



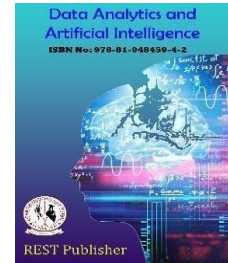
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Machine Learning Based Prediction of Computation Efficiency in Quantum Computing: An SVM and Random Forest Comparative Study

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Abstract: Introduction: Quantum computing is one of the most advanced technologies which surpasses other conventional approaches in solving complex computations. Evaluation of the system based on the Qubit Count, Gate Fidelity, Decoherence Time, and Computation Efficiency is important. Machine learning algorithms have been used effectively to model these variables. In this research, the importance of computation efficiency modeling within the context of quantum computing is emphasized. Besides, this research has shown some important considerations that influence the performance of the system. Moreover, it has demonstrated the possible application of machine learning algorithms in improving this variable. Support Vector Regression and Random Forest regression models were used in this study to examine the relationship between computation efficiency and other parameters of quantum computing. The performances of the models were evaluated statistically. From the results obtained, the Support Vector Regression model was much more effective than the Random Forest regression model. This is because it provided accurate predictions with negligible prediction errors. This study underscores the usefulness of Support Vector Regression in predicting computation efficiency within the context of quantum computing.

Keywords: Quantum Computing, Support Vector Regression, Computation Efficiency

1. INTRODUCTION

The application of quantum computation marks a breakthrough for the field of computer technology because it has managed to solve the limitations in computing machinery [1]. In contrast to the conventional computers that employ bits as their basic building blocks, quantum computers utilize quantum bits. Thanks to superposition, the qubits can exist in various states simultaneously [2]. As a result of superposition, quantum computing machines are empowered to manipulate an extensive amount of data in parallel. The result of such operations is the increased computational capacity that allows quantum computing machines to solve complex problems, which are impossible for classical computers [3]. Superposition provides additional computing power to quantum computing machines by letting qubits exist in several states at once [4]. Entanglement is another important idea that implies a relationship between qubits; therefore, whatever happens to one of them will affect another irrespective of distance between them. In other words, entanglement helps perform synchronized computations on quantum computers [5]. Finally, quantum interference improves computing accuracy by discarding wrong calculation paths and supporting the right ones. [6] In order to implement these principles into practical applications, cutting-edge quantum computing technologies are being introduced [7]. The quantum processor, the quantum annealer, and the gate-based quantum computer are among the quantum computing technologies that have been created. Quantum processors, which are manufactured by the world's best technology corporations, are meant to execute tasks utilizing quantum bits and quantum gates [8]. On the other hand, quantum annealing computers are meant to solve optimization issues by locating the ground state of the system. Gate-based quantum computers are highly adaptable and can execute various quantum algorithms [9]. The most exciting thing about quantum computing is that it can transform many different sectors [10]. In cryptography, quantum

computers have the ability to solve common encryption protocols like RSA and ECC by finding integer factorization and discrete logarithms [11]. Quantum computing has therefore been used to develop quantum-safe cryptography for the protection of data in the future [12]. Also, quantum computing can be used to solve optimization problems in several industries, including logistics, transportation network flow, and finance [13]. Another challenge posed by quantum computing technology relates to the sensitivity of the quantum state, which is highly sensitive to any changes in the environment, including temperature and electromagnetic radiation [14]. This makes the stabilization of qubits among the biggest challenges for researchers at present [15]. Quantum computing has led to the advent of NISQ technologies that can conduct quantum computations to a certain extent [16]. These machines are not yet powerful enough to be able to challenge supercomputers when it comes to handling computational processes [17]. Nonetheless, they provide a good platform for researchers who will use quantum computing in the future to test their algorithms. Scientists are trying to find ways to integrate classical and quantum computers into a unified system [18]. As a result, quantum computers can potentially revolutionize the way we approach problem-solving by taking advantage of quantum mechanics [19].

2. MATERIALS AND METHOD

Qubit Count: The sum of quantum bits applied in a quantum processor is referred to as qubit count. Contrary to classical bits, quantum bits have a lot of differences since they can take various states because of quantum superposition. The higher the amount of qubit count is, the more capabilities a quantum computer possesses, allowing for its exponential growth. For example, quantum computers can easily solve optimization, cryptanalysis, and molecule simulation problems. Nonetheless, the existence of many qubits is not enough for quantum computing; they need to be reliable. At present, researchers strive to achieve maximum qubit count without compromising their reliability.

