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A Hybrid Quantum Machine Learning Model for Optimal Quantum Error Correction in Surface Codes

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ABSTRACT

Surface code is an important class of topological quantum error correction codes that utilizes geometrical properties of stabilizers to detect and correct quantum errors by measuring the error syndromes. Though surface code is an effective strategy for fault-tolerant quantum computing, the fragile nature of qubits and noisy gate operations reduces the reliability of syndrome measurement. Various machine learning algorithms and their quantum counterparts have recently exhibited phenomenal superiority in quantum error correction tasks. In this research study, we have proposed a hybrid machine learning approach consisting of the Quantum Approximation Optimization Algorithm (QAOA) and Quantum Neural Networks (QNN) to enhance the effectiveness of the syndrome decoding in surface codes. The performance of the proposed hybrid machine learning model is compared with existing surface code decoding methods *viz.* Neural Networks (NN) and Coevolutionary Neural Networks (CNN) for code distance of $D_1 = (3,5,7)$ and $D_2 = (5,7,9)$ which shows that the hybrid approach achieves a higher threshold of 0.176 and 0.178, respectively. This superiority of the hybrid quantum machine learning model in decoding syndrome for surface codes will be pivotal in the development of a practical, scalable, and robust quantum error correction framework.

Keywords: Quantum error correction codes, hybrid quantum machine learning model, surface code, syndrome measurement, quantum approximate optimization, quantum neural networks.

1. 1. INTRODUCTION

Quantum computing is a paradigm shift in the information science landscape that offers unbounded and unparalleled computational powers. The success of such a phenomenal computational approach primarily depends upon the feat of quantum error correction (QEC) [1] to protect the information (quantum state). The errors appearing in the quantum systems are inherently different from their classical counterparts and their copying and simultaneous measurement are impossible. This issue can be overcome by developing effective quantum error-correcting codes by suppressing several physical qubits into a single logical qubit by introducing redundant (ancilla) qubits and decoding them to extract the original information and errors through syndrome measurement [2]. This is typically accomplished by encoding a single logical qubit with numerous physical qubits to minimize error-proneness while retaining the ability to manipulate and measure the logical qubit [1,2]. Such QEC codes allow the execution of quantum calculations in a noisy environment with errors below a limit set by the "quantum error threshold theorem".

Surface code is a topological code that utilizes global geometrical properties of error-correcting stabilizers for quantum error mitigation by encoding physical qubits into logical qubits and decoding by measuring the syndrome with ancilla without disturbing the original quantum state (information) [3]. Apart from physical errors, the logical qubits may also be exposed to errors, if not processed carefully, and such an error is known as a logical error. Regretfully, qubits are exceptionally sensitive to their environment, and their data may be lost due to decoherence or collapse of the quantum state during syndrome measurement [3,4]. The errors may also propagate among the encoded faulty physical qubits through qubit crosstalk and decoherence. Therefore, optimal decoding to keep the physical-to-logical error ratio minimum is also challenging in the surface codes [5,6]. Various decoders and approximation schemes have been developed to overcome the issues, but none is a flawless tool [7,8,9].

Various artificial intelligence (AI) approaches have recently been explored to decode the surface codes, yielding a promising result in overcoming the syndrome measurement issue in surface codes [9,10]. Such machine learning (ML) approaches convert the syndrome detection problem into a classification problem where various traditional methods, such as neural networks (NN) and convolution neural networks (CNN), are available for effective delivery [11]. A hybrid classical-quantum algorithm known as the quantum approximate optimization algorithm (QAOA) is also an effective tool to solve combinatorial optimization problems on noisy intermediate-scale quantum computers [12]. QAOA has the ability to find the approximate solutions by minimizing the cost function, while QNN trains the system by using multiple layers of stochastic gradient descent, leveraging the principles of quantum mechanics for potential speedups. Therefore, QAOA and QNN hold complementary properties in the machine learning domain, which can be explored collectively for quantum speed-up of a system involving a complex Hamiltonian.

