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ORIGINAL RESEARCH

Quantum machine learning with Qiskit: Evaluating regression accuracy and noise impact

Amit Kumar[1] | Neha Sharma[1] | Nikhil Kumar Marriwala[2] | Sunita Panda[3] | M. Aruna[4] | Jeetendra Kumar[5]

[1]Chitkara University Institute of Engineering & Technology, Chitkara University, Rajpura, Punjab, India

[2]Electronics and Communication Engineering Department, University Institute of Engineering and Technology, Kurukshetra University, Kurukshetra, Haryana, India

[3]Department of Electrical, Electronics and Communication Engineering, GITAM School of Technology, Bengaluru, Karnataka, India

[4]Faculty of Engineering and Technology, Department of Computing Technologies, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu, India

[5]Department of Computer Science and Application, Atal Bihari Vajpayee University Bilaspur, Bilaspur, Chhattisgarh, India

Correspondence
Nikhil Kumar Marriwala.
Email: nikhilmarriwala@gmail.com; nmarriwala@kuk.ac.in

Abstract

Quantum machine learning (QML) can be employed in solving complicated machine learning tasks although the performance in examining the regression processes is only barely understood. Knowledge gaps are intended to be closed by studying modelling performance of QML in regression tasks, with emphasis being dedicated to scaling up and ability to resist noise. The regression part offers the following functions that include straight line and complex operations. Furthermore, the authors employ quantum neural networks generated using Qiskit to perform experiments. The results demonstrate that QML has a remarkable level of accuracy in basic regressions, reaching a maximum of 97%. Nevertheless, there are difficulties in representing intricate functions, such as $5 \times \cos(x)$, which results in a noticeable decline in performance. The work deals with the influence of noise and IERs from imperfect hardware on the efficiency of QML algorithms providing insight into the core obstacles. The result of a detailed examination of the results that have tested the powers and limits of QML in the development of regression applications is represented. The future direction of research and development will be defined by the results obtained in it.

KEYWORDS

quantum communication, quantum computing, quantum computing techniques, quantum cryptography

1 | INTRODUCTION

Quantum machine learning (QML) stands for one of the most appealing intersections between quantum computing and machine learning, as it enables them to solve certain problems that cannot be performed deterministically using classical computers. In the last decade, the study and activity of QML have gained not only a strong interest but the results of the study as well. Therefore, this introduction will first present the overall artificial intelligence in QML nowadays and then review the related work for key technologies and checkpoints in this industry. QML has been a growing sector in recent years with a pace of rapid advancement being dictated by hardware and algorithm breakthroughs in the field of quantum computing. Experts have designed diverse QML models and developed algorithms within this umbrella of technology tackling a multitude of machine learning tasks, such as classification, regression, clustering, and optimisation. These quantum models implement non-classical principles of quantum mechanics for carrying out computations in ways that have nothing in common with previous approaches; this may mean an exponent in the order of the speedup for the performance. Studies projected in the most recent past examined different techniques in QML: quantum neural networks (QNNs) and kernel methods as well as variational algorithms. QNNs attracted attention from the experts in particular due to their capacity to learn complex patterns and relationships in the data by transforming the classical inputs into the quantum circuits. Conversely, quantum kernel methods obtain a reading order of features using a quantum feature space that achieves the completion of machine learning tasks rapidly and efficiently. In the related line development, the probabilistic approaches, such as quantum variational classifiers and quantum variational autoencoders, provide hybridised structures for tissue approximation and optimising the network requirements. The occurrence of QML represents a strong paradigm shift in artificial intelligence theories with the aim of solving more complex computational tasks. Kyriaki and her associates have a clear-cut tutorial that explains what QML is, together with the key steps and technologies of the methodology [1]. Subsequent to this furnishing, the research piece of Seongwook presents a different perspective whereby tensor network approaches are used in the analysis of QML revealing the mystery side of quantum mechanics and machine learning [2]. Furthermore, another trend is the work of Alexander et al. with regard to the use of QML in image classification tasks, to show the possibility of employment of QML in this field as a tool to improve the traditional machine learning algorithms. Joseph Mawuli Lindsay and Ramtin Zand put forward a new LSTM model that draws inspiration from QML. They propose some quantum-friendly approaches for the recurrent neural networks for which they highlighted relevant strategies that are based on quantum principles [3]. Admin iteration Sarkar analyses QML, applying new articles and defining basics for further study [4]. Meanwhile, A.C and V.M. contribute with their study-focused analysis of QML (a technical word used here), they critically examine the current methodologies, and then identify the most promising approach for future research [5]. They stress out the need for bridging the dichotomy between theoretical ideas and real-word utilisation and boost for institutions to sophisticate the advancements on QML in their respective sectors. Tancara et al. conduct the same research throwing a light on QML possibilities to capture non-Markovianity by employing the regressor models based on the kernel [6]. Towards the end, Manjunath and Bhowmik share their thoughts on recent developments in QML, discovering latest breakthroughs, and expanding trends as this field is still being developed [6]. Integrating these studies helps build a stronger knowledge base on QML theory, which promotes methodological innovation of practical applications in future research.

Table 1 summarises review articles in the area of QML that were identified from the literature. Every row is the representation of a research independent of other ones describing all the necessary information, for instance, name(s) of the authors, publication year, study title, and main contribution of the work. The table briefly presents some important quants and machine learning fields, which are overview, analysis, image classification, novel model development, reviews and further advanced studies [10–14]. This compilation is affordable because of the multiplicity of research areas that are covered. This multiplicity encourages specialisation, thereby making it possible to create unique perspectives concerning diverse contributions made by researchers in the QML field [15, 16]. This research aims to evaluate the performance of QNNs in regression tasks, particularly focusing on their scalability and resistance to noise. Even minimal levels of noise can result in decoherence, which results in the loss of superposition and entanglement capabilities of qubits. The loss of quantum information can invalidate computations and restrict the scale and intricacy of viable quantum algorithms. We investigate how hardware limitations and noise affect QML algorithms and propose methods to mitigate these issues. This paper has the goal of being a part of an ongoing discourse by analysing how QML models work in regression tasks, discovering their weaknesses, and suggesting new avenues for research and development.