Gate Fidelity: Gate fidelity is the metric showing the level of quantum gate accuracy during quantum calculations with qubits. Quantum gates, just like classical logic gates, are regarded as the basic components of quantum processors that perform quantum calculations. Gate fidelity means that there is minimal interference in the work of quantum gates, which leads to reliable quantum computations. Because of the delicate nature of quantum computers that are highly sensitive to any form of disturbance, high gate fidelity is needed for receiving accurate results. Any slight difference from the usual process may have negative impacts on the functioning of the quantum computer.

Decoherence Time: Decoherence time can be defined as the time during which information from a quantum bit or qubit is lost due to interaction with the environment surrounding it. Decoherence time is a significant term since it determines the level of quantum computing that can be achieved. Quantum computations can even be performed for complex processes without loss of any information if there is sufficient decoherence time. The challenge in handling quantum bits is their sensitivity to the environment; even minimal disturbances like temperature fluctuations and magnetic radiations can lead to the loss of information stored by quantum bits.

Computational Power of Quantum Computer: A quantum computer with high computational power can perform complex calculations much faster than a traditional computer. Usually, those problems which deal with huge amounts of data or have combinatorial complexity are deemed to be computationally difficult. A number of factors determine the amount of computational power of a quantum computer. These factors include the number of qubits being used, the accuracy of gates operation, coherence time, and efficient quantum algorithms. Due to noise and other issues, it becomes difficult to get high computational power from a quantum computer.

3. MACHINE LEARNING ALGORITHMS

Random Forest Regression: Random Forest Regression is a common machine learning algorithm that helps to determine the value of the dependent variable based on the set of decision trees [20]. The key aim of Random Forest Regression is to generate a significant amount of decision trees and find the average value of their predictions [21]. In contrast to common decision trees, Random Forest Regression prevents overfitting because it uses different subsets of data to build the model. It means that every decision tree uses different samples and features, which allows for achieving better diversity and efficiency of the model. Moreover, Random Forest Regression is a good technique since it works effectively even in cases of working with complicated problems based on large amounts of data with non-linear relations between the features. However, such technique needs considerable resources for functioning properly, and the results may not be easily interpreted [22].

Support Vector Regression: Support Vector Regression is an application of the support vector machine that belongs to the supervised learning techniques used in machine learning [23]. In essence, the SVR technique is used in regression problems where the model tries to learn the underlying pattern by fitting the model using an epsilon band. The SVR algorithm transforms the data using the kernel trick into a higher dimensional space to discover the nonlinear relationship between data points [24]. Kernel functions such as linear, polynomial, and radial basis function kernels have been widely used in support vector regression to map non-linear relations between points. SVR algorithm is suitable for a smaller sample size and can effectively handle data whose variables do not show a linear relationship. Generalization is another significant advantage of this algorithm, but choosing optimal kernel parameters can be difficult [25].

4. RESULT AND DISCUSSION

TABLE 1. Descriptive Statistics

	Qubit_Count	Gate_Fidelity	Decoherence_Time	Computation_Efficiency
count	250.0000	250.0000	250.0000	250.0000
mean	5139.8280	0.9210	74.3920	71.0249
std	2803.1234	0.0416	26.1586	11.0897
min	72.0000	0.8510	30.0000	45.0936
0.2500	2712.0000	0.8873	52.0000	63.6756
0.5000	5416.0000	0.9260	76.0000	72.5524
0.7500	7414.0000	0.9558	95.7500	79.2079
max	9994.0000	0.9890	119.0000	94.2796

Table 1 presents that, the mean number of qubits is around 5,139, which covers a large spectrum of values from 72 to 9,994. It shows great variation in the size of computers. In terms of gate fidelity, the mean value is 0.921, indicating little variation. From the perspective of quantum computations, it means that the computers work in a reliable way. The mean decoherence time is around 74, and the value shows moderate variation. It means that some quantum computers can maintain their quantum state for more extended periods than others.