This research aims to develop a hybrid machine learning model by leveraging the complementary powers of QAOA and QNN to enhance the accuracy, scalability, and efficiency in syndrome decoding for robust quantum error correction. The QAOA module in the model will optimize the task by fine-tuning the parameters while the QNN module learns the system from past data for effective syndrome decoding without undergoing the complex intricacies of ansatz in surface codes. In the rest of this paper, section 2 carried out a systematic review of the most recent literature in the regime of machine learning for the syndrome decoding task. This section will present an account of the existing research gap in the literature as motivation for the present study. Section 3 will present the research methodology adopted in this paper and the terms required for a proper understanding of the subject matter. Section 4 will implement the proposed model with an analytical discussion on the implementation results. Finally, section 5 will conclude the paper with meaningful inferences and present an account of the future direction of research in this regime.

2. LITERATURE REVIEW

This section reviews the academic and scholastic literature on the state-of-the-art methods and approaches in the domain of syndrome decoding through machine learning approaches. M. Swathi and B. Rudra developed a reproducible and asymmetric approach for identifying and mitigating phase-flip and bit error correction. Fixing the issue using this method was simple by applying the same error again. The suggested procedure is effective in overcoming the decoherence and noise surmounted due to entanglement [13]. A. Li *et al.* used a CNN with a hexagonal code to determine the decoding threshold. However, their decoder enhances the performance while performing poorly in terms of latency and resource utilization [14]. The work of D. Bhoumik *et al.* provided an ML decoder for surface codes, which can rectify the depolarizing noise in symmetric and asymmetric minimum train-test [15]. M. Sheth *et al.* combined the arbitrary decoders to lower the rates of logical errors [16] drastically. R.W.J. Overwater *et al.* explored fully connected NN decoders for short-range surface codes. The research aims to achieve competitive decoding performance while minimizing the neural network's complexity. The model works well for large data sizes while exhibiting overfitting for small data sizes [17]. B. Debasmita *et al.* introduced an ML decoder for topological code that enhances decoding performance by utilizing a revolutionary gauge equivalency-based method. The physical error probability serves as the pseudo-threshold for a QEC code [18]. Research by C. Kim *et al.* is more relevant to NISQ era requirements. They have developed ML-based quantum error mitigation techniques to reduce the errors without the requirement of comprehensive error characterization [19]. Savvas Varsamopoulos *et al.* applied a distributed Neural Network (d-NN) to solve the issues that occur in the surface codes. They proved that all NN-based decoders struggle for scalability because of the exponential rise in training samples for effective decoding [11]. H. Wang *et al.* developed an efficient decoder that operates adequately to prevent data-squeezing issues in NN-based decoders [20]. Smith et al. explored the power of QAOA for surface code correction for NISQ devices. However, this research effectively optimizes the bit-flip and phase-flip errors arising in the quantum circuit but faces the difficulty of overestimation and poor latency during the training phase [21].

However, various researchers found initial success in dealing with the surface codes with ML-based methods, but many have still faced challenges. The research by N. Delfosse *et al.* expressed problems in coping with the intricacy of longer distances by the neural decoder. The work of Patra *et al.* highlighted limitations of the convolution-based method in the effective representation of error syndrome associated with the specified topological code [22]. The primary constraint on pairwise readout is the fact that the two-qubit subspace can only yield a single bit of information. Three methods to get over this restriction and take advantage of the extra ancilla qubit are provided below. This can guarantee that no single circuit error event can cause errors that shorten the surface code's code distance [23].

The above literature review reveals that a plethora of research studies have explored the applicability of ML-based methods for effective handling of surface code, which have produced both promising and challenging outcomes. However, hardly any study has explored leveraging the complementary properties of QAOA and QNN for effective syndrome decoding in surface codes. This research gap motivates us to conduct the present research study.

3. RESEARCH METHODOLOGY

The primary goal of this work is to improve the QEC decoding performance for surface code by leveraging the mutual strengths and complementary benefits of the proposed hybrid QAOA-QNN decoder to meet the error threshold. The input is assigned as data qubits and additional redundant information is assigned as ancilla qubits initialized through the quantum states. The surface code encodes the information in the quantum state using the topological properties of stabilizers. The encoded data may get corrected while being transmitted over a noisy channel. The stabilizer generates a syndrome vector to determine the exact location and frequency of an error in the encoded state. The most expensive process is detecting and correcting such errors during encoding. Several detectors, including ML approaches, that have nearly ideal error correction rates have been presented in the literature. The QNN classifier is trained to predict the optimal parameter for decoding syndrome that can effectively optimize accuracy, computational speed, and scalability. This method enhances decoding performance for quantum error correction by combining the flexibility and efficiency associated with classical neural networks with the optimization characteristics of QAOA.