Research contributions: our primary contributions in this paper include the following:

1. **Comprehensive Evaluation of QNNs:** We provide a detailed analysis of QNN performance on regression tasks, highlighting their accuracy and limitations.
2. **Noise Impact Analysis:** We investigate the effects of noise and imperfect error recovery on QNNs, providing insights into how these factors degrade performance.
3. **Hardware Limitations:** We examine how current hardware constraints impact the efficacy of QML algorithms, offering a pathway for future improvements.
4. **Methodological Innovations:** We propose novel methodologies for scaling QNNs and mitigating noise, which are validated through extensive simulations.
5. **Future Directions:** We outline potential advancements in quantum error correction and fault-tolerant quantum computing, suggesting how these developments could enhance QML applications.

These contributions aim to bridge existing gaps in QML research, offering both theoretical insights and practical solutions.

The initial step is the unfolding of the research methodology that has been utilised in this study as well as the analysis of the outcome and the implications that they have. Furthermore, it will be highlighted that the essay ends with a conclusion and more ideas are being explored with research.

2 | METHODOLOGY

The methodology section considers the investigation of regression tasks using QML models via methodology. QML stands for a new wave of machine learning based on the

TABLE 1 Summary of selected literature on quantum machine learning.

Author	Year	Study	Main contribution
Kyriaki A., et al. [1]	2023	Quantum machine learning—an overview	Provides an overview of quantum machine learning
Seongwook S., et al. [2]	2023	Analysing quantum machine learning using tensor network	Investigates quantum machine learning using tensor network
Alexander S., et al. [7]	2023	Quantum machine learning for image classification	Explores quantum machine learning for image classification
Joseph Mawuli L., et al. [3]	2023	A novel stochastic LSTM model inspired by quantum machine learning	Introduces a novel stochastic LSTM model inspired by quantum machine learning
Soumya S. [4]	2023	Quantum machine learning: A review	Offers a comprehensive review of quantum machine learning
A. C., V. M. [5]	2023	Research oriented reviewing of quantum machine learning	Conducts a research-oriented review of quantum machine learning
Liu J. [8]	2023	Towards real-world implementations of quantum machine learning	Explores the path towards real-world implementations of quantum machine learning
Tancara D., et al. [6]	2023	Kernel-based quantum regressor models learning non-Markovianity	Investigates kernel-based quantum regressor models for learning non-Markovianity
Manjunath T. D., et al. [9]	2023	Quantum machine learning and recent advancements	Discusses recent advancements in quantum machine learning

principles of quantum mechanics, which may outpace the classical methods and have higher performance due to exponential speed up. Our approach aims to be as systematic as possible in gauging the ability and weakness of the QML models in performing regression tasks over an extensive set of conditions.

Figure 1 outlines the process by visually representing each step of the process in a sequential manner. Below is a simplified flowchart depicting the key steps involved in evaluating the performance of QML models in regression tasks:

The flowchart graphically displays the methodology starting with the regression tasks selecting and ending with training results analysis. Here comes model implementation, dataset preparation, training, evaluation, and the result performance metric calculation [17]. In this way, each step is logically connected to the next, and finally we arrive at the analysis of the reliability of QML models in regression problems.

Algorithm 1: QML regression task.

```
Input: Quantum dataset D, QNN parameters θ
Output: Trained QNN model
  1: Initialise QNN with parameters θ
  2: for each epoch do
  3:     for each batch in D do
  4:         Encode batch into quantum states
  5:         Apply quantum circuit with
current θ
  6:         Measure output and compute loss
  7:         Update θ using gradient descent
  8:     end for
  9: end for
  10: Return trained QNN model
```

Methodology encompasses the following key steps:

1. **Selection of Regression Tasks:** Our analysis commences with the choice of a set of regression tasks that will indicate the performance of the models on the other tasks. Here, we will look at the variety of tasks carried out using math functions, some of which are simple linear, polynomial, or sinusoidal/exponential functions. To this end, the regression tasks will be modified to reflect the possibility of capturing diverse data representations with the knowledge of machine learning models being assembled from QML.
2. **Quantum Neural Network (QNN) Implementation:** In terms of our experiments, we simulate QNN models through the Qiskit package, which is a quantum computing platform quickly accessible to a community contributed by developers. QNNs represent QML's leverage in the ability to process quantum data using the models of quantum circuits [18–21] parameterised by quantum gates. To fabricate the QNN architectures appropriately fitted to all regression tasks, one will need to configure the necessary parameters, such as the number of qubits and layers as well as parameters particular to the complexity of the task.
3. **Dataset Preparation:** To generate synthetic datasets for each of the regression tasks so as to have enough data points that can reflect the inherent correlation among the underlying function patterns, in order to effectively apply machine learning algorithms. The datasets are divided into two parts for testing and training that enable to monitor and optimise the model's accuracy and efficiency.
4. **Training and Evaluation:** To run the QNN models on the training datasets using the gradient-based optimisation algorithms, such as the stochastic gradient descent and the Adam optimisation algorithm. This adjustment is done in an iterative manner until a preset loss function has been achieved, which is a weighted measure of the error in the values of inputs and outputs [22–26].