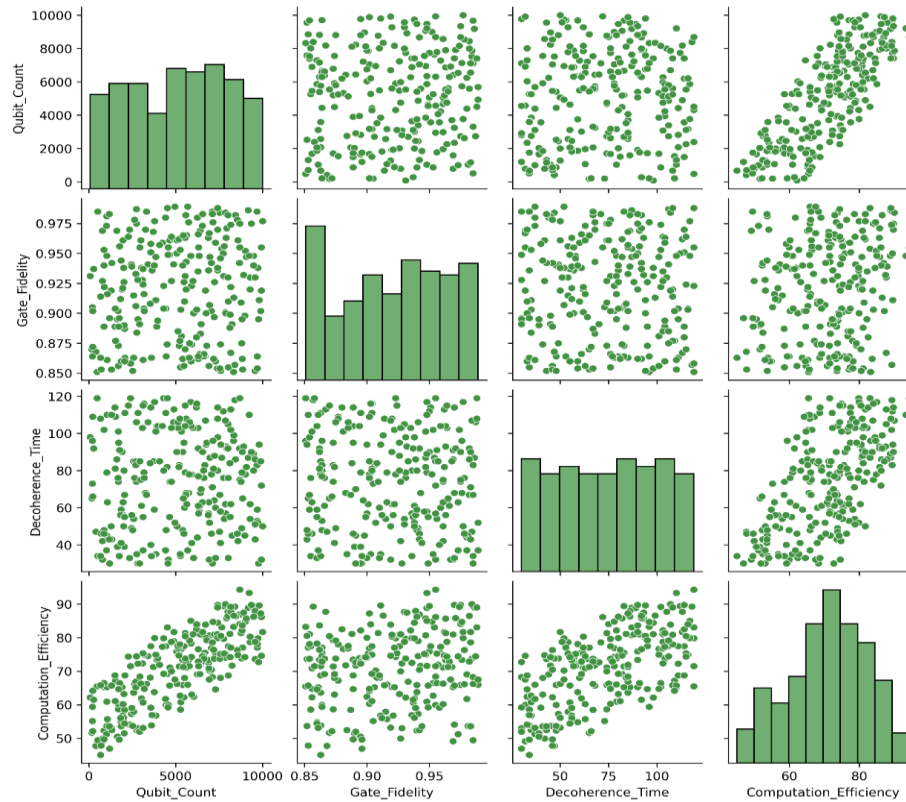


FIGURE 1. Correlation and Distribution of the Number of Qubits, Gate Fidelity, Decoherence Time, and Computation Power

Figure 1 shows the correlations and distributions of the number of qubits, gate fidelity, decoherence time, and computation power; these are the four most important components in quantum computing. Histograms that appear on the diagonal indicate how the distributions of each component are distributed individually. From Figure 1, we observe that the distributions of qubits and decoherence time are broadly distributed. On the other hand, the gate fidelity is narrowly distributed. This indicates that the gate fidelities are consistent throughout. Scatter diagrams reveal how these variables correlate with each other.

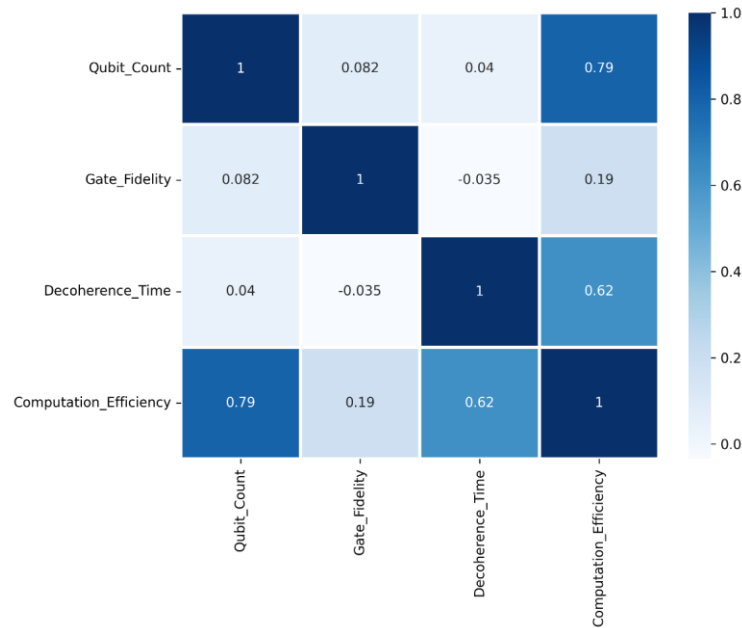


FIGURE 2. Correlation Matrix for Number of Qubits, Gate Fidelity, Decoherence Time, and Computation Efficiency

Figure 2 below is a correlation matrix showing the correlations between the variables under analysis. The study shows that there exists a positive correlation between Qubit Count and Computation Efficiency with a coefficient value of 0.79. It shows that systems having more qubits have high computational efficiency. Moreover, Decoherence Time has a positive correlation with Computation Efficiency having a coefficient value of 0.62. It indicates that decoherence time influences computation efficiency to a great extent. Gate Fidelity and Computation Efficiency have a low positive correlation value of 0.19.

