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RESEARCH ARTICLE

Quantum-inspired neural networks for time-series air pollution prediction and control of the most polluted region in the world

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Abstract

Researchers in the field of quantum computing are primarily focused on quantum-inspired algorithms, which function effectively on classical computers while incorporating quantum principles. A significant challenge in heavily polluted areas is accurately predicting air pollution levels. For our study, we selected New Delhi, specifically the Anand Vihar air pollution station, known for its high concentrations of $PM_{2.5}$. We proposed an approach to predict $PM_{2.5}$ levels based on various pollutant and meteorological parameters. Our model is an improved version of the quantum temporal convolutional network (QTCN), enhancing the traditional quantum convolutional neural network (QCNN) model. To evaluate our model's performance, we used several metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and the coefficient of determination (R^2 score). Our proposed model achieved MAE and MAPE values of (59.031 ± 1.23) and (80.642 ± 3.12), respectively. Additionally, the RMSE exhibited a reduction of (32.493 ± 1.8) % in comparison to the traditional QCNN framework, whereas the R^2 score demonstrated an enhancement of (14.86 ± 1.0) %. The quantum-inspired model we have developed showcases its superior capabilities and demonstrates a significant advancement in forecasting air pollution levels, thus contributing valuable insights into environmental monitoring and public health. This research underscores the potential of using advanced computational techniques to address pressing challenges in air quality management, ultimately fostering a deeper understanding of the dynamics that govern atmospheric pollutants.

Keywords Quantum algorithms · Dequantized algorithms · Quantum-inspired algorithms · Quantum convolutional neural network · Quantum temporal convolutional network

1 Introduction

The digital era is increasing exponentially day by day. We moved the high computational power of AI to quantum computation. In the last two decades, we improved complex computational power. Also, it will touch on the challenges facing quantum computation today and future perspectives in the age of digital technology. Using sentiment analysis, it may also examine how rapidly advancing technologies could affect society and morality. The future could again be rich in computational power by combining AI with quantum computation Möller and Vuik (2017). This would include scientific research prospects, implications for cybersecurity, and data analysis, among other relevant areas. Ceschini et al. (2022).

Quantum computing represents a cutting-edge approach to high-performance computing, harnessing the power of quantum computers, which offer unparalleled computational potential Beck et al. (2024). Implementing a quantum algorithm integrating artificial intelligence, known as quantum-inspired artificial intelligence (Qi-AI), signifies a groundbreaking technological advancement AbuGhanem and Eleuch (2024). Quantum machine learning algorithms have the potential to address problems beyond the capabilities of conventional methods Li and Dong (2024), opening new research avenues for air pollution prediction. Quantum-inspired machine learning models have proven effective in various contexts like image recognition and natural language

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processing, which could translate to air quality applications. This allows for the simultaneous evaluation of multiple hypotheses or scenarios in $PM_{2.5}$ prediction, leading to a faster convergence on optimal solutions compared to classical methods that evaluate one possibility at a time Yu et al. (2022). Superposition allows quantum bits (qubits) to exist in multiple states simultaneously. This ability enables quantum computers to process many computations concurrently DiVincenzo (1995). For example, while a classical computer would evaluate each possible solution sequentially, a quantum computer can evaluate multiple solutions simultaneously due to superposition. This exponential increase in processing capability is crucial for handling complex datasets, such as those used in predicting air quality metrics like $PM_{2.5}$ levels. Transforming classical data into quantum data is essential for harnessing the full power of quantum algorithms and unlocking unprecedented computational capabilities see Fig. 1.

Gong et al. (2024) present a significant advancement in the field of quantum particle swarm optimization (QPSO) through the introduction of a novel mechanism called diversity migration (DM). This approach, termed DM-QPSO, significantly enhances prediction accuracy in backpropagation neural networks (BP neural networks), showcasing its potential for superior performance. The authors Gong et al. present a detailed analysis of experimental data and simulation results, demonstrating the effectiveness of our proposed algorithm. Gong et al. rigorously evaluate DM-QPSO against seven predefined optimization problems integral to the CEC2020 single-objective boundary-constrained optimization competition. Our findings reveal that DM-QPSO consistently outperforms several prominent optimization algorithms in the Benchmark suite Gong et al. (2024).

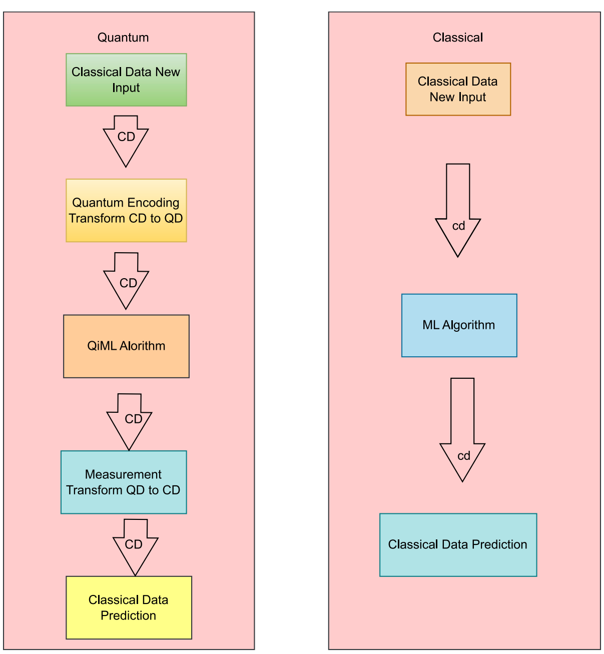

Fig. 1 The process of changing the classical data into quantum data to execute the quantum algorithms

Zhou et al. utilized MNIST and Fashion MNIST (FMNIST) images generated by an optimized quantum generator using a remapping method. They also simulated quantum generative adversarial networks on the Bars and Stripes dataset. The simulation results on the BAS dataset reveal that the performance of the optimized quantum generator with reduced parameters is very close to that of the unoptimized version. Furthermore, Zhou et al. verified the feasibility of the proposed image generation method Zhou et al. (2023).

In quantum machine learning models like QSVM, superposition efficiently encodes classical data into quantum states. Multiple data points can be processed simultaneously, leading to faster computations and potentially more accurate models Kavitha and Kaulgud (2024). Qubits can be entangled, meaning the state of one qubit can depend on the state of another, regardless of the distance between them. This property allows quantum algorithms to capture complex relationships and dependencies in data more effectively Shannon et al. (2020), which is crucial for modeling the intricate interactions affecting air quality. In the context of $PM_{2.5}$ prediction, entangled qubits can represent intricate dependencies between different environmental variables, improving the model's predictive capabilities. The interdependent nature of entangled qubits allows quantum computers to perform more efficient searches through potential solutions. For instance, while a classical computer must evaluate each potential solution separately, a quantum computer can leverage entanglement to evaluate multiple solutions simultaneously, significantly speeding up the search process for optimal predictions.