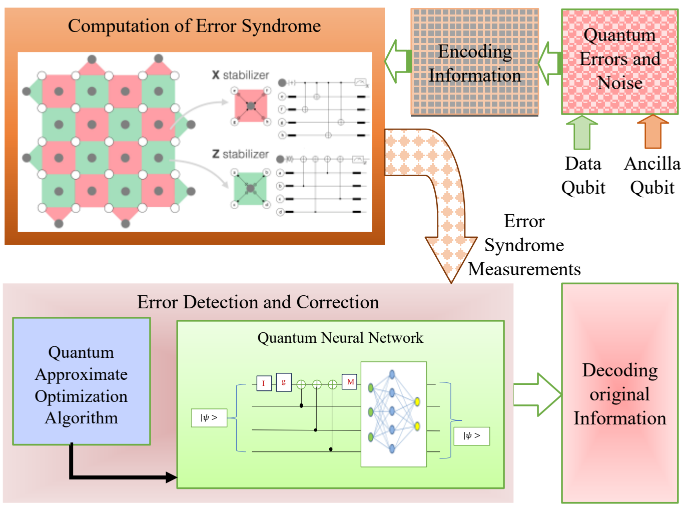

Figure 1: Proposed Methodology for Hybrid QAOA-QNN

The schematic representation of the methodology used in this study is illustrated in Figure 1, envisaging the complicated interplay of the proposed model for more robust and accurate quantum error correction.

A crucial first step toward the development of syndrome decoding of quantum computing is the emergence of QEC codes. Since surface codes can be easily expressed in local stabilizer formalism and are relatively easy to analyze, to convert 'l' logical qubits into 'k' physical qubits in a 2^l-dimensional Hilbert space ($\mathcal{H}_C$) created by placing actual qubits on the edges of the lattice. In simple terms, only a certain number of qubits are influenced by each stabilizer generator of a surface code, which is not easy to decode because the syndrome only reveals the boundaries of surface error sequences. The data and ancilla qubits are initialized in quantum states to rectify errors. The computation would be ruined if qubits are measured during the process because measurement collapses the superposition states. To avoid such unwanted situations, redundant qubits are introduced as ancilla qubits or collaborator qubits. An operator is applied to detect such qubits through a parity check known as a syndrome measurement. For instance, when operators were anti-commute, an ancilla qubit with Z-ancilla qubit would be able to detect a Y-error on a data qubit, whereas a Y-ancilla qubit will detect Z-errors.

3.1. Encoding

Several physical qubits are suppressed into a logical qubit during the encoding phase. Repetition codes utilize more than two qubits and the majority value produced from the parity check is taken as a logical qubit such as $|0\rangle_{\mathrm{Lq}} = |0\rangle \otimes |0\rangle \otimes |0\rangle = |000\rangle$ where the logical qubit $|000\rangle$ is obtained by encoding three physical qubits and $|0\rangle_{\mathrm{Lq}}$. The value of the logical qubit will remain unchanged if one of the physical qubits undergoes a bit-flip as $Z_3|0\rangle_{\mathrm{Lq}} = |001\rangle$. It can be evaluated as a logical $|0\rangle$-qubit in the computation, as most of the physical qubits are still error-free. However, if most of the physical qubits underwent the flips $Z_{2,3}|0\rangle_{\mathrm{Lq}} = |011\rangle$ will result in a 'logical error'.

3.2. Quantum Channel

The encoder maps the input data to the quantum channel, which will pass on the output as a mixed state of 'n' qubits through the decoder. A quantum channel for quantum systems 'C' and 'D' underlying the Hilbert spaces '$\mathcal{H}_C$' and '$\mathcal{H}_D$' respectively with linear operators $\mathcal{B}(\mathcal{H}_C)$ and $\mathcal{B}(\mathcal{H}_D)$ will impart a linear, fully trace-preserving map $\Gamma: C \to D$. The condition $\varphi_C = |\varphi\rangle\langle\varphi|_C$ will generate a pure quantum state φ_C with a unit rank which can be described with a normalized vector $|\varphi\rangle_C \in \mathcal{H}_C$. The ideal rate of accurate quantum information transmission via the quantum channel can be characterized by the capacity $Q(\Gamma)$ channel map, $\Gamma: C \to D$. Regarding the operational problem of entanglement creation $Q(\Gamma)$. The inner code 'φ_{RC}' influences the rate of entanglement over the channel.

