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Explainable hybrid quantum neural networks for analyzing the influence of tweets on stock price prediction

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ABSTRACT

Stock price prediction is a complex and challenging activity for organizations and investors to predict future returns. While machine learning and deep learning methods are widely used for stock closing price prediction, these methods have some drawbacks, including high scalability, slow convergence, and poor generalization performance. Furthermore, because those models are inherently black-box, it is challenging to comprehend the logic underlying their forecasts. This study presents an explainable hybrid quantum neural network to investigate the influence of tweets on a stock price prediction. The datasets used in this analysis include the stock prices of six different organizations as well as the 4 million+ tweets written on X (previously Twitter). The proposed methodology finds the average sentiment score of daily tweets using a transformer model which is combined with historical stock data. The proposed hybrid genetic algorithm based quantum neural network predicts the future stock closing price more accurately and uses explainable artificial intelligence methods to investigate the influence of average sentiment score of tweets and compute each attribute contribution towards the outcome. The proposed hybrid quantum neural network outperforms the other existing classical machine learning and quantum inspired machine learning algorithms by achieving a model accuracy (R^2) greater than 99% in the prediction of stock prices for the six different organizations. Further, based on the explainability analysis, we observe that the tweets do not influence stock price to a greater extent.

1. Introduction

Stock market prediction is the process of predicting the future direction of stock prices and overall market trends. Traders, analysts, and investors utilize various methods, instruments, and strategies to understand market patterns, economic indicators, historical data, and other relevant factors [1]. Quantitative, technical, and fundamental approaches are commonly used for stock market prediction [2–5]. However, the complexity arises from factors like geopolitical events, investor sentiment, organizational performance, and unforeseen circumstances, making accurate predictions challenging (Ding et al. 2020).

Stock price prediction with sentiment analysis of tweets analyzes the sentiment of tweets related to a specific stock of a company and uses that sentiment to arrive at predictions about its future stock price movements [6–9]. By understanding the prevailing sentiment, investors could assess the potential for price volatility and market downturns and could achieve insights into how the market might react to specific news or events. While negative tweet sentiments might result in price drops and selling pressure, positive tweet sentiments might enhance buying activity and drive up stock prices. It plays an important role in analyzing market

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dynamics and making informed investment decisions with identified trends, by hedging strategies, adjusting portfolio allocations, or implementing risk mitigation measures [10].

The ability of machine learning (ML) and deep learning (DL) approaches to comprehend large volumes of data, recognize intricate patterns, and make predictions based on correlations that have been trained makes them valuable tools for stock prediction [11]. At the core of ML and DL for stock prediction is the concept of feature extraction. Financial data contains various variables such as stock prices, economic and technical indicators, trading volumes, news sentiment etc. These variables are utilized to establish meaningful features that capture relevant stock information. DL techniques, such as artificial neural networks (ANNs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) are implemented to process time-series and sequential data, allowing them to be suitable for stock market analysis. Large amounts of data may be handled by these models, which can also extract non-linear correlations and reveal complex patterns that conventional statistical techniques might find difficult to identify.

However, predicting stock closing price using ML/DL techniques is computationally prohibitive in case of huge volume of stock price dataset and requires more computation time. Alternatively, quantum inspired machine learning and deep learning techniques are capable of modeling stock price prediction in effective way. As the quantum process works based on qubits, which are represented as superposition states $|0\rangle$ and $|1\rangle$, quantum algorithms perform superior than the classical algorithms in various applications. Quantum approaches generate the distribution by using less number of gate operations, which is not attained by the classical computers [12]. Hence, in this paper, we propose a hybrid genetic algorithm based quantum neural network to predict the variations of stock prices based on their corresponding tweet dataset. Quantum neural networks extract the patterns for making the trading prediction from historical data by modeling as a quantum process. As compared to machine learning and deep learning models, hybrid quantum neural networks with the optimized parameter tuning by genetic algorithm have potential to solve complex problems more accurately and be able to perform the multiple operations simultaneously.

Explainable artificial intelligence (XAI) provides clear explanations for the actions and decisions taken by machine learning/deep learning algorithms as those are black box typed. XAI is a crucial field of study that helps determine the relative relevance of each feature by equitably allocating its contribution. As the predictions arrived by the hybrid quantum neural networks are black box typed, understanding and trusting the predictions are central challenges [13,14]. To overcome this limitation, we use explainable artificial intelligence models [15] to analyze the predictions of hybrid quantum neural networks.