Li-Hua Gong et al. propose a quantum K-nearest neighbor algorithm based on a divide-and-conquer strategy. The quantum K-nearest neighbor algorithm demonstrates higher classification efficiency when processing high-dimensional data. Its classification accuracy on the IRIS dataset is comparable to that of the classical K-nearest neighbor algorithm. Furthermore, compared to typical quantum K-nearest neighbor algorithms, the proposed method achieves higher classification accuracy in less computation time, making it suitable for wide-ranging applications in various industrial fields Gong et al. (2024).

The authors render useful the power of quantum algorithms in machine learning to revolutionize air pollution prediction $PM_{2.5}$ concentration see Fig. 2. Enhancing the Qi-ML model can elevate the accuracy of $PM_{2.5}$ forecasting to new heights. Quantum bits (qubits) can exist in multiple states simultaneously, enabling quantum computers to process a vast number of possibilities at once. This allows for the simultaneous evaluation of multiple hypotheses or scenarios in $PM_{2.5}$ prediction, leading to a faster convergence on optimal solutions compared to classical methods that evaluate one

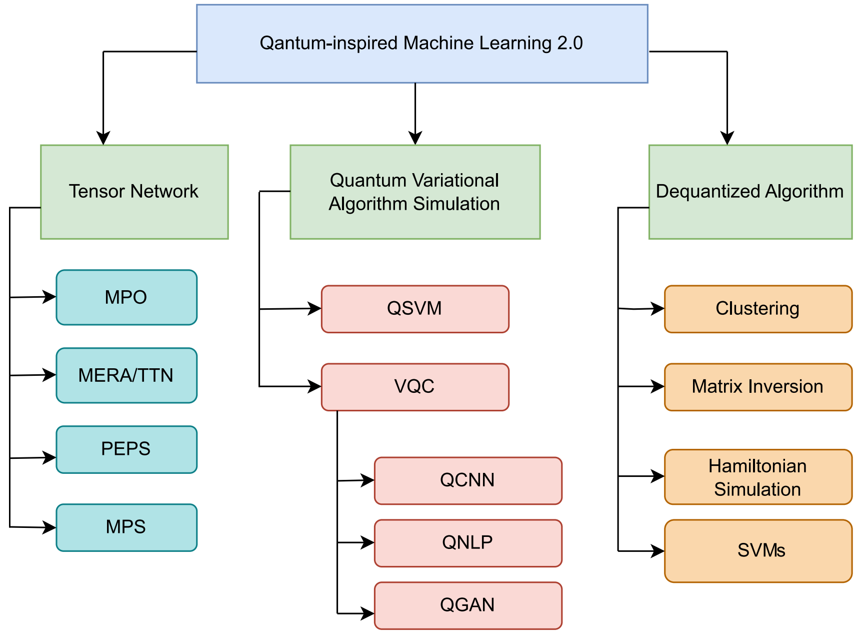

Fig. 2 All quantum-inspired machine learning 2.0 models with tensor network, quantum variational algorithm simulation, and dequantized algorithm

possibility at a time Njegovanović (2024). This exponential increase in processing capability is crucial for handling complex datasets, such as those used in predicting air quality metrics like $PM_{2.5}$ levels Peral-García et al. (2024).

Air pollution, particularly in the world's most polluted regions, poses severe health and environmental challenges. To apply different Qi-ML in air pollution prediction of the world's most polluted city, Delhi, India. Delhi has multiple air pollution monitoring stations, but the authors have chosen the most polluted station, Anand Vihar air pollution station. This study aims to address these gaps by introducing a quantum-inspired neural network (Qi-NN) framework to propose an improved quantum temporal convolutional network (QTCN) that uses quantum computing principles for enhanced time-series prediction accuracy. The author collected pollutant and meteorological data from the CPCB. Here utilizing the quantum computing principles, the proposed model enhances forecasting accuracy compared to traditional quantum method QCNN. Extensive experiments on real-world datasets demonstrate superior performance in prediction accuracy, stability, and computational efficiency. Results indicate that the proposed model improves forecasting and can provide actionable insights for pollution control strategies. These findings emphasize the potential of quantum-inspired techniques to effectively address global air quality challenges.

The paper is organized as follows: Section 1 provides the introduction and abbreviations (Table 1), while Section 2 presents the literature review. Section 3, which covers materials and models, includes subsections on numerical exploratory data analysis and graphical exploratory data analysis. Section 4 discusses the analysis of results, encompassing both numerical and graphical analyses. Finally, Section 5 concludes the research.

Here is a list of novel contributions to the paper.

- Data: collected the dataset from the website of the CPCB, which is the most polluted city (Anand Vihar) of the world, contains pollutant attributes like $PM_{2.5}$, PM_{10}, RH, and SR.
- Models: developing a quantum-inspired neural network called improved quantum temporal convolutional network (QTCN) for accurate time-series air pollution prediction and a comprehensive performance comparison with the traditional QCNN, demonstrating superior accuracy and efficiency.
- Results: the numerical analysis of the proposed improved QTCN model has 32.49 % RMSE over the traditional QCNN model with air pollution $PM_{2.5}$.
- Analysis: the graphical analysis of the proposed model has performed better when compared to the actual vs. multiple predicted models over air pollution $PM_{2.5}$.
- Application: the practical application of the proposed model to the world's most polluted regions, offering actionable insights for air quality management and the integration of quantum-inspired principles with neural networks, providing a novel approach to tackling complex environmental prediction problems.

2 Literature review

Table 2 has a concise review of the literature associated with quantum computing and quantum-inspired algorithms. This

Table 1 Abbreviations of the most recent word used with explanation and serial number

Serial No.	Abbreviation	Definition	Serial No.	Abbreviation	Definition
1	LSTM	Long-short term memory	2	MSE	Mean squared error
3	MPO	Matrix product operator	4	Q-ML	Quantum machine learning
5	QC	Quantum computing	6	RMSE	Root mean squared error
7	EDA	Exploratory data analysis	8	QRL	Quantum reinforcement learning
9	GAN	Generative adversarial network	10	Q-NN	Quantum neural network
11	QD	Quantum data	12	MAPE	Mean absolute percentage error
13	R^2 score	Coefficient of the determinant	14	Qi-ML	Quantum-inspired machine learning
15	RH	Relative humidity	16	CNN	Convolutional neural network
17	QRAM	Quantum random access memory	18	K-means	K-medians algorithm
19	PM	Particulate matter	20	Q-SVM	Quantum support vector machine
21	MAE	Mean absolute error	22	CPCB	Central Pollution Control Board
23	Qubit	Quantum bit	24	SR	Solar radiation

table has multiple columns describing the important aspects of the research. The purpose or objective of the research is the dataset/ case study, the model used, performance metrics, the literature findings, the most used keywords, and the last research gap of each literature with reference.