3.3. Syndrome Measurement by Stabilizer Surface Code

In surface codes, facets serve as stabilizers while the vertices contain the data qubits encoded into a significantly wider Hilbert space in a QEC stabilizer protocol. Various values of observables coupled with operators called stabilizers are used to mark distinct sectors of this enormous Hilbert space. A logical qubit in the surface code is created by joining physical qubits using CNOT gates. Hence, it performs significantly better than the physical qubit. Error-correcting code can be applied repeatedly to remedy single-qubit errors. For instance, an incorrect 'Y'-error can only be impacted by a Z-measurement and cannot be fixed by 'Y' itself. Table 1 shows the lists of four eigenstates along with the corresponding eigenvalues determined by $\widehat{Y_a}\widehat{Y_b}$ and $\widehat{Z_a}\widehat{Z_b}$ transactions through Bell states. If $\widehat{Z_a}$ error is applied to the state $|00\rangle + |11\rangle$ with eigenvalues $(+1, -1)$ the state changes to $|10\rangle + |01\rangle$ with eigenvalues $(-1, +1)$. It is evident that the same ultimate state would also result from a $\widehat{Z_b}$ error. $\widehat{Y_a}$ and $\widehat{Y_b}$ errors also have the same ultimate state. The stabilizers maintaining the quantum states are crucial for error-correcting codes.

Table 1: Eigenstates with Corresponding Eigenvalues Associated with Stabilizers

$\widehat{Y_a}\widehat{Y_b}$	$\widehat{Z_a}\widehat{Z_b}$	$\lvert\psi\rangle$
+1	+1	$(\lvert 00\rangle + \lvert 11\rangle)/\sqrt{2}$
+1	−1	$(\lvert 00\rangle - \lvert 11\rangle)/\sqrt{2}$
−1	+1	$(\lvert 01\rangle + \lvert 10\rangle)/\sqrt{2}$
−1	−1	$(\lvert 01\rangle - \lvert 10\rangle)/\sqrt{2}$

3.4. Syndrome Measurement by Stabilizer Surface Code

In surface codes, the data qubits are arranged in a 2-dimensional grid protected by stabilizer operations on X- and Z-type plaquettes. The syndrome is measured through ancilla qubits without disturbing the data qubit to locate the quantum error. A typical quantum for 'Y' and 'Z' stabilizer measurement, realized through Hadamard (H), CNOT (X), and S (Sdg) gates in Qiskit, is depicted in Figure 2. The topological arrangement of data and ancilla qubits in an X-type stabilizer is shown in Figure 3, with data qubits displayed as green and ancilla qubits as blue in the surface code grid.

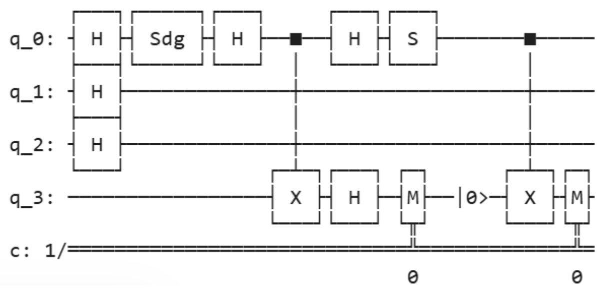

Figure 2: Circuit for 'Y' and 'Z' Stabilizer Measurement

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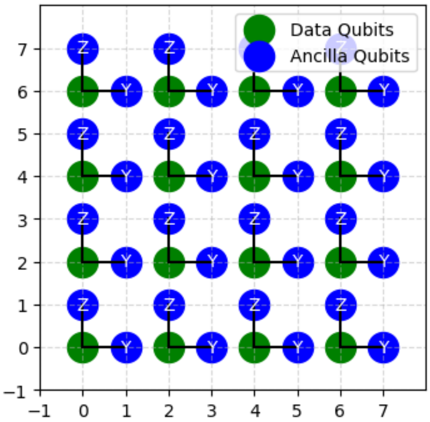