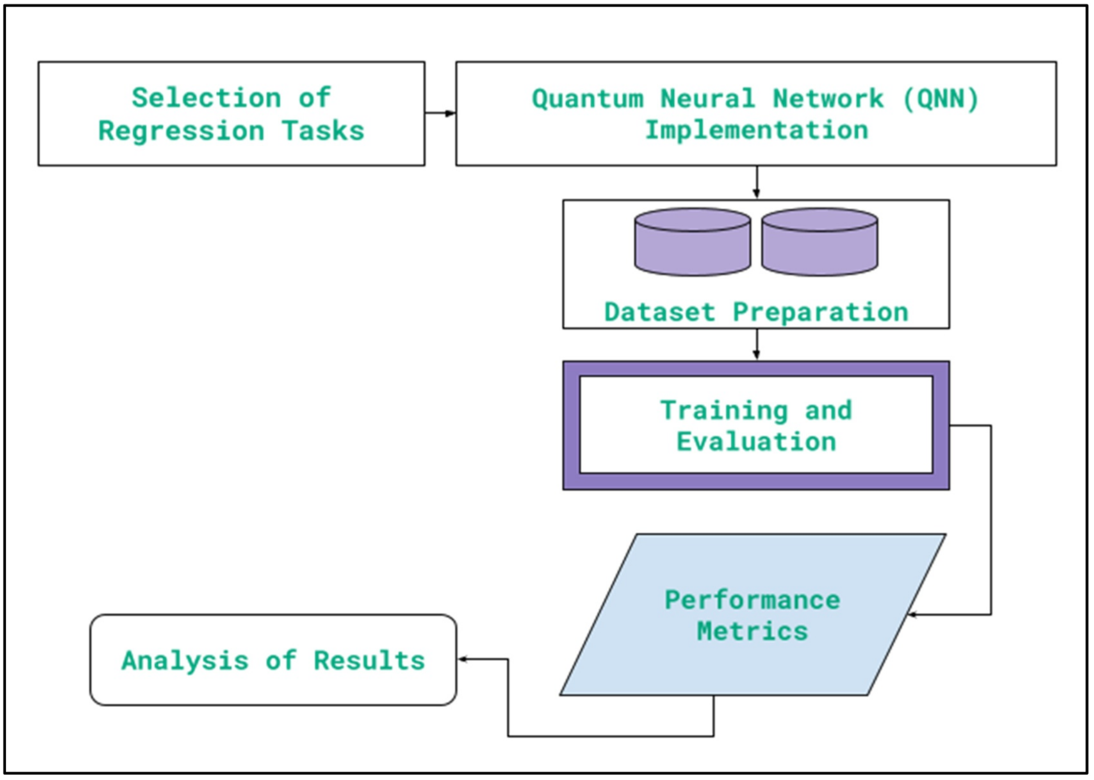

FIGURE 1 Methodology flowchart for evaluating quantum machine learning (QML) models in regression tasks.

5. **Performance Metrics:** To determine the performance of trained QNN models, we apply diagnostic metrics prepared specifically for regression tasks. These metrics include MSE (mean squared error), MAE (mean absolute error), R^2 score (coefficient of determination), and accuracy percentage to analyse the results. These metrics tell about the quality, accuracy, and generalisation aspect of models in regression tasking [11, 27–31].
6. **Analysis of Results:** The analysis will be done to investigate the strong and weak points of the QML models in regression. The model's performance on the different regression jobs can be analysed for discerning patterns and trends in the results, and the implications of the findings for the future research and development in the discipline can be discussed [17, 32–36].

This systematic approach is intended to deliver a detailed account of how QML models perform in regression tasks, enriching our understanding of what QML is capable of and what it cannot do in applied scenarios [14, 37–42].

3 | PROPOSED MODEL: QUANTUM NEURAL NETWORK FOR REGRESSION

In this study, the development of the QNN model for regression is being expounded. In QNN architecture, we are going to take advantage of the vast computational power of quantum computing to accurately solve the problems of regression with continuous output values based on input data. The intended model comprises of the quantum circuits, the optimisable parameters, and the optimisation techniques. Figure 2 depicts the model architecture together with the structured diagram.

1. **Input Features:** The model takes input features from the dataset as its input. These features could include various numerical or categorical variables relevant to the regression task.
2. **Quantum Circuit (QNN):** The input features are encoded into quantum states and processed through a parameterised quantum circuit shown in Figure 3, which forms the core of the Quantum Neural Network [3]. The quantum circuit consists of qubits and quantum gates, with trainable parameters that are optimised during the training process. The two qubits, (q_0,q_2), each undergoing a single-qubit rotation around the Y-axis of the Bloch sphere. The rotation angles are parameterised by $\theta[0]$ for q_0 and $\theta[1]$ for q_1. There is no direct interaction between the qubits in this circuit and each rotation gate acts independently on its respective qubit. This circuit can be utilised in variational quantum algorithms or quantum state preparation tasks, where the rotation angles are adjusted to achieve desired quantum states or computational outcomes.

In QML, the efficacy of given parametrised quantum circuits strongly depends on their generalisation feature, which, ideally, should include most of the state members which can be

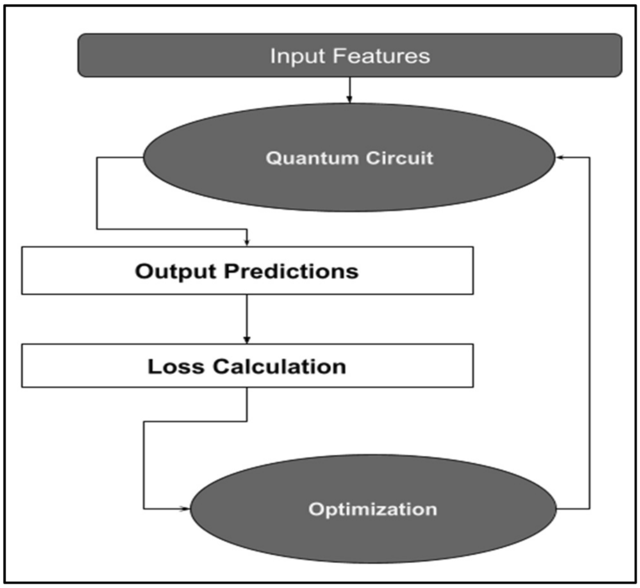

FIGURE 2 Proposed quantum neural network architecture for regression.