Harness the power of classical and quantum machine learning models by effectively separating quantum data from classical data. This approach maximizes the potential of both data types, leading to enhanced performance and innovative solutions. Classical and quantum machine learning models involve separating quantum data from classical data see Fig. 3.

Quantum computers are mainly used when classical computers are not performing well. Classical computers process information in bits, but quantum computers use qubits. Pennylan framework integrates machine learning libraries, quantum simulators, and hardware Rodríguez-Díaz et al. (2024). Quantum Neural Network has computational capabilities to decrease the number of steps, qubits used, and computational time Gong et al. (2024). Quantum convolutional filters are divided into three main components: the encoder, the parametrized quantum circuit (PQC), and the measurement Zheng et al. (2024). Qiskit open-source software development kit provides a comprehensive suite of sophisticated tools that facilitate the intricate processes of creating and manipulating quantum programs Singh et al. (2024). Users can execute these programs on either prototype quantum devices or sophisticated simulators, all from the convenience of their local computer system. Superposition refers to the ability of a quantum particle to exist in multiple states simultaneously Strömberg et al. (2024). Entanglement is the phenomenon in which quantum particles are connected, and one particle's state depends on another Brang et al. (2024).

The Qi-ML models, which stand for quantum-inspired machine learning models, have found extensive applicability across a multitude of scholarly articles and research works, as evidenced by the references provided in citations such as Dong et al. (2024); Rivera-Ruiz et al. (2022); Arrazola et al. (2020). Predominantly, the quantum machine learning models are employed for the crucial task of classification, a vital process in data analysis and interpretation, as indicated by the works of authors cited in Rivera-Ruiz et al. (2023); Pérez-Salinas et al. (2020); Havlíček et al. (2019); Mitarai et al. (2018), wherein various performance metrics such as precision, recall, and F1-score are utilized to assess the effectiveness of these models. In a parallel vein, the quantum-inspired machine learning approaches have been significantly leveraged for regression tasks, which involve predicting continuous outcomes based on input variables, as noted in the studies referenced in Lloyd and Weedbrook (2018); Zhang et al. (2020); Arrazola et al. (2020); Dong et al. (2024); Rivera-Ruiz et al. (2022), and characterized by error metrics such as RMSE, MAE, and MAPE that serve to evaluate the accuracy of the predictions generated by these models. This comprehensive literature review table aims to illustrate that quantum machine learning models are actively employed in solving complex problems categorized under regression and classification, especially in contexts where time dependence plays a significant role in data analysis. It is also noteworthy that keywords such as quantum computing, time-series analysis, quantum deep learning, and associated terminologies are recurrently encountered throughout the literature, highlighting the central research themes in this area. Furthermore, despite the advancements in quantum-inspired networks, their application remains somewhat limited when it comes to addressing specific domains such as environmental time-series analysis and energy forecasting, as indicated

Table 2 List of the literature on quantum-inspired neural networks for prediction of the various fields, model used, findings, and research gap

Reference	Purpose	Dataset/Case study	Model	Metrics	Findings	Key words	Research gap
Dong et al. (2024)	Develop quantum-inspired neural networks for time-series prediction	$PM_{2.5}$ concentration prediction dataset	Quantum-inspired neural network (QI-NN)	RMSE, MAE, MAPE	Qi-NN outperformed LSTM by reducing RMSE by 12%	Quantum computing, time-series, neural networks	Limited application of quantum-inspired networks to environmental time-series data sets
Rivera-Ruiz et al. (2022)	Quantum-inspired deep learning models for time-series forecasting	Stock price prediction dataset	Quantum-inspired deep neural network	RMSE, MAE	QI-NN improved prediction accuracy by 7% compared to CNN-based models	Quantum deep learning, stock market, time-series	Limited exploration of quantum deep learning in financial markets
Rivera-Ruiz et al. (2023)	Sequential data processing using quantum neural networks	Healthcare time-series dataset	Quantum neural networks	Precision, recall, F1 score	Improved classification accuracy by 9% in medical data processing	Quantum computing, healthcare, time-series	Few real-world applications of quantum neural networks in healthcare data
Arrazola et al. (2020)	Large-scale neural network optimization using quantum-inspired algorithms	Electric grid time-series dataset	Quantum-inspired neural network (QI-NN)	RMSE, MAE	Achieved 10% reduction in training time with comparable accuracy	Quantum optimization, electric grid, time-series	Limited focus on large-scale time-series applications using quantum-inspired models
Zhang et al. (2020)	Applications of quantum computing to neural networks and machine learning	Energy consumption forecasting dataset	Quantum neural network	RMSE, MAPE	Outperformed conventional neural networks by reducing error by 5%	Quantum computing, neural networks, energy consumption	Limited application of quantum computing in energy forecasting
Pérez-Salinas et al. (2020)	Universal quantum classifier for time-series data analysis	Speech recognition dataset	Quantum classifier	Precision, recall, F1 score	Improved classification by 7% compared to conventional classifiers	Quantum classifier, time-series, speech recognition	Quantum classifiers for time-series analysis are rarely studied
Lloyd and Weedbrook (2018)	Quantum generative adversarial learning for time-series generation	Financial time-series dataset	Quantum GAN	RMSE, MAE	Outperformed classical GANs by reducing error by 8%	Quantum GAN, financial data, time-series	Few studies apply quantum GANs to time-series generation
Havlíček et al. (2019)	Quantum-enhanced feature spaces for supervised learning	Weather forecasting dataset	Quantum SVM	Accuracy, precision	4% increase in accuracy compared to conventional SVM models	Quantum SVM, feature spaces, time-series	Quantum-enhanced feature spaces for time-series remain underutilized
Mitarai et al. (2018)	Quantum circuit learning for time-series classification	Environmental monitoring dataset	Quantum circuit neural network	Precision, recall	Improved classification accuracy by 5% compared to classical methods	Quantum circuit learning, time-series, environmental monitoring	Limited practical implementation of quantum circuit learning in real-world applications