Figure 3: Circuit for measuring Z-type stabilizer

3.5. ML-based Methods for Error Syndrome Decoding

To decode an observed syndrome appearing in the underlying data, the qubit error (E) steps are taken to identify any erroneous configuration that restores the condition to the original code space without resulting in a logical error. The ML approach firstly defines a decoding problem as a machine learning classification problem by splitting the error (E) into the multi-qubit Pauli operators as $E = S.C.L$ where $'S'$ is a stabilizer, $'C'$ is a unique Pauli operator, and $'L'$ is a logical Pauli operator. Each input in a classification problem has a low-dimensional label, while the inputs are typically high-dimensional. Since uncontaminated errors can be easily discovered in feed-forward neural networks (NN) while $'L'$ having four values *i.e.* $\vec{I}, \vec{X}, \vec{Y}, or\ \vec{Z}$ can be labelled by assigning a minimum cost function having an average cross-entropy of the established cost function as$\langle H(p,y)\rangle\alpha - \sum_{(\vec{p},\vec{x})\in T} \vec{p}.ln(\vec{y}(\vec{x}))$; where $'T'$ is the training set made-up of input values $'\vec{x}'$ and desired distributions $'\vec{p}'$. The stochastic gradient descent to minimize this function can be implemented using TensorFlow. The training set can be produced by direct sampling, having a single physical error probability. This physical error probability is selected to allow for the production of a wide range of error syndromes while maintaining the possibility of rectification. For larger codes, the size of the training set should not more than more than 10^6 samples, while sampling of any range is feasible for smaller surface codes. The weighted output of QNN can be obtained as $\vec{y} = \sigma(\widehat{W_0}\sigma(\widehat{W_h}\vec{x} + \overrightarrow{b_h}) + \overrightarrow{b_0}$, where $\sigma(\vec{w}.\vec{x} + \vec{b})$ is the output produced by individual neurons, $\vec{w}$ represents the weights, $\vec{b}$ represents a bias of a local set and $\sigma(x) = (1 + \exp(x))^{-1}$ represents a non-linear activation function. By assembling the parameters of weights and biases into vector graphics, respectively. The QNN output is fed to the QAOA algorithm to enhance the performance of the error-correcting decoding syndrome.