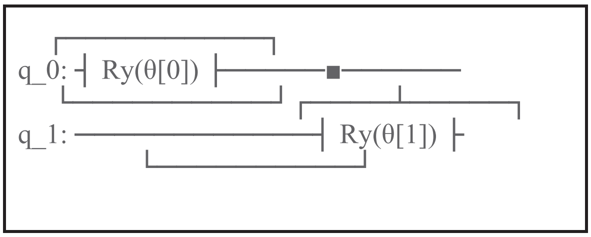

FIGURE 3 Parameterised quantum circuits.

found in the output Hilbert space. This 'space' which is virtual in quantum mechanics is a multiple-dimension inner product space with the norm and completeness properties. An increased expressibility of a quantum circuit with circuit parameters has a direct impact on the area of the Hilbert space, which in other words defines the hypothesis space. These circuits, however, with their high degree of expressibility can depict all the diverse unitaries, therefore increasing their potential to employ-general. Parameterised quantum circuits serve two primary functions in QML: quantum information science, data encodings, and quantum modelling. They realise digital data as every parameter dynamically adjusts for input features and plays the role of a quantum model by doing such parameter optimisation processes which gives them a better advantage in recognising these complex patterns. Feature maps are the fundamental ingredients that drive learning in machine learning as well as in image processing and pattern recognition tasks. The resultant compressed and interpreted data contains only relevant and non-duplicated features which can be efficiently used for developing the next stage such as feature selection and dimensionality reduction—an important component of succeeding learning and generalisation processes, which increases the efficiency and interpretability of the algorithm.

3.1 | Mathematical model for noise analysis

In the context of quantum computing, noise can significantly impact the performance of quantum algorithms, including those used for machine learning. The primary sources of noise in quantum systems are decoherence and gate errors. Here is a mathematical model for analysing these noise effects.

Decoherence: Decoherence refers to the loss of quantum coherence due to the interaction of the quantum system with its environment. It can be modelled using the density matrix ρ of the quantum state and the Lindblad equation:

$$\frac{d_t}{d_p} = -\frac{i}{h}[H,\rho] = \Sigma_k \left(L_k \, \rho \, L_k^{\dagger} \; - \; \frac{1}{2}\left\{ L_k \, L_k^{\dagger}, \rho \right\} \right)$$

where H, is the Hamiltonian of the system, L_k are the Lindblad operators representing different noise processes, and $\{\cdot,\cdot\}$ denotes the anticommutator.

Quantum Gate Errors: Quantum gate errors occur during the implementation of quantum gates. These can be modelled using a noise channel ε that acts on the quantum state. For a single-qubit gate, the noisy operation can be represented as follows:

$$E(\rho) = (1-p)U\rho U^{\dagger} + p\frac{I}{2}$$

where U is the ideal unitary operation, p is the probability of an error occurring, and I is the identity matrix representing the complete depolarisation.

3.2 | ZZ feature map

The ZZ Feature Map, one of the gates in Qiskit, imports classical data into the quantum computer in a tailored way by mapping the operations of qubits. It is designed to extract the higher-order interactions between the conventional data characteristics, ultimately submerging 2-feature pairs into the data set. Figure 4 depicts an optimal feature map that places a sizeable emphasis on CZ gates or controlled Z-rotations for data relationship encoding while harnessing the inherent quantum principles to compress such complex data interactions into a simple feature map. Qiskit provides access to tools such as TwoLocal, NLocal, and QAOA which allow users to conveniently use parameterised circuits. Such schemes provide a wide range of manipulating tools for swift assemblage of customised-to-task quantum circuits used in machine learning or optimisation. Integrating these frameworks, researchers and practitioners are able to engineer quantum circuits with variable parameters; thus, these frameworks facilitate the implementation of flexibility and adaptability while meeting

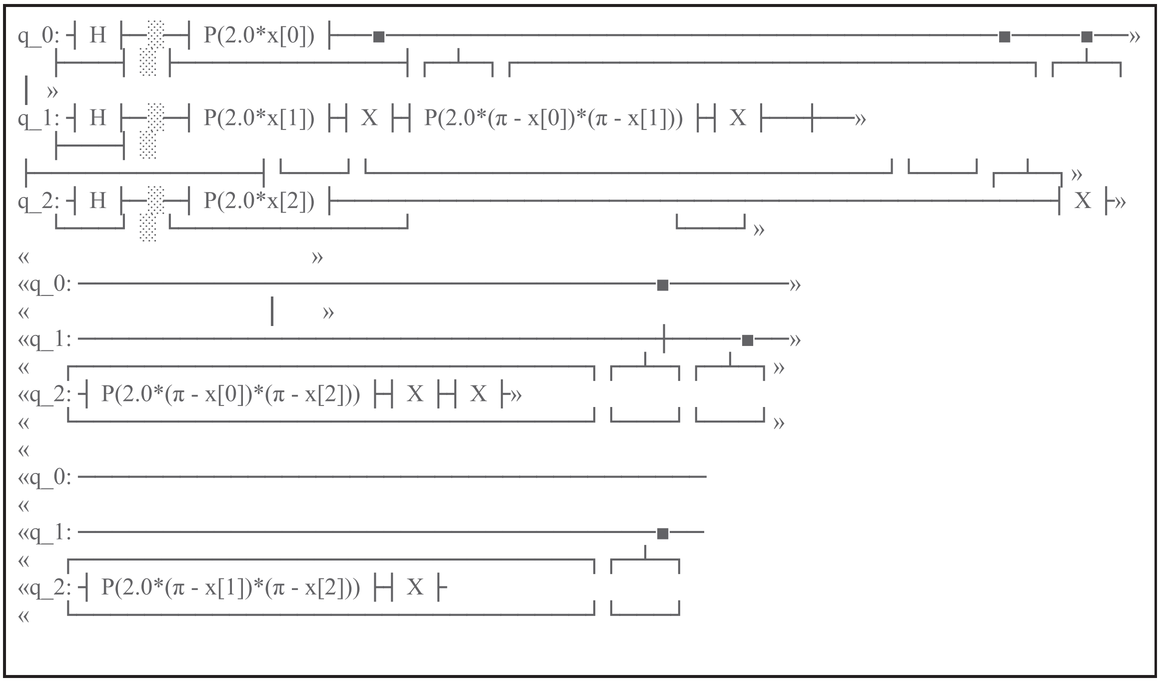

FIGURE 4 Parameterised circuit in Qiskit.

diverse computing requirements inside QML and optimisation domains simultaneously.