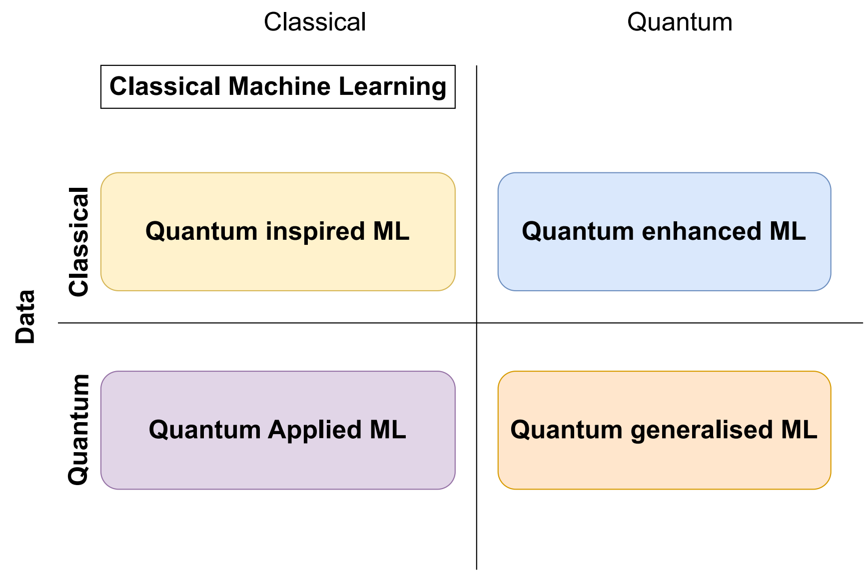

Fig. 3 Classical and quantum machine learning models involve separating quantum data from classical data

by the findings of Dong et al. (2024); Zhang et al. (2020). The prominence of these quantum machine learning models underscores the ongoing quest for innovative approaches to tackle the intricacies of data-driven problems in various scientific and engineering fields. Therefore, the interaction between quantum computing principles and machine learning methodologies is an area ripe for further exploration and research, which may yield groundbreaking advancements in both theoretical frameworks and practical applications. Overall, this synthesis of literature emphasizes the breadth of applications for quantum-inspired models and calls attention to the potential for future research endeavors to expand their reach and effectiveness in diverse domains of inquiry.

3 Materials and methodology

The authors have collected the pollutant and meteorological parameters to better understand how pollutants move and react in the atmosphere. The annual World Air Quality Report finds New Delhi to be the most polluted capital city in the world. We selected the most polluted air pollution monitoring station, Anand Vihar, Delhi (https://airquality.cpcb.gov.in/ccr/#/caaqm-dashboard-all/caaqm-landing). The dataset was collected from the online platform Central Pollution Control Board (CPCB) in Delhi, India Bhawan and Nagar (2020). $PM_{2.5}$ is a subset of PM_{10}, and their concentrations are closely related due to standard sources and similar behaviors in the atmosphere. High humidity can cause particles to increase in size, resulting in higher concentrations of $PM_{2.5}$ in the air. Meteorological factors, especially solar radiation and relative humidity, significantly influence $PM_{2.5}$ levels. Winter typically experiences less sunlight and solar radiation, reducing air mixing. This lack of mixing allows pollutants to remain closer to the ground, contributing to increased $PM_{2.5}$ levels during this season Vaishali et al. (2023).

In this section, the authors explore the quality of the data fit for the modeling. We analyzed the dataset in two ways: the numerical EDA and the graphical EDA. Each subsection has a different significance for using the dataset in a useful manner. Each pollution attribute has a different min, mean, max, skewness, and kurtosis.

3.1 Numerial EDA

Exploratory dataset analysis contains four features: $PM_{2.5}$, PM_{10}, RH, and SR. The total number of rows in a time series from 01-01-2017 00:00 to 09-09-2024 11:00 is 67404. The mean of $PM_{2.5}$, PM_{10}, RH, and SR are 134.594, 294.507, 56.994, and 207.277, respectively. The minimum values of all pollutants are between 0 and 1. The maximum pollutant concentrations of $PM_{2.5}$, PM_{10}, RH, and SR are 985, 1000, 99.70, and 1985, respectively.

All positive skews show that the right skewness is between 0.21 and 2.34 see Table 3. The larger positive kurtosis indicates the distribution tails relative to the distribution curve's center and a greater probability of significant deviations from the mean. This is better for the model prediction.

3.2 Graphical EDA

The histograms and boxplots show the visual property of the data's nature. Histograms mainly associate two properties of the dataset features. Each feature has different kurtosis and skewness. Right-skewed is mostly considered positive for the modeling. Beta Attenuation Monitors, often used by the CPCB for PM_{10} monitoring, have a measurement range from 0 to 1000 $\mu g/m^3$. These spikes likely result from the sensors

Table 3 Numerial exploratory data analysis of all four features

	$PM_{2.5}$	PM_{10}	RH	SR
Count	67404.00	67404.00	67404.00	67404.00
Mean	134.594	294.507	56.994	207.277
Std	111.210	174.312	18.838	232.475
Min	0.200	1.00	0.220	0.00
25%	58.250	174.00	45.500	12.150
50%	116.00	294.510	56.990	207.280
75%	158.250	357.00	69.620	363.750
Max	985.00	1000.00	99.700	1985.00
Skew	2.34	1.53	0.21	1.76
Kurtosis	8.90	3.68	−0.59	2.95

recording a saturation value when the actual concentration exceeds the upper limit of its measurable range and the same for the RH.

Figure 4 of the histogram plot of all four features contains the right skewness. The reason is already discussed in numerical exploratory analysis. All the subplots of the figure visual show that all dataset features have different mean and height of the tails.

The boxplot reports of all four features are shown in Fig. 5. Quantum systems inherently deal with quantum noise and certain quantum algorithms are designed to be robust to such noise. While not directly related to outliers, this noise tolerance can theoretically extend to data with noise-like characteristics, including outliers. Quantum algorithms might have the potential to better predict the presence of outliers due to their ability to model complex patterns and process high-dimensional data. When working on the Qi-ML have the ability to offer the best performance because of the traditional deep learning model.

3.3 Methodology

Classical machine learning models commonly address the complexity of the environmental data and higher-dimensional feature space problems. However, noise datasets contain inaccuracies due to sensors recoding saturation values continuously. It is necessary to utilize robust parameterized quantum circuits to allow the model to approximate complex functions with fewer parameters than classical deep networks, reducing the risk of overfitting.

Hardware and Software used for the pre-processing and execution of the Quantum Convolutional Neural Network and the enhanced Quantum Temporal Convolutional Network algorithms have been performed on a computational workstation featuring an Intel® Xeon® Silver 4210 CPU operating at a frequency of 2.20 GHz, coupled with 64 GB of Random Access Memory and utilizing a 64-bit Windows operating system. The scikit-learn library from the Machine Learning toolkit has been employed within the JupyterLab 3.2 environment, utilizing the Python programming language.