4. PROPOSED HYBRID MACHINE LEARNING MODEL FOR QEC

The QNN classifier effectively detects errors by locating errors and determining their frequency of occurrence. This information is taken as a syndrome vector input that can emerge through the optimistic QAOA. The QAOA method fine-tunes the classifier parameters through successive iterations by adapting the parameters to enhance the accuracy, scalability, and syndrome decoding efficiency. The mechanism for the optimization seems to be an optimal solution, whose distance from the global optimum to the value of the returned solution can be verified using an objective function $Q: \{0,1\}^s \to \mathbb{R}$ that needs to be optimized. $'i^*'$ is the solution achieved by the approximation algorithm such that $\frac{Q(i^*)}{Q_{max}} \geq \in^*$ where $' \in^* '$ is the approximation ratio of the maximum value of the optimization function (Q_{max}). The QAOA alternates between two intervals of controlled evolution to produce approximations of solutions. A mixing Hamiltonian (M_H) along with a problem Hamiltonian (M_Q) in QAOA produces these evolutions. The mixing Hamiltonian usually takes the configuration of a global transverse field as $M_H = \sum_{k=1}^{s} Z_k$. The problem Hamiltonian of $'n'$ qubits can be created by mapping the classical cost function to a Hamiltonian through the formula $i_x = (1 - j_x)/2$ where $j_x \in \{-1,1\}$. Finally, by substituting the Pauli operator σ_x^j for j_x, the cost function $Q(j)$ is converted into $'M_Q'$ such that $M_Q|j\rangle = Q(j)|j\rangle$ and $M_0(l) = [1 - n(l)]M_H + n(l)M_Q$ where the stroboscopic function $n(l) = \begin{cases} 1 & : \ l \in \Delta l_k^Q \\ 0 & : \ l \in \Delta l_k^{H} \end{cases}$, describes an alternate between time evolutions that are weighted and produced by $'M_H'$ and 'M_Q'. The periods during which $'M_Q'$ and $'M_H'$ influence on the evolution is defined by the time intervals $\Delta l_k^Q = [l_{2k-2}, l_{2k-1}]$ and $\Delta l_k^H = [l_{2k-1}, l_{2k}$. The variational parameters that regulate the time travel across which $'M_H'$ and $'M_Q'$ are applied are $\beta = (\beta_1, .. \beta_q)$ and $\alpha = (\alpha_1, .. \alpha_q)$. The evolution operators $V_H(\alpha) = c^{-x\alpha M_H}$ and $V_Q(\beta) = c^{-x\beta M_Q}$ are parameterized by each (β_k, α_k) which are real-valued. These numbers also characterize the entire algorithmic runtime $U = \sum_{k=1}^{q}(|\beta_k| + |\alpha_k|)$. The application of QAOA evolution is made to a state that is initially set up in the ground state of $'M_H'$ or superposition among computational base states to converge towards the situation $\mu(0) = |\Psi 0\rangle\langle\Psi(0)| = |+\rangle\langle+|^{\otimes s}$ where the computational basis states of single qubits are $\{|0\rangle, |1\rangle\}$ define $|+\rangle = 1/\sqrt{2}(|0\rangle + |1\rangle)$. Following the QAOA development, the state is then provided by$\mu_0(U) = V_0^{(q)}(\beta,\alpha)\mu(0)V_0^{(q)}(\beta,\alpha)^{+}$. The variational parameters are optimized by utilizing a traditional optimization procedure $R(\beta,\alpha) =< M_Q >_{\beta,\alpha}$ with the QAOA approximation ratio defined by $\in \equiv \frac{R(\beta,\alpha)}{Q_{max}}$ with $\in \geq \in^*$. The optimization QAOA-QNN involves training the parameters of the syndrome extraction for overall efficiency.

The proposed model is implemented on the Google Colab CPU platform, with a Python environment with Qiskit libraries loaded in MS Windows 10. The decoding threshold of a quantum error correction code is calculated for code distance of $D_1 = (3,5,7)$ and $D_2 = (5,7,9)$ for NN, CNN, and QAOA-QNN models. Figures 4, 5, and 6 envisage the quantum error decoding threshold of NN, CNN, and QAOA-based QNN models for the surface code of distance (3,5,7), respectively. Similarly, Figures 7, 8, and 9 envisage the quantum error decoding threshold of NN, CNN, and QAOA-based QNN

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models for the surface code of distance (5,7,9), respectively. The calculated value of the error threshold is summarized in Table 2.

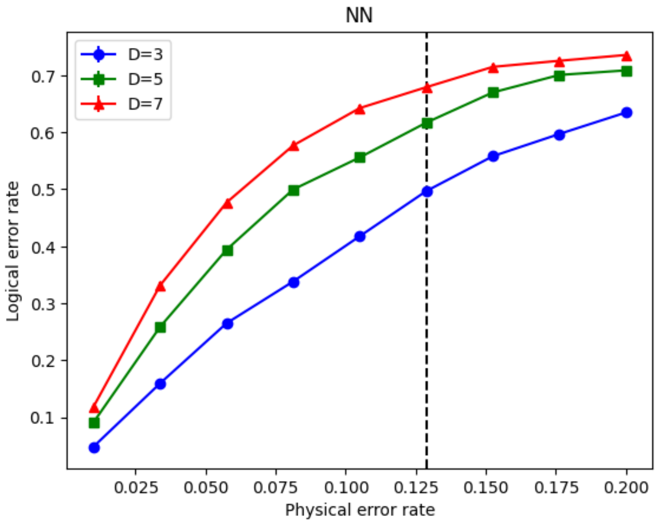

Figure 4: Quantum Error Decoding Threshold of NN Model for Surface Code Distance ($D_1 = 3, 5, 7$)

