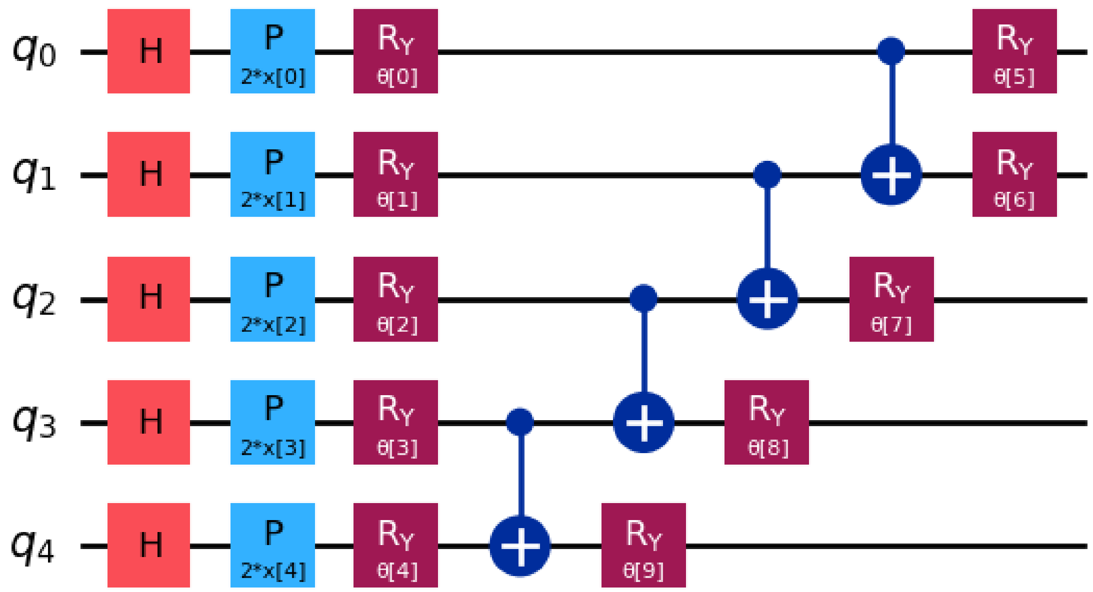
Pauli Feature Map (Depth=1) with Ansatz Depth 1



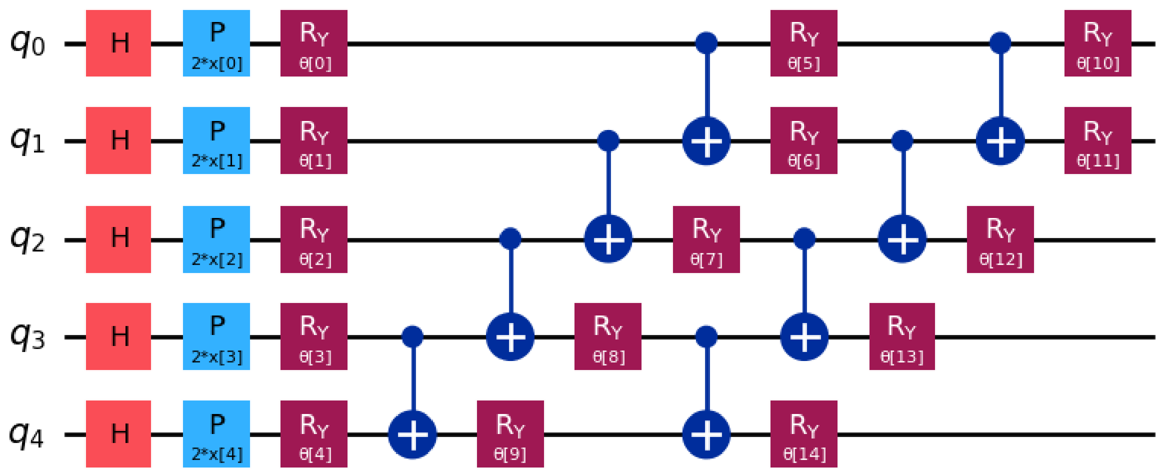
Pauli Feature Map (Depth=1) with Ansatz Depth 2



Z Feature Map (Depth=1) with Ansatz Depth 1



Z Feature Map (Depth=1) with Ansatz Depth 2



Z Feature Map (Depth=2) with Ansatz Depth 2