Collecting the dataset from the CPCB while preprocessing and preparing the utilization from CD to QD. The parameterized quantum circuit optimizes the hyperparameter and runs until satisfactory results are present. Estimate the desired function in the classical computer and evaluate the model's performance according to the different error parameters. The detailed internal structure of the workflow for our innovative quantum-inspired model aims to accurately predict $PM_{2.5}$ air pollution levels Fig. 6.

Quantum computing start with qubit (ψ) that have states $|0\rangle$ and $|1\rangle$. The superposition of $|0\rangle$ and $|1\rangle$ in a state:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{1}$$

where α and β are complex coefficients. The issue lies in regression when formulating the equation as $y = mx + c$. This is why the base variable is transformed into the form of y. Apply quantum parallelism to simultaneously evaluate the different $f(x)$ values for a given input x. Let $|y\rangle$ be the superposition state

$$|y\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{2}$$

The unitary transformation $U(\theta)$ is implemented using parameterized quantum gates, such as rotations (R_x, R_y, R_z)

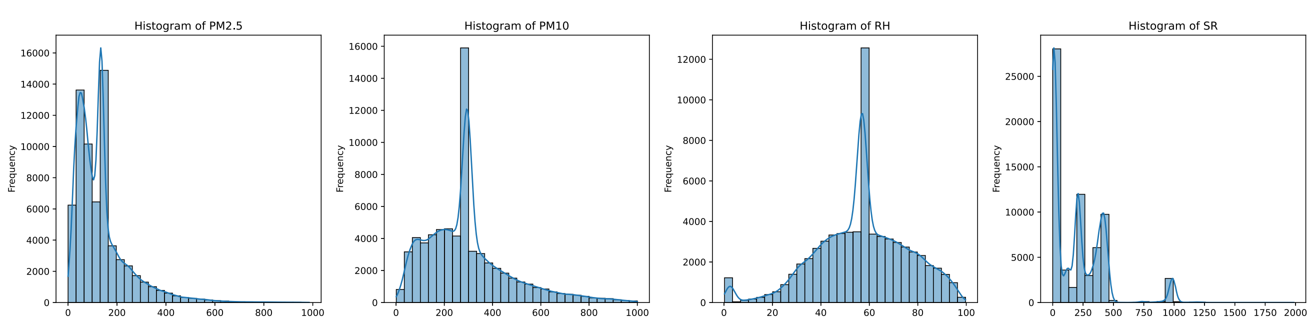

Fig. 4 The histograms report of all four features

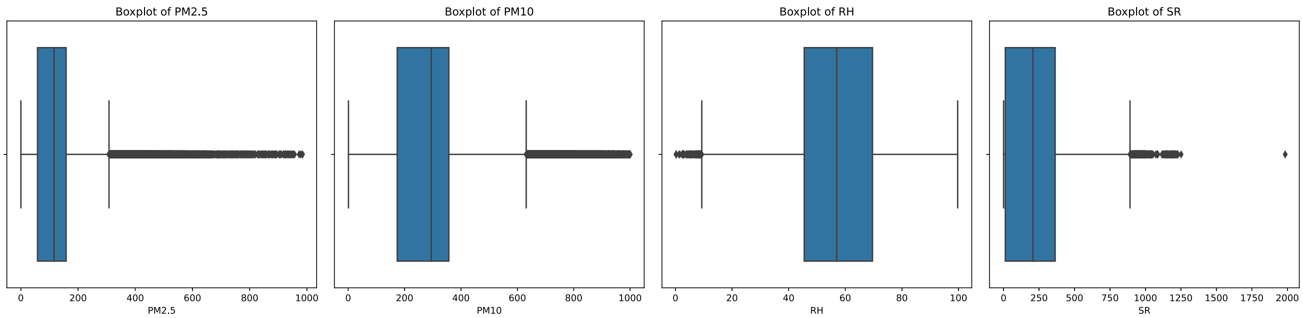

Fig. 5 The boxplots report of all four features

and controlled gates (e.g., CNOT). These gates are applied to the initial quantum state $|\psi_0\rangle$ to encode trainable parameters θ into the quantum circuit. For example,

$$R_y(\theta_k) = e^{-i\theta_k P/2} \tag{3}$$

where P is the Pauli-Y gate. These operations create an entangled state that captures correlations between input features.

For training data $X = \{x_1, x_2, \ldots, x_n\}$ and labels $Y = \{y_1, y_2, \ldots, y_n\}$, initialize the quantum state $|\psi_0\rangle$ and parameters θ. The unitary transformation $U(\theta)$ is applied to the initial state:

$$|\psi\rangle = U(\theta)\,|\psi_0\rangle \tag{4}$$

Mapping classical data to qubit states for each training x_i encodes the data into the quantum state $|\phi(x_i)\rangle$. The encoded