In this case, the circuit is composed of Hadamard gates (*H*), Pauli gates (*P*), and controlled gates (controlled-NOT gates, or CNOT, represented by X). Each line represents a qubit and the operations are applied sequentially from left to right. Gates are applied to qubits indicated by the lines they're connected to. q_0 has a Hadamard gate (H), followed by a Pauli gate $P(2.0*x[0])$, followed by some controlled operations involving other qubits. q_1 has a similar structure with a Hadamard gate (H), followed by a Pauli gate $P(2.0*x[1])$, and further operations. q_2 again starts with a Hadamard gate (*H*), followed by a Pauli gate $P(2.0*x[2])$, and more operations. The controlled operations seem to involve some Pauli gates and further controlled operations, possibly involving the qubits $q\_0, q\_1, and\ q\_2$.

3.3 | Training of parameterised QCs

While the classical machine learning method involves the implementation of the learning process as the minimisation of a cost function or loss function that is mathematically expressed, the QML setting is similar to training parameterised quantum circuits where the loss function or cost function is shown in Figure 5. Yet, in QML, the purpose is to minimise the expected value, not the excitement of the parameters. While classical machine learning uses plenty of algorithms and neural nets to solve learning tasks, QML uses QNNs in order to find the best way for working with qubit-based computing.

The QNNs' construction is targeted at parameterising quantum circuits that are optimised through variational classical optimisers with specific hardware. Such circuits consist of a featurised map, with the training stanza connecting its inputs to its weights. In general, Do NNs embody the principle of a classical neural network in the quantum realm to resolve challenging issues through the capabilities of quantum computation. Pi for QNA applications, Qiskit makes it all possible either through simulation or on real hardware. Although a simulation provides an opportunity to utilise both flexibility and accessibility, being granted time on quantum hardware has its own dynamics because you then require joining a queue and logging into platforms such as IBM Qiskit. By the use of the NeuralNetwork class in qiskit-ml, all QNNs are provided with the interface for the forward and backward trainable passes. The interface utilises data samples and trainable weights classification as in and out. The quantum networks are just out of state during the learning procedure, each network in the quantum system itself has no learning capacity and cannot hold the values for the training weights. Therefore, training progresses to specific algorithms or tools, that is, classifiers or regressors, in which the determined trainable parameters are used to accomplish inferences or predictions.

EstimatorQNN initialises a QNN by taking a parameterised quantum circuit as input "input parameters" (*q*) where input[1] indicates 'input features' and weight[3] "Weight parameters" represent the tunable parameters within the QNN along with an optional list of observables. It computes the expectation value, offering a means to gauge the performance of the QNN. Additionally, users can include a list of observables to enhance the complexity of the neural network. In quantum mechanics, observables represent operators that ascertain properties of a quantum state through specific sequences of operations. As shown in Figure 6, the performance

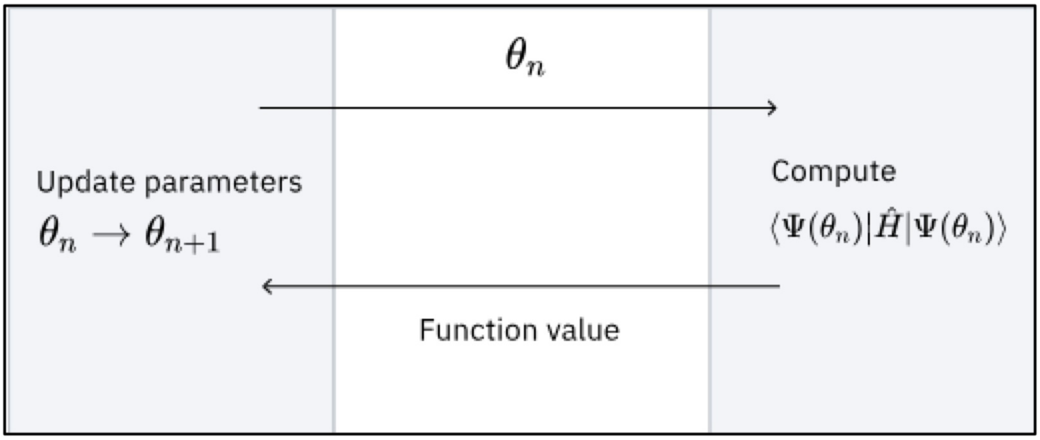

FIGURE 5 Cost function/loss function (the objective function).

metrics indicate a high level of accuracy for basic regression tasks.

SamplerQNN is an example of ways around, rather than a substitute of EstimatorQNN, in the initialising of QNNs with their own strategies of observation. Unlike EstimatorQNN, SamplerQNN does not have to be run along with the observation on its own. Hence, it does not need custom observables to use. Rather than this, the neuromorphic chip provides a short-and-sweet way, that is, through trimming down the steps and bypassing the need for substantial customisation. This makes the deploying and implementing processes of qubit observables relatively simpler by avoiding complicated procedures such as explicitly defining observables. Figure 7 further illustrates the impact of noise on the regression models.