Random Forest Regression

Predicted vs Actual Computation_Efficiency(Training data)

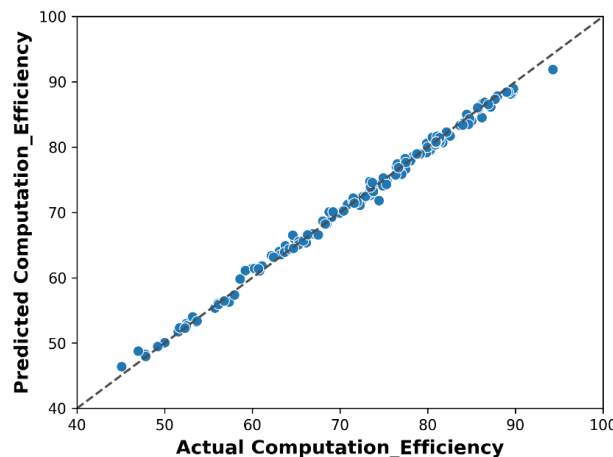


FIGURE 3. Prediction vs. Actual Values for Computational Proficiency from the Training Set

From the above figure 3, it becomes evident how the actual and predicted values of computational proficiency vary in the training set. It is clear from the above graph that most of the points lie on the straight line, which means that there exists perfect accuracy in the predictions. This signifies that the model has successfully learned the underlying patterns of the data and has the potential to make predictions with higher precision. Another prominent aspect illustrated by the above graph is the presence of no outlier.

Predicted vs Actual Computation_Efficiency(Testing data)

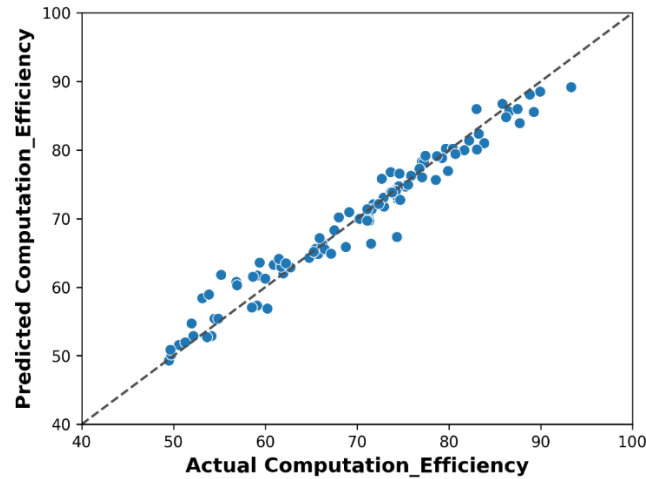


FIGURE 4. A illustrating the comparison between the predicted and actual values of computational efficiency for the test dataset.

Figure 4 indicates that the algorithm has learned from its experience, retained its predictive capabilities, and is now performing exceptionally well on the test set as well. From the above graph, it can be seen that the data points have clustered themselves very close to the reference line, which shows that there are correct predictions made. The above figure shows the graph where the predicted and actual value of computational efficiency of the testing dataset is shown. Even though the dispersion is slightly higher compared to the training data, but still it is minimal.

Support Vector Regression

Predicted vs Actual Computation_Efficiency(Training data)

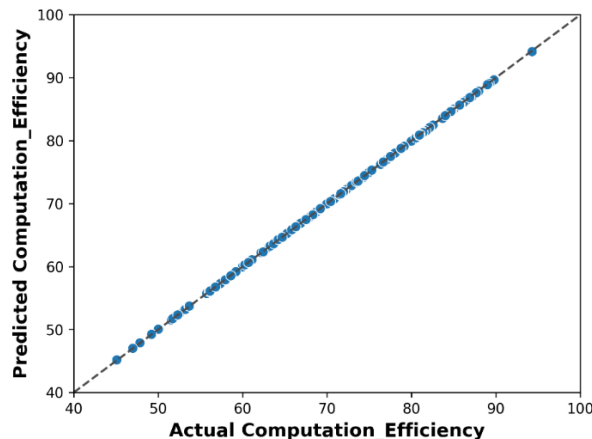


FIGURE 5. Predicted and Observed Values of Computational Efficiency (Training Set) – Best Performance Model

Figure 5 Shows that, there is near-perfect correspondence between the predicted and observed values of computational efficiency within the training data set. As such, it clearly suggests that the model has performed extremely well in predicting computational efficiency, given its input parameters, and the trend is well captured by it. There is no

dispersion among the values depicted in the graph, suggesting that the accuracy of the predictions was exceptionally high for all data points.