This paper explores the impact of tweets on stock price prediction using an explainable hybrid quantum neural network. The proposed methodology uses a transformer model to determine the daily average sentiment score, which is then fused with historical stock information of an organization and fed into hybrid quantum neural networks. The hybrid quantum neural networks optimized by genetic algorithm predict the future stock closing price more accurately. The predictions arrived from the hybrid quantum neural networks are analyzed by the explainable artificial intelligence models. These XAI models visualize the importance of each feature to arrive at the decision. The proposed explainable hybrid quantum neural network is transparent with respect to fair distribution of each feature importance, adoptable to predict the future stock closing price, and minimize the number of computations to predict the outcomes by performing qubit operations. The salient contributions of the proposed methodology are as follows:

- Fusion of tweets with the historical stock price data of an organization by calculating the average sentiment score for each day using a transformer model.
- A novel explainable hybrid quantum neural network predicting the accurate stock closing price and explaining the significance of each feature influencing the stock closing price.

The identified research questions, research objectives, and research outcomes are presented as follows.

Research Questions

- RQ1: Does the sentiment score of tweets influence the stock price?
- RQ2: Can hybrid quantum neural networks predict the stock closing price accurately?
- RQ3: Are the outcomes generated by the hybrid quantum neural networks explainable?

Research Objectives

- RO1: To compute the average sentiment score of tweets by fusing the stock data using a transformer based sentiment analyzer.
- RO2: To propose a novel hybrid quantum neural network approach to investigate the factors that influence the closing price of a stock.
- RO3: To interpret and analyze the predictions arrived by the hybrid quantum neural networks using explainable artificial intelligence techniques.

Research Outcomes

- ROT1: Hybrid quantum neural networks achieves more accuracy compared to other state of the art quantum inspired ML/DL algorithms (RQ2).
- ROT2: The stock closing price is not influenced by the average sentiment score of tweets to a greater extent based on the results of the proposed method on six different stock data of organizations (RQ1).
- ROT3: Applying the explainable artificial intelligence models on the outcomes of the proposed method clearly demonstrates the non-obvious impact of the average sentiment score in predicting the stock price (RQ3).

The remainder of this paper is organized as follows: Section 2 describes the existing methods for analyzing and predicting stock market prices, particularly with social media sentiment analysis. Section 3 proposes an explainable hybrid quantum neural network for predicting the future stock closing prices accurately. Section 4 discusses the results obtained by the proposed model including explainability analysis, statistical analysis, and ablation studies. Conclusion and future work are discussed in Section 5.

2. Related work

Li and Pan [16] proposed a novel deep learning technique to forecast the stock movement, using a blended ensemble approach to combine two recurrent neural networks with a fully connected neural network. This ensemble blended model captures the patterns of the stock data to perform future predictions. However, the model fails to identify the complex patterns of the stock data. Carta et al. [17] proposed a multi-ensemble, multi-layer stock trading model with hundreds of deep neural networks for preprocessing. The meta model integrates with the deep learning, deep reinforcement learning approaches. Various metalearner trading judgments are combined to create a more robust trading strategy, with multiple trading agents involved in the decision-making process. However, the model is affected by the effects of overfitting. Ni et al. [7] proposed a tweet node model to anticipate the stock price movements based on the historical stock price data and tweets embeddings. The model is designed to interact visually to display the prediction outcomes. However, the constructed neural network seems biased and the fails to analyze the patterns of stock data to analyze the impact of tweets.

Swathi et al. [18] investigated the correlation among the tweets information and historical stock price with the help of learning and teaching based optimization and LSTM approaches. The correlation of tweets are used to identify the impact of sentiment of the users on the stock market. The impact of the sentiment patterns used to investigate the abnormal changes in the stock prices. However, the identified features may be extracted in an effective manner to train the model to enhance the accurate predictions. Li et al. [19] compared a LSTM model performance with the support vector machine and multiple kernel learning models by incorporating news sentiments and stock price to predict the stock price movements. The numerical stock data is modeled as a technical indicator based on technical analysis and the combined data is fed to the deep learning model to perform stock price predictions. However, the model fails to provide the explainability of the predictions arrived by the deep learning model. Chaudhari and Thakkar [9] proposed a quantization-based data fusion approach combining LSTM, back propagation neural network, and deep neural network to predict the stock trend movements. With the fusion of data using quantization, this model achieves the reduction of the amount of data to be transmitted while maintaining as well as improving the stock trend prediction accuracy. However, the model lacks to provide the explainability of the proposed network.