In a QNN, the 'input parameters' (q_0,q_1) refer to the variables representing the input data or features provided to the QNN. In this case, `input[0]` and `input [1]` indicate that there are two input features. On the other hand, the 'weight parameters' represent the tunable parameters within the QNN that are adjusted during the training process to optimise the network's performance. These parameters influence the behaviour of the quantum circuit and its ability to make accurate predictions. The labels weight[0], weight[1], weight[2], and weight[3] suggest that there are four trainable weights in the QNN model.

1. **Output Prediction:** The processed quantum states are then applied to formulate the forecast corresponding to the desired targets' output values. These projections take into account a series of non-stop values that correspond to the regression coefficients which are calculated for each feature space of the input.
2. **Loss Calculation:** The predicted output values are compared with corresponding true targets from the dataset to measure how much they differ. This defines their loss or error. Diverse loss functions may be used to define the deviation of the output from the actual instance, for example, MSE or MAE.
3. **Optimisation:** The optimisation step uses the adjustment of the quantities of partial input parameters to reduce the loss function. This is usually achieved by the employment of gradient-based optimisation methods, like the stochastic gradient descent or the Adam optimisation. Here, the optimisation technique is used repeatedly for the parameter updates, such that the model is able to increasingly aim at the task of regression.

Relation to Research The QNN model is our key research methodological unit in this research play that is quantifying the performance of QML models in the case of regression problems. Through applying quantum power to the QNN model, the approach brings greater precision and adequacy that it offers over traditional machine learning methods. We will use exhausting explorations in analysing the effectiveness of the suggested model as we want to present the findings that would add knowledge to the general QML community.

Physical Realisation: The research presented here has, further proved to be the right direction for QML for regression tasks that introduced novel algorithms, and physicalised it as well. The specific problem solving method which is referred to as the QML framework consists of the development of QNNs, which are actually QNNs that are possible thanks to the Qiskit tool. We push the boundaries; regression analysis is not an exception, and we tackle complex issues with multiple high-dimensional data and complex functions, where QNNs are the right tools for us. Lastly, we use both software emulations and quantum circuits of Qiskit (which stands for Quantum Information Software Kit). We then place our QML models into Qiskit and test them with an available IBM's quantum system to perform experiments. Being able to conduct the benchmarks helps us to identify the limitations of our numerical matrix, such gate accuracy, and connectivity among the qubits as well as error rates. With implementing this approach, we are basically two concurrent processes: from one side, we contribute to the development of the basic theory of QML and from another side, and we also provide insights into

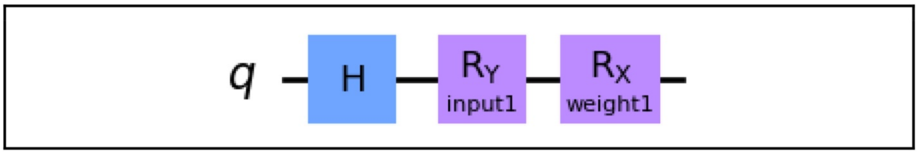

FIGURE 6 EstimatorQNN [43].

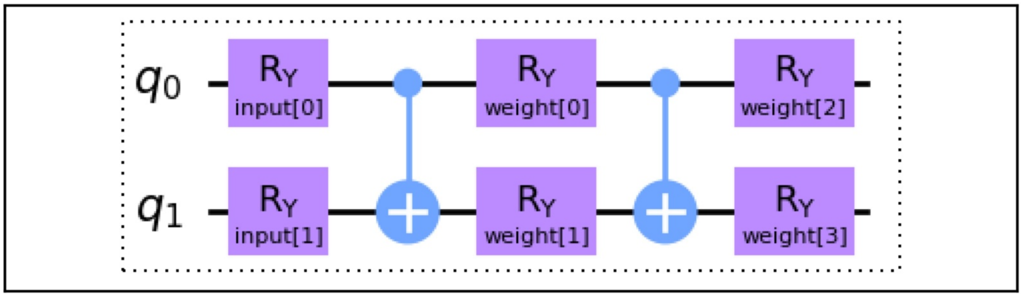

FIGURE 7 SamplerQNN [43].

its practical application, which are very essential for the whole field.

3.4 | Results and discussion

The quantitative results of this work are presented in the section that consists of the obtained outcomes after the QNN training process on custom data. Through hard experimentation and evaluation, we study the performance, transferability, and functionality of the QNN applied to the task as trained. This section reveals the truth about the QNN accuracy, computational ability, interpretability, and scalability which gives an overview of its strengths and limitations in the physical world. We will scope off and analyse the obtained results and thus we expect to get a deeper insight into the QML capacities and issues of their applications to the elaborate real-world problems.

Forward pass and Backward pass: In the first step of forward pass, the SamplerQNN network is with two input features and 4 trainable weights, resulting in (1, 4) output shape and values [[0.23851185 0.1411135 0.3367757 0.28359895]]. These weights are purposefully used for the forward pass, considering that the weighted sums precisely establish the values of the actual neural network during the training process. After the forward pass is done the backward pass phase begins. During the backward pass, the input gradients are calculated while the weight gradients are determined as [[[0.00609879 −0.30661818 −0.1834591 −0.28341665] [−0.02969169 0.17866236 0.1834591 −0.20004909] [−0.37812738 0.30266095 −0.30904568 0.28341665] [0.40172028 −0.17470512 0.30904568 0.20004909]]]. These gradients allow the parameters in the network to keep being tweaked, during the training process. The gradient descent algorithm has been used in succession of forward and backward passes, to make the QNN trained with gradients. This underpins the fact that the network can be customised suitably to fact the data efficiently, the QML process has therefore highlighted the range and capabilities of these techniques.