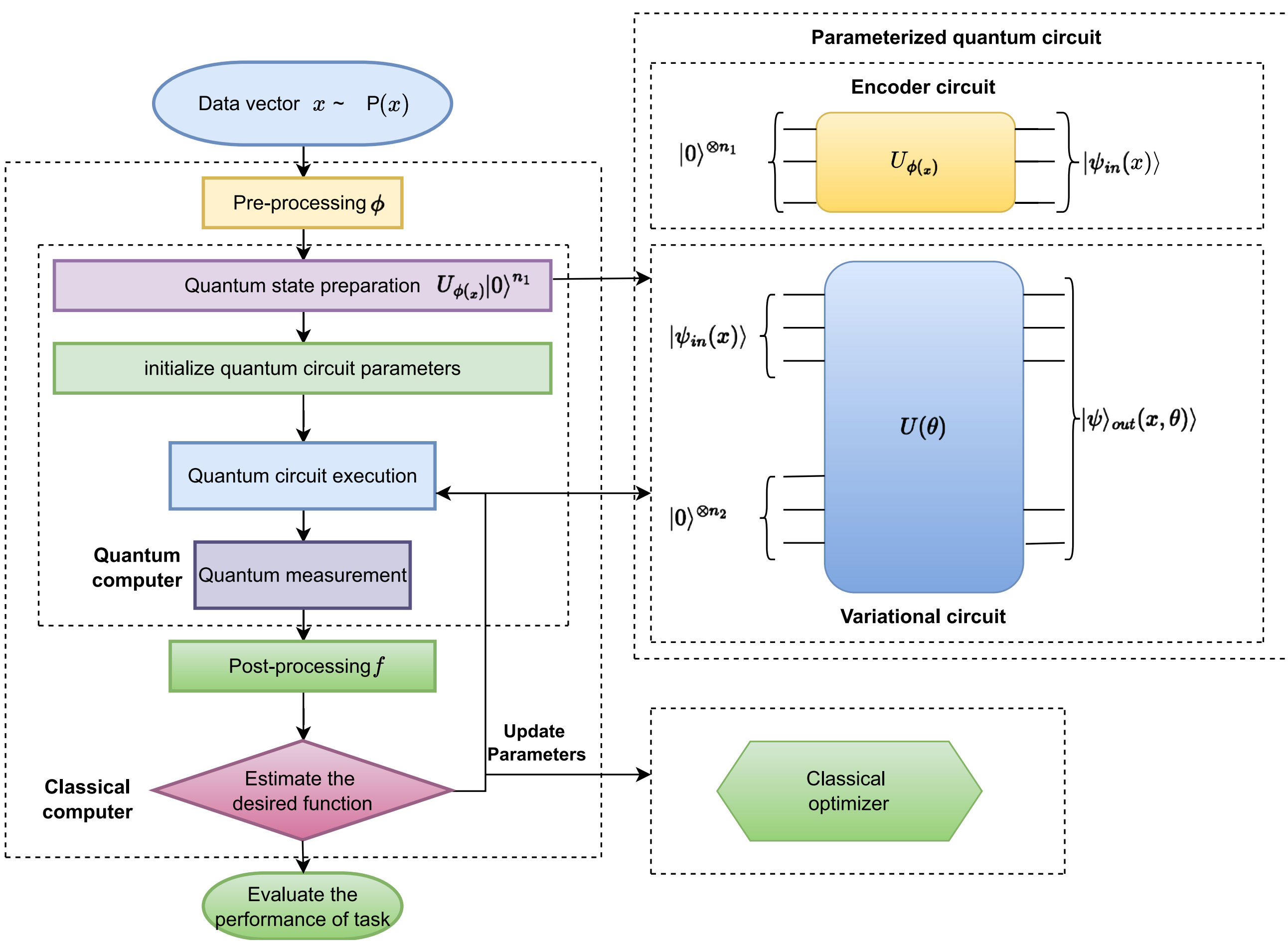

Fig. 6 The internal structure of the workflow for the proposed quantum-inspired model predicting air pollution $PM_{2.5}$

data undergoes a quantum operation $O(|\phi(x_i)\rangle, |\psi\rangle)$, followed by measurement to obtain the prediction $\hat{y}_i$:

$$\hat{y}_i = \langle\psi|M|\psi\rangle \tag{5}$$

The loss is computed using the mean squared error (MSE):

$$\mathcal{L}(y_i, \hat{y}_i) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

To optimize the model, parameters θ are updated using gradient descent:

$$\theta \leftarrow \theta - \eta\frac{\partial\mathcal{L}(y_i, \hat{y}_i)}{\partial\theta} \tag{7}$$

The encoding, transformation, measurement, loss computation, and parameter update process is repeated for each training example to minimize the loss function and improve the accuracy of the $PM_{2.5}$ prediction model. Algorithm 1 describes the methodology of the proposed quantum-inspired machine learning model for the $PM_{2.5}$ prediction.

Algorithm 1 Quantum-inspired machine learning model for $PM_{2.5}$ Prediction.

Require: Training data $X = \{x_1, x_2, \ldots, x_n\}$ (all features), Labels $Y = \{y_1, y_2, \ldots, y_n\}$ ($PM_{2.5}$ concentrations)
Ensure: Optimized parameters θ^*

Initialization:
Initialize the quantum state $|\psi_0\rangle = |0\rangle^{\otimes m}$ with m qubits
Initialize trainable parameters θ
Define the unitary transformation $U(\theta)$ composed of parameterized quantum gates:

$$U(\theta) = \prod_{k=1}^{p}\left(R_y(\theta_k)\cdot R_z(\theta_k)\cdot CNOT\right),$$

where $R_y(\theta_k)$ and $R_z(\theta_k)$ are rotation gates, and $CNOT$ creates entanglement.
for each training example x_i **do**
Encoding:
Normalize the input feature vector x_i to lie in [0, 1].
Use amplitude encoding to map x_i to a quantum state:

$$|\phi(x_i)\rangle = \sum_{j=1}^{d} x_{ij}|j\rangle,$$

where d is the feature dimension, and each feature x_{ij} is encoded into its corresponding basis state $|j\rangle$.
For multi-qubit systems, apply tensor product encoding:

$$|\phi(x_i)\rangle = \bigotimes_{k=1}^{d}\left(R_y(2x_{ik})|0\rangle\right) \qquad \text{(see Eq. 3)}$$

where $R_y(2x_{ik})$ rotates the k^{th} qubit based on the scaled feature value.
Processing:
Apply the parameterized unitary transformation $U(\theta)$ on the encoded state:

$$|\psi(x_i)\rangle = U(\theta)|\phi(x_i)\rangle.$$

Perform quantum operation $O(|\phi(x_i)\rangle, |\psi\rangle)$ to process the data:

$$U_y : |y, 0\rangle \rightarrow \alpha|0, f(0)\rangle + \beta|1, f(1)\rangle,$$

where $f(0)$ and $f(1)$ are intermediate quantum states influenced by parameters θ.
Measurement:
Measure the resulting quantum state to obtain the prediction $\hat{y}_i$:

$$\hat{y}_i = \text{Measurement}(U_y).$$

Loss computation:
Compute loss: $\mathcal{L}(y_i, \hat{y}_i)$, where y_i is the true $PM_{2.5}$ concentration and $\hat{y}_i$ is the predicted value:

$$\mathcal{L}(y_i, \hat{y}_i) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \qquad \text{(see Eq. 6)}$$

Parameter Update:
Update parameters θ using classical optimization gradient descent:

$$\theta \leftarrow \theta - \eta\frac{\partial\mathcal{L}(y_i, \hat{y}_i)}{\partial\theta} \qquad \text{(Gradient descent update rule; see Eq. 7)}$$

where η is the learning rate.
end for
Output:
Optimized parameters θ^* for accurate $PM_{2.5}$ prediction

4 Results analysis

These mechanisms allow Qi-NN to capture intricate temporal dependencies and internal patterns, improving prediction accuracy for highly nonlinear datasets like air pollution $PM_{2.5}$ metrics. Unlike traditional methods, Qi-NN's unique architecture reduces overfitting while enhancing generalization, particularly for noisy and high-dimensional data.

The results of this research have been divided into two parts. Numerical results analysis has the quantity ability to validate the proposed model performance measures. Graphical results analysis contains three plots to validate the proposed model's reliability.