Rezaei et al. [20] proposed multiple hybrid approaches, such as EMD-CNN-LSTM and CEEMD-CNN-LSTM to extricate the time series sequences and the features. These features were fed to the trained model for stock price prediction. The collaboration of multiple models may enhance the analytical power of the model by partitioning the time series data into different frequencies. However, the complexity of the model needs to be optimized for handling the bias in the future predictions. Long et al. [21] described a deep neural network model using the desensitized transaction records and public market information to predict stock price trend by incorporating the knowledge graphs and DL techniques for the financial decision making. The features used for trading are clustered to ensure the robustness of the model and the relevant features are identified based on the knowledge graphs to enhance the model effectiveness. However, the model fails to improve the efficiency of the model in identifying the patterns of the data. Leow et al. [22] proposed a hybrid model by combining BERT model with the genetic algorithm to capture the market conditions through robo advisor to analyze the twitter sentiments for predicting the price movements. The parameters of the model may be updated in an effective manner to analyze the stock patterns in an effective manner. Xu et al. [6] combined a generative adversarial network and cooperative network to propose a self generated adversarial network model to anticipate the stock movements. This model effectively optimizes the overfitting and stochasticity issues simultaneously from the financial text data and stock price historical data. The model lacks to optimize the parameters in an effective manner and the outcomes of the model are not interpreted.

Fiok et al. [23] proposed a transformer based model on the semeval-2017 dataset with the help of NLP techniques to perform sentiment analysis based on twitter tweets and used XAI tools to elaborate the prediction outcomes. However, the accuracy of prediction may be enhanced by using the advanced state of the art models. Xu et al. [24] incorporated the attention model and semantic embedding approach to predict the stock movements by combining local and contextual attention mechanisms. This reduces the noises in the high level fabricated representation to enhance the performance. However, the model does not provide the interpretation for the outcomes. Liu et al. [25] introduced an industry–stock Pearson correlation matrix and uses a matrix factorization approach to extract a vector that fully describes the industry attributes of stocks. This allows the industry attributes to be used to the stock prediction. Additionally, to create a dynamic correlation between stocks and market preference, the past market preference is modeled based on the industry attribute of the companies. This correlation is then merged with the historical price features that the temporal convolutional network retrieved to predict company ranking. However, the model fails to analyze the daily frequencies of stock data and bridge balance between the short and long sides of trading.

Shi et al. [26] proposed a hybrid approach by combining ensemble model and deep learning approach to identify the rich feature extraction using several hidden layers. The weights used in this network are assigned with the help of closed form solution. However, the parameter updation in the model needs to be performed in an effective manner.

Paquet and Soleymani [27] proposed a hybrid approach to perform quantization and measurement of financial trajectories. The approach uses encoders to transform the partitions of the financial data and quantum neural network to predict the density matrix. The model lacks the ability to update the parameters effectively and the outcomes of the model are not interpreted. Liu and Ma [1]

Table 1
Summary of existing models.

Reference	Model(s)	Objectives	Remarks
Ni et al. [7]	Tweet node algorithm	Price prediction based on tweets embeddings and historical data.	The tweets considered from social networks may be biased.
Swathi et al. [18]	Learning and teaching based optimization and long short term memory	Investigate the correlation between tweets and stock price to make predictions.	Feature selection may be improved.
Chaudhari and Thakkar [9]	DNN, LSTM, and BPNN models	Quantization based data fusion method to anticipate the stock price data.	The predictions are block box typed.
Leow et al. [22]	BERT model and genetic algorithm	Robo advisor to analyze the tweets and optimize the portfolio.	The model will not perform the short sellings.
Xu et al. [6]	Self-regulated generative adversarial network	Stock prices prediction based on historical information and tweets.	The predictions are not interpreted.
Fiok et al. [23]	Transformer models	Twitter sentiment analysis with explainable artificial intelligence to analyze the predictions.	Adoption of transformer models can be improved.
Liu et al. [25]	Matrix factorization algorithm	To anticipate the stock price movements with construction of correlation matrix.	The feature correlation is not influenced.
Shi et al. [26]	Deep random vector functional link.	To investigate the performance of the deep learning approach based on RVFL networks.	The parameter can be updated in an effective manner.
Paquet and Soleymani [27]	Quantum neural networks.	To perform quantization and measurement of financial trajectories.	The parameters can be updated in an appropriate way.
Liu and Long [28]	Elman quantum neural network.	To perform the stock market price analysis.	The model may fail to provide the transparency of outcomes to enhance the reliability of predictions
Proposed methodology	Hybrid genetic algorithm based quantum neural network	Influence of tweets on stock price prediction.	Considers the average sentiment scores of the tweets for fusing the data.

Table 2
Symbols and representations.

Symbol	Representation
η	Step size
L	Number of hidden layers
m_l	Number of units in layer l
$\dagger$	Hermitian conjugation
τ_{max}	Strides and number of networks
Δ	Window size
n	Number of qubits
$K_j^{(l)}$	Parameter matrix
Υ	Resulting quantum circuit or unitary transformation
p	Number of tweets in a day

proposed an approach combining Elman neural network and quantum physics to predict the stock prices. The model fails to provide the transparency of outcomes to enhance the reliability of predictions.