3.5 | Regression analysis

Regression analysis is a statistical method for assessing (a) one or more independent variables and their relation (b) to a dependent variable. It is most often applied for forecasting and prediction in such areas within the economy, biology, mechanics, engineering, and social sciences. As synthetic data presented by Figure 8 depict, the regression task is in effect with additive noise. The plot gives the output corresponding to the input variables and illustrates these in a dataset of simulated graphs.

The blue dots located in Figure 8 have been accepted from the dataset's synthetic points for the regression application. Here, the combined work of each blue dot equals the total weight of a pair of input and output variables. These data points are around it so the fact can be seen that due to the presence of noise in such examples is what real life examples look like where observations may not be aligned perfectly with the ideal function. A True red dotted line exhibits the real mechanics which are the cosine function $(cos(x))$. This line demonstrates the ideal relationship between the input and output variables without any noise. It acts as a reference to show how well the synthetic data points approximate the true function. Therefore, the blue dots indicate the synthetic data points, while the red dotted line indicates the true underlying function.

Figure 9 represents the increase in a function value over time through which the optimisation indicates the process's dynamics. The x-axis labels the iterations, and they are shown successively to represent the process of step by step algorithm improvement. On the other hand, the x-axis graphics show the

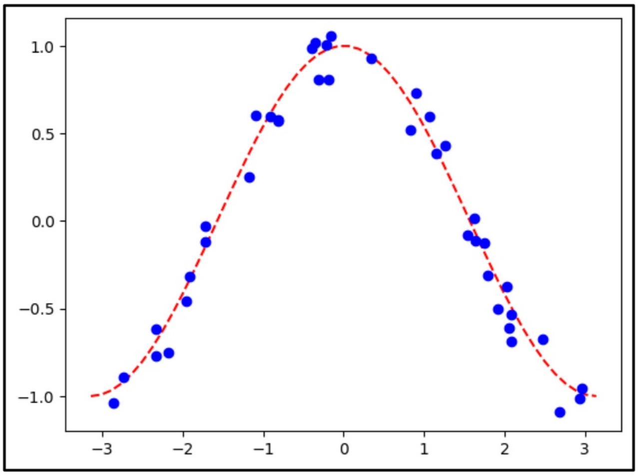

FIGURE 8 Synthetic data generated for regression with noise.

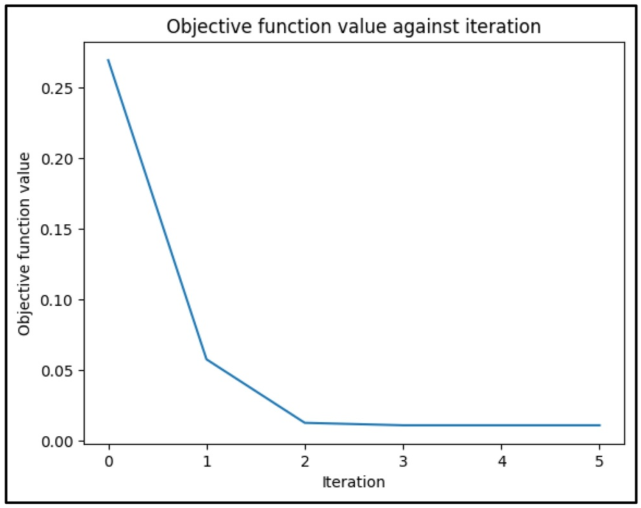

FIGURE 9 Objective function value against iteration.

optimisation objective function value which is closely associated with the effectiveness of the process. To begin with, the value of objective function at iteration 0 ranges between 0.25 and 0.30, which is very close to the target value of the function. The next following step, which is to be noticed during the optimisation process, is that the objective function value reduces gradually. By the seventh iteration the function value has definitely dropped to somewhere between 0.00 and 0.05, which shows a noticeable improvement in the quality of the process of optimisation. The monotonic decline of the objective function rendering is an indication for the optimisation algorithm's iteration process of correcting the parameters again and again, thus improving the model performance and better embodying the objectives.

Hadamard gates are used to create superposition states, which are essential for exploring multiple possibilities simultaneously in quantum algorithms. Pauli gates (X, Y, Z) are used to manipulate the qubit states in various ways, such as flipping the state or introducing phase shifts, which are crucial for implementing complex quantum operations.

Performance evaluation: The evaluation criterion, an instrument of paramount importance in determining the viability and reliability of regressor in our scientific investigations, is the performance evaluation metric. The combination of an R squared value of 0.9756 is a reminder of the close match between the predictions of the regressor and the actual weather patterns. This number is a reflection of the level of the regression line in conveying the variations of the target variable sustained using the features as inputs. For instance, the achieved score of no more than 0.9756 indicates that the regressor successfully conveys as much as 97.56% of the variance in the target variable. Such a wonderful achievement is the noticeable fact that the regression model which we built has a high level of accuracy as well as reliability. Therefore, this model is recommended precisely for our research objectives. Figure 10 shows the green line which is the regression line overlaid to the blue dots, which are the scatter plot. Despite achieving a relatively high score of 97% on the displayed data,

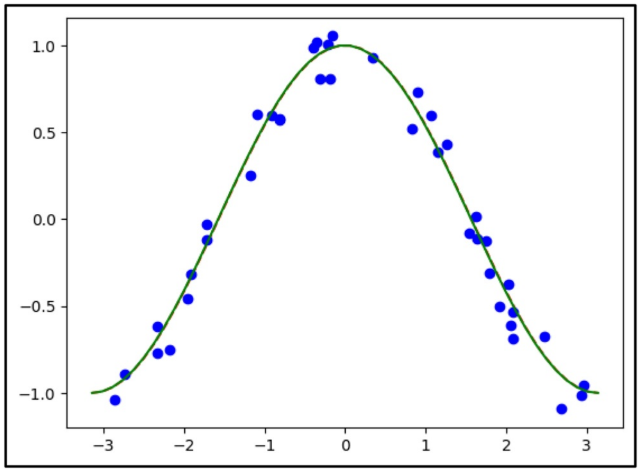

FIGURE 10 Objective function value against iteration.

the model's performance appears suboptimal, especially when confronted with simple data distributions such as (*5 * times cos(x)*).