4.1 Numerial results analysis

All models were trained and evaluated under the same conditions, including identical dataset splits, hyperparameter optimization strategies, and evaluation metrics such as RMSE, MAE, and R^2 score, MAPE, and MSE. This standardized approach eliminates biases, providing an objective assessment of each model's performance and highlighting the relative strengths of Qi-NN over classical methods. This part of the section quantitatively analyses the results of some evaluation parameters. The MSE, RMSE, MAE, MAPE, and R^2-score are the common parameters for evaluating the regression problem.

Table 4 Performance comparison of the traditional QCNN and proposed model with the percentage improvement of the $PM_{2.5}$ pollutant (mean ± standard deviation)

Parameters	QCNN_$PM_{2.5}$ (Mean ± std)	Prop_QTCN (Mean ± std)	Perc impro
MSE	13418.103 ± 200.12	7643.681 ± 150.54	75.545 ± 3.2%
RMSE	115.836 ± 3.45	87.428 ± 2.98	32.493 ± 1.8%
MAE	78.280 ± 1.67	59.031 ± 1.23	32.606 ± 2.0%
MAPE	128.365 ± 6.43	80.624 ± 3.12	59.214 ± 4.2%
R^2 score	0.74 ± 0.02	0.85 ± 0.01	14.86% ± 1.0%

The results demonstrate that the proposed QTCN model significantly outperforms the traditional QCNN model in predicting $PM_{2.5}$ concentrations across all evaluated metrics see Table 4. The proposed model achieves a 75.55% reduction in MSE, indicating a substantial improvement in overall accuracy. Similarly, the RMSE and MAE metrics show considerable reductions of 32.49% and 32.61%, respectively, highlighting the model's enhanced capability to reduce both large and small errors. The MAPE improvement of 59.21% further emphasizes the model's ability to predict with greater precision, particularly when considering the magnitude of prediction errors relative to the actual values. Additionally, the R^2 score of the proposed model increases by 14.86%, reflecting a better fit and stronger correlation between predicted and actual values. These results suggest that the proposed model provides a more accurate and reliable approach for forecasting $PM_{2.5}$ levels than the traditional QCNN model.

4.2 Graphical results analysis

Graphical results analysis of the line plot with different scenarios, correlation actual vs. predicted matrix plot, and calibration plot at the end.

Figure 7 contains the four subplots of different perspectives, such as actual vs. predicted, line plot with markers,