The shortcomings of the current literature include biased feature selection, non-linear interactions among the features, inappropriate feature correlation, and non-explainability (see Table 1). Further, the researchers have applied the classical machine or deep learning approaches for anticipating the stock prices based on the sentiment of the tweets. These classical machine learning/deep learning models may not have the desired speed, accuracy, and scalability. Further, the predictions are block box typed (non-explainable) in most of these research works. To overcome these limitations, in this paper, we present an explainable hybrid quantum neural network to analyze the stock trends from the data to forecast the accurate stock closing price, by applying the explainable artificial intelligence models for evaluating the importance of each feature on the prediction outcomes.

3. Proposed methodology

In this section, we present a methodology for analyzing the sentiments of the tweets and predicting the stock prices using explainable hybrid quantum neural networks, combining the power of quantum computing, transformer model based sentiment analysis and neural networks in an explainable manner (see Fig. 1). This proposed methodology comprises (i) Transformer model to perform computation of average sentiment score and fusion with stock data, (ii) Designing of hybrid genetic algorithm based quantum neural networks (iii) Explainability analysis over hybrid quantum neural networks. Table 2 lists the symbol table of the important notations used in the paper.

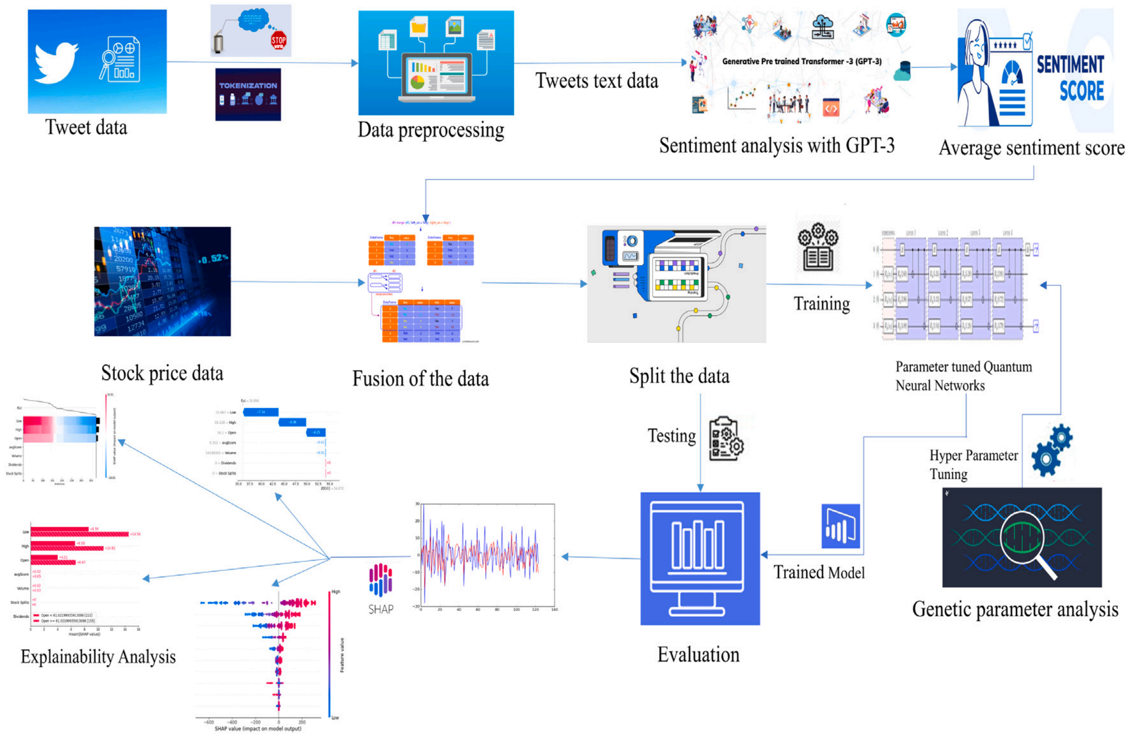

Fig. 1. Framework for explainable hybrid quantum neural network for stock prediction.

3.1. Transformer model for computing sentiment score and fusion with stock data

In the context of tweets and stock data, null values could occur if certain fields are not filled or if data is not available for certain dates or tweets. Removing null values make sure that the data used for analysis is accurate and tweets can be used for further data sentiment analysis. Sentiment analysis aims to discern the emotional polarity for a piece of text or sentiment, such as a tweet. Transformer based GPT-3 is a sentiment analysis model that works based on unlabeled large data to assign sentiment scores to the corresponding sentence [29]. The steps involved in the transformer based sentiment analysis