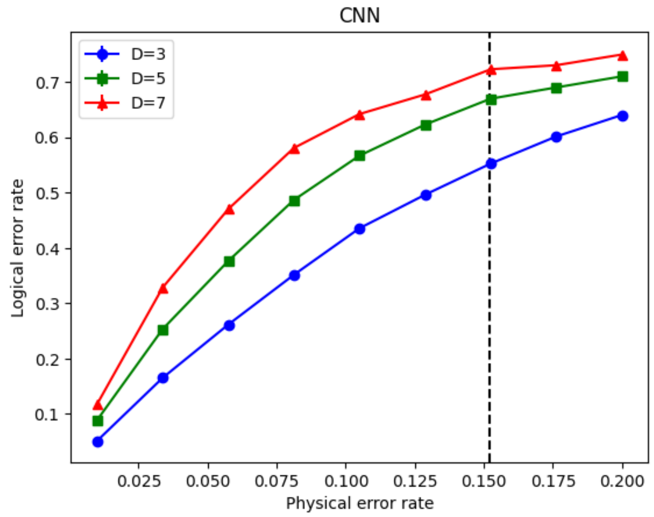

Figure 5: Quantum Error Decoding Threshold of CNN Model for Surface Code Distance ($D_1 = 3, 5, 7$)

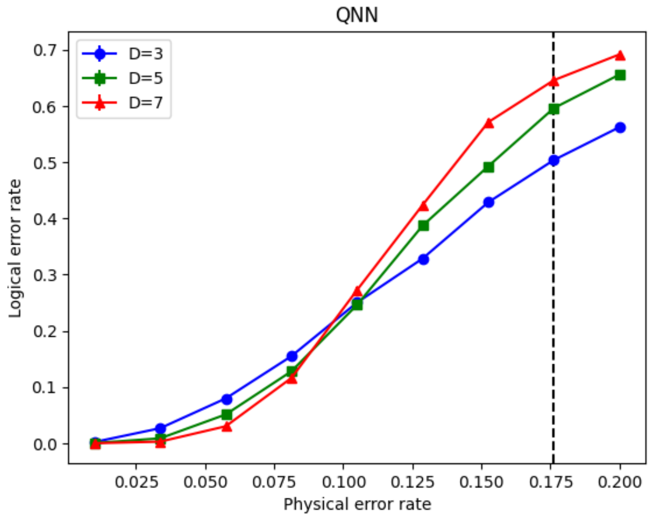

Figure 6: Quantum Error Decoding Threshold of Hybrid QAOA-based QNN Model for Surface Code Distance ($D_1 = 3, 5, 7$)

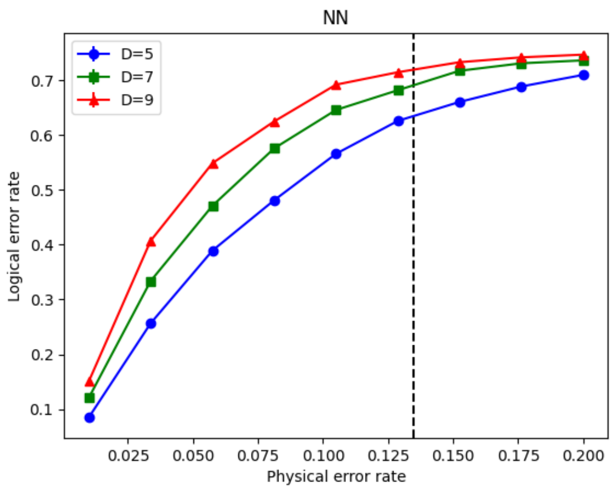

Figure 7: Quantum Error Decoding Threshold of NN Model for Surface Code Distance ($D_2 = 5, 7, 9$)

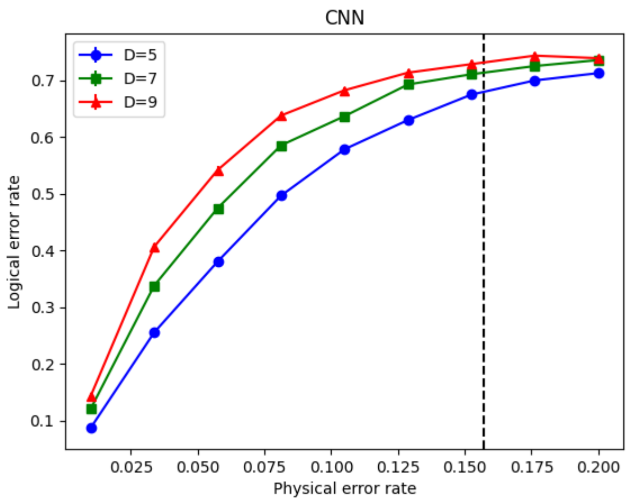

Figure 8: Quantum Error Decoding Threshold of CNN Model for Surface Code Distance ($D_2 = 5, 7, 9$)