Such a gap indicates an underlying flaw in the simplicity factor as an important driver of the ideal performances. In addition, the most complex models founded on the use of QML for some complex functions still face the problem of performance level in matching with the classical machine learning algorithms. In the same way, this frat sorry demonstrates the fact that the field of QML is undergoing rapid evolution but is definitely in an initial stage, which requires more research, adequate developments, and testing. QML is another ML framework on the block that shows great promise but is currently hindered by the gap with the traditional ML algorithms. Yet, it has to be mentioned that the fields of classical artificial intelligence which include computer vision, GANs, and NLP have been successfully implementable into the quantum area as well. This convergence signals a solid way that QML could go, despite the fact that it will need extra effort and advances to manifest its full potential.

4 | DISCUSSION

The discussion section delves deeper into the implications of the results obtained and provides insights into the broader context of QML research.

Model Performance and Limitations: The fact that the quantum AI model regarded the test results as primarily a success points out its strengths and weaknesses at the same time. A model attains an outstanding 97% percent score of accuracy on simple data though stumbles in its performance when confronted by more intricate functions. This margin shows us the challenges contained in applying the measurements of quantum mechanical learning to ordinary world applications in places where the distribution of data is stereotypical.

Comparison with Classical ML Algorithms: However, classical algorithms which are being used in machine learning are still considered superior in form, as they tend to outperform their quantum equivalents in various scenarios. Classical algorithms that have been long-studied and improved so much over the many past decades are robust models that perform well in different areas. Contrary to these facts, the quantum analogue of machine learning has only just started and the algorithms in the early stages of creation are still under refinement. Therefore, being able to recognise classically digestible designs as the basis for achieving parity with them is still a significant challenge.

Future Research Directions: The current study revealed the limitations. The limitations found in this study will serve as the basis for future research initiatives on the topic of QML. Exploring the future of QNNs requires the development of different ways of improving model expressivity, efficient optimisation methods, and the design of quantum circuits which consume less resources. The research direction should be developed in terms of developing the hybrid approaches that combine the strengths of both the classical and quantum features of machine learning to outplay the unique shortcomings of quantum computing hardware.

Practical Applications and Real-World Impact: Surmounting the present challenges, QML features profound potential for resolving extreme real world problems. In areas such as drug discovery, financial modelling, or optimisation, QML is a new kind of science that allows us to look at varied industries in a quantitatively different way. Through the implementation of quantum computing, scientists can resolve problems that are non-workable under the classical approach. The promise of quantum computing is bringing the solutions to these, which is leading to innovative advances in science and industry.

Ethical and Societal Implications: As with any emerging technology, QML will be accompanied by accompanying ethical and social concerns, which must be addressed. They encompass topics such as data privacy, algorithmic bias, as well as democratisation of quantum computing resources. One of the most critical responsibilities of researchers and policymakers is the joint development of such frameworks and regulations that will be used in the implementation of QML technologies.

Future Prospects for Universal Quantum Computers Advancements in Error Correction Codes: Error correction is crucial for building fault-tolerant quantum computers. Techniques such as the surface code and the colour code are promising because they can correct arbitrary errors on qubits. Research is ongoing to make these codes more efficient and practical for large-scale quantum systems.

Fault-Tolerant Quantum Computing: Combining quantum error correction with fault-tolerant techniques ensures that quantum computations can proceed reliably even in the presence of errors. This involves encoding logical qubits into multiple physical qubits and using operations that correct errors dynamically.

Scalability and Hardware Improvements: Significant progress in hardware, including the development of more stable qubits, better control systems, and cryogenic technology, will be essential. Companies, like IBM, Google, and Rigetti, are making strides in these areas, aiming for scalable quantum processors.

5 | CONCLUSION

The research considered QML as one of the tools which involve regression tasks into the quantum world. Our accuracy results for simple datasets give evidence about a prospect for striking similar results but they also bring to light difficulties with more elaborate functions. These revelations thus underline the vital importance of another attempt of research and development in the expanding operations. As we move forward, certainly, augmenting the expressivity and the speed of our quantum circuits remains the biggest challenge ahead. With advanced tools such as novel features maps, analysis, and optimisation techniques exactly made for the QML tasks in use, there might be an emergence of more complicated and scalable solutions. Additionally, classical and QML tech approaches can be integrated through hybrid models and are expected to fulfil the purpose by overpassing the current officers' limitations. When two techniques used are classical optimisation techniques and the power of quantum computing, hybridised algorithms can unravel better performance in many disparate domains and problems. As a further step, applications of QML to real life issues like drug discovery, materials, and finances, introduces research that will be adorable, and unimaginably potent. Ensuring that issues dealing with data privacy, algorithmic bias, and scalability are being addressed will help to harness QML to the limit, in order to resolve the complex and high-dimensional problems and propel the innovation forward. Future research should focus on enhancing error correction techniques and developing more robust quantum algorithms. Additionally, exploring QML applications in more complex and real world datasets could significantly broaden the scope of quantum computing.

AUTHOR CONTRIBUTIONS

Amit Kumar: Data curation; formal analysis; investigation; software. **Neha Sharma**: Project administration; supervision; validation; visualization; writing – original draft. **Nikhil Kumar Marriwala**: Conceptualization; formal analysis; methodology; project administration; resources; writing – original draft; writing – review & editing. **Sunita Panda**: Formal analysis; investigation; validation. **M. Aruna**: Resources; validation; writing – review & editing. **Jeetendra Kumar**: Formal analysis; resources.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

ORCID

Nikhil Kumar Marriwala https://orcid.org/0000-0002-1093-630X

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