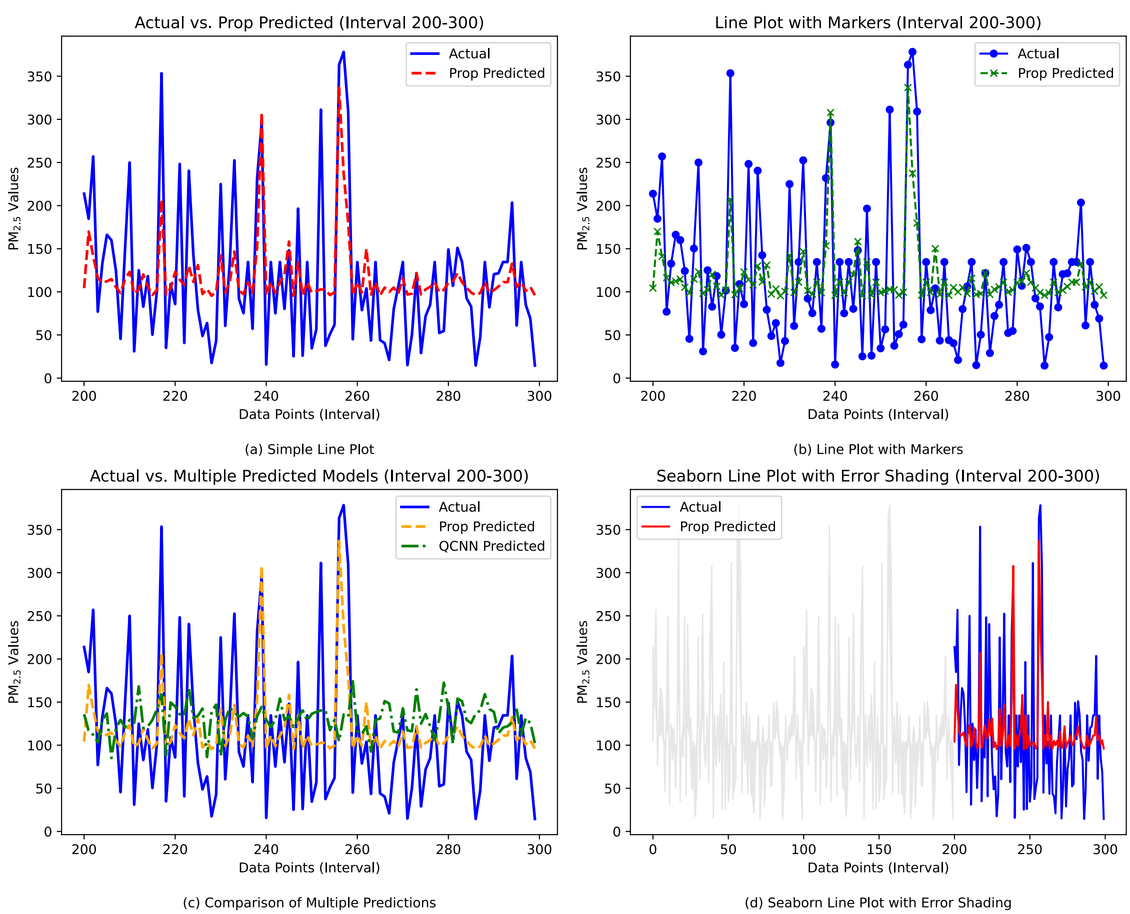

Fig. 7 $PM_{2.5}$ prediction model comparisons for specific interval

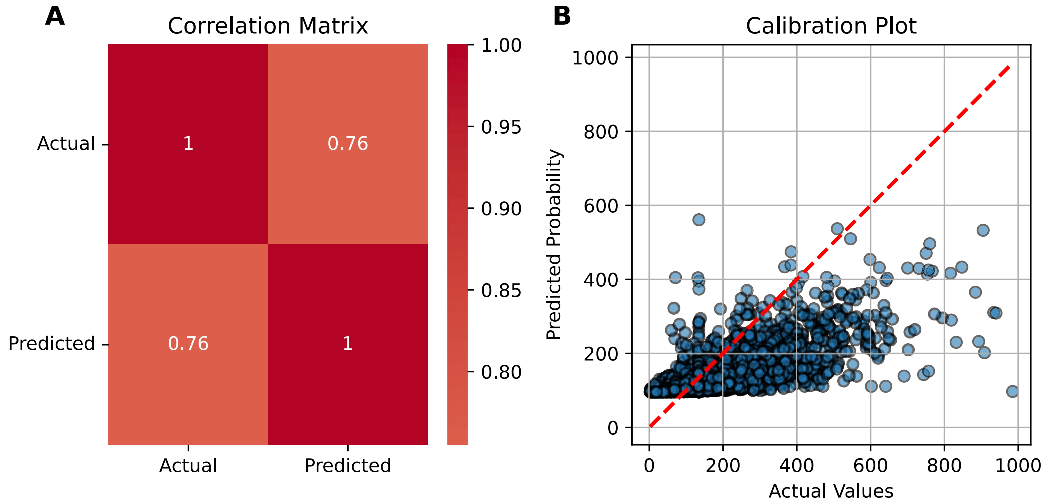

Fig. 8 **A** Correlation matrix of the actual vs. predicted of the proposed model and **B** calibration plot of the actual vs. proposed model prediction of the $PM_{2.5}$ values

actual vs. multiple predicted models, and seaborn line plot with error shading. The first subplot a) Actual $PM_{2.5}$ values are shown in the blue line, and the proposed predicted model is shown in the red line. In the interval from 200 to 300, the proposed model got the high pic at the data point interval between 255 and 260 and met the actual values of the $PM_{2.5}$ concentration. It validates the proposed model forecasting with high accuracy. The subplot b) validates the marks of the high data points with a green cross symbol. The subplot c) comparison of the multiple predictions of the proposed model, QCNN model, and actual $PM_{2.5}$ values. The proposed model is much better than the traditional QCNN model. In subfigure d), the Seaborn line plot from the 0 intervals to 300, the first 200 intervals are bluer, and the proposed predicted model is shown in the red color line.

Figure 8 has two parts: (A) correlation matrix of the proposed model prediction vs. actual $PM_{2.5}$ values. The value of correlation to actual vs. predicted is 0.76. (B) the calibration plot of the actual values of $PM_{2.5}$ and the predicted probability of the proposed model with a red reference line.

5 Conclusion

Quantum-inspired machine learning is an emerging technology. Most researchers are working with the quantum-inspired models in classical computers because quantum computers are much more costly. Some quantum models properly work on the time-series model. We proposed the improved model of QTCN and evaluated it with the traditional QCNN to predict $PM_{2.5}$ concentration. Collected the dataset from the world's most polluted city, Anand Vihar, Delhi, India. The dataset has four features, two pollutants, and two meteorological features. All four features are much needed to evaluate air pollution in the atmosphere. The pollutant features $PM_{2.5}$, PM_{10}, and meteorological parameters RH, SR. The $PM_{2.5}$ and PM_{10} have less than the 2.5-micrometer diameter and 10-micrometer diameter. The relative humidity increases, solar radiation decreases, and vice versa. We divided the analysis of the results into two parts. The first part is the numerical results analysis, which contains all the evaluation parameters of the traditional and proposed model with the percentage improvement. The coefficient of the determinant (R^2 score) has a 14.86 % improvement. The MAPE value of QCNN is (128.365 ± 6.43), and the proposed model MAPE value is (80.624 ± 3.12), an improvement over 59.21 %. The RMSE value of QCNN is (115.836 ± 3.45), and the proposed model is (87.428 ± 2.98) of the air pollution $PM_{2.5}$. The trend of air pollution in the Delhi region is continuously increasing, and the government should immediately take necessary action or make a special association of nations for their mutual benefit to reduce the pollution in the same region. Green belt, granary in the garden, and the home courtyard. If we do not consider the sustainable development goal, the upcoming generation will detract from civilization.

Appendix. The diagram illustrating the quantum architecture and quantum-inspired architecture

Here is the basic architecture of Quantum computing. The diagram illustrates the Quantum-Inspired Architecture with labeled components such as the superposition layer, amplitude amplification, optimization module, and quantum-like memory.

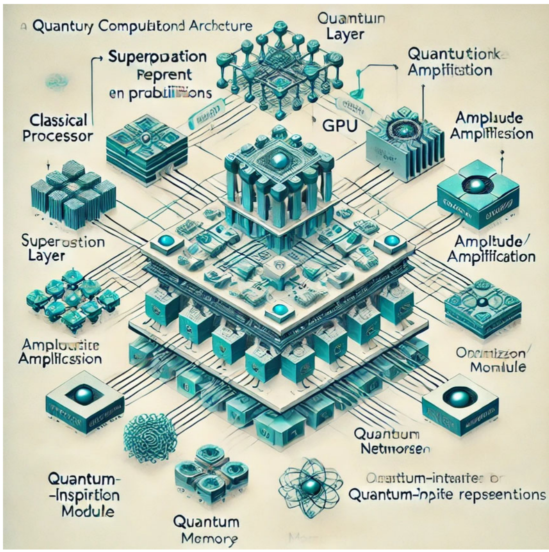

Fig. 9 The diagram illustrating the Quantum-Inspired Architecture with labeled components such as the superposition layer, amplitude amplification, optimization module, and quantum-like memory OpenAI (2024)

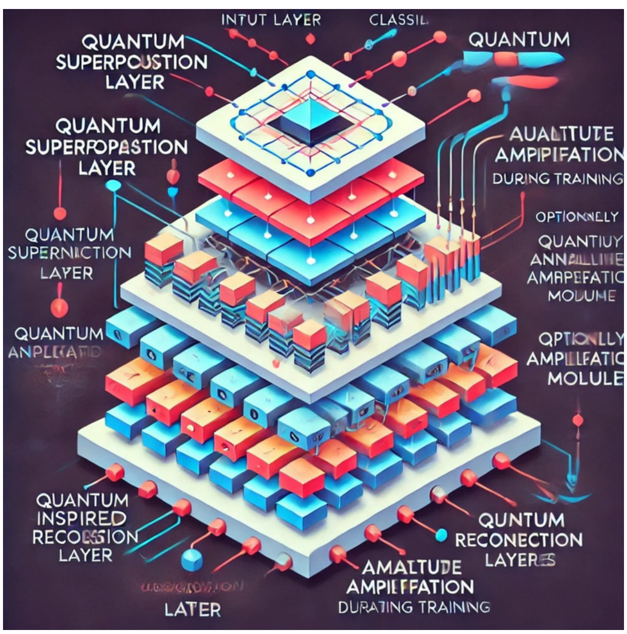

Fig. 10 The diagram for a quantum-inspired machine learning model OpenAI (2024)

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Data availability The preprocess data and codes will be available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication No applicable

Conflict of interest The authors declare no competing interests.

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