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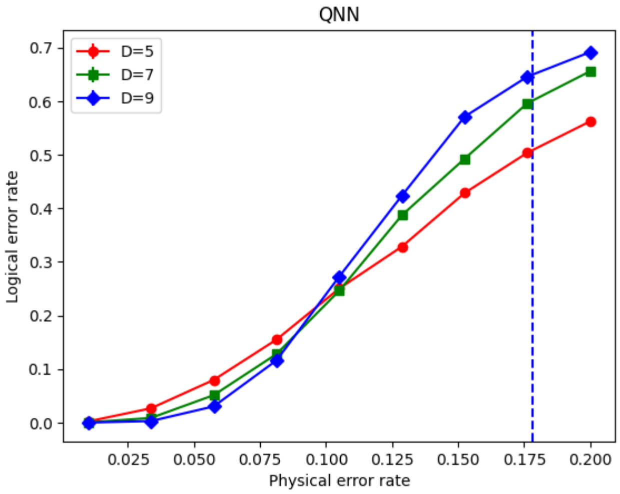

Figure 9: Quantum Error Decoding Threshold of Hybrid QAOA-based QNN Model for Surface Code Distance ($D_2 = 5, 7, 9$)

Table 2: Quantum Error Decoding Threshold for Surface Code Distance

Codes Distance	Error Decoding Threshold Value for Different Models		
	NN	CNN	QAOA-based QNN
$D_1 = 3, 5, 7$	0.129	0.136	0.176
$D_2 = 5, 7, 9$	0.152	0.157	0.178

Quantum error decoding threshold is the measure of growth in logical error rate with an increase in the number of qubits in the ancilla system. Since the hike in the number of ancillas is a natural requirement for better error-correcting codes, maintaining a lower threshold is essential to avoid generating logical errors during the encoding process. The above implementation results show that for each model, the error decoding threshold improves with an increase in code distance. For the NN model, the threshold value achieved for the code distance $D_1 = 3, 5,7$ is 0.129 while for the code distance $D_2 = 5,7, 9$ is 0.152. Similarly, for the CNN model, the threshold value achieved for code distance $D_1 = 3, 5,7$ is 0.136, while for the code distance $D_2 = 5,7, 9$ is 0.157. QAOA-based QNN demonstrates high decoding efficiency with values of 0.176 and 0.178 for code distance $D_1 = 3, 5,7$, and $D_2 = 5,7, 9$, respectively. The horizontal and vertical performance in Table 2 reveals that the QAOA-based QNN is the best performer in comparison to other state-of-the-art models.

5. CONCLUSION

The surface code is an important class of non-Pauli topological codes to mitigate the errors that arise in quantum circuits. It successfully utilizes the geometrical properties of stabilizers for syndrome measurement, but the development of an optimal decoder is still a long way away. This research proposed and tested a hybrid QAOA-based QNN decoder that utilizes complementary benefits of QAOA and QNN to achieve a better decoding threshold for optimal quantum error correction. The performance evaluation of the proposed model shows that the proposed model achieved the highest threshold of 0.176 and 0.178 for the code distance of $D_1 = (3,5,7)$ and $D_2 = (5,7,9)$ respectively. The study concludes that QAOA-based QNN exhibits better accuracy, scalability, and efficiency in syndrome decoding for robust quantum error correction. The study also reveals that the error correction threshold improves with code distance. Therefore, a wider scope exists to expand this research for higher code distances.

Declaration: *The authors declare no competing interests. There is no ethical issue involved in the data supporting the conclusions of this article and will be made available by the corresponding authors, without undue reservation. The corresponding author contributed to conceptualization, methodology, software, investigation, formal analysis, and writing–the original draft, while the role of the second author is confined to reviewing and editing the paper. The first author supervised and reviewed the work at all stages. No funding was received from any source for this manuscript's study design, preparation, or publication.*

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