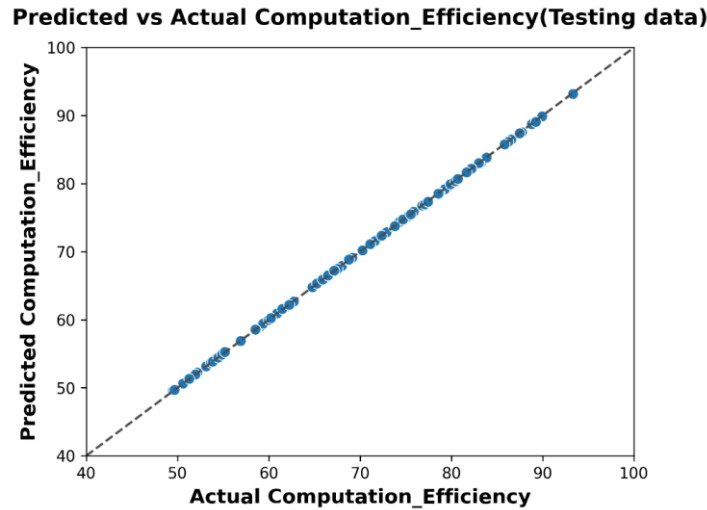


FIGURE 6. Comparison between Predicted and Real Computation Efficiency Values of SVM Regression Model on Test Data Set.

Figure 6 presents the performance of the SVM regression model in predicting the values of computation efficiency in the test data set. The close fit of the points to the straight line means that the SVM regression model is highly accurate in estimating the values of computation efficiency throughout the range of the variable from about 49 to 93. This graph displays the correlation between the real values of computation efficiency (on the x-axis) and the estimated values (on the y-axis). The x-axis and y-axis values range from 40 to 100.

TABLE 2. Model Performance Comparison on Training Dataset

Data	Symbol	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	RFR	0.995609	0.995611	0.553578	0.744028	0.573228	2.609256	0.000114	0.446465
Train	SVR	0.999984	0.999984	0.002061	0.045395	0.036883	0.100399	4.42E-07	0.031602

The performance indicators of the training phase are adopted to measure the performances of the RFR model and SVR using different measures of assessment. The predictive capability can be observed in both models, although it is significantly higher in the SVR model. As far as accuracy goes, the R^2 score for RFR is around 0.9956, while for SVR, this figure becomes a near-perfect 0.999984, which indicates better modeling and fitting capabilities. Regarding the error measures, the MSE value of RFR is approximately 0.5536, whereas its RMSE value is 0.7440. However, for SVR, the MSE value is extremely low, at 0.0021, and so is its RMSE value at 0.0454.

TABLE 3. Model Performance Comparison on Testing Dataset

Data	Symbol	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Test	RFR	0.959389	0.959394	4.655567	2.157676	1.589143	6.986334	0.001039	1.131735
Test	SVR	0.999978	0.999978	0.002508	0.050081	0.039864	0.145531	5.28E-07	0.031856

These results offer us a perfect comparison between the abilities of generalization of Random Forest Regression (RFR) and Support Vector Regression (SVR) models. Indeed, RFR provides us with good prediction results, but the R^2 is high only – equal to 0.9594, and EVS equals 0.9594 as well, which means that the variance is quite well covered by the model. Still, the error measures are rather large – 4.6556 for MSE, 2.1577 for RMSE, and 1.5891 for MAE. On the contrary, SVR provides us with an excellent prediction power due to its R^2 and EVS equal to 0.999978. It should be noted that the prediction measures are close to 1; hence, we may conclude that the model has good ability to generalize the information. The error measures are extremely low, namely, MSE equals 0.0025, RMSE is equal to 0.0501, and MAE is 0.0399.

5. CONCLUSION

The prediction of Computation Efficiency level in this study has been considered in a broader context using the regression support vector machine (SVM). The objective of the research was to develop an efficient model for predicting Computation Efficiency level. The entire process was carried out using the machine learning approach that entailed the training, validation, and testing stages. These processes involved data pre-processing, feature selection, model development, and evaluation of the developed model. Based on the results of this study, the efficiency of the regression model was very high since there was a very high correlation between the predicted and actual Computation Efficiency levels. As illustrated in the Predicted vs. Actual graph, it was observed that the outputs of the model followed a close path to the reference line. Deviation in prediction was insignificant, there was no bias, and generalization capabilities were strong. Therefore, it can be concluded that the regression SVM model is effective enough and can solve the discussed problem. The model had consistency across all ranges of Computation Efficiency and was, therefore, stable and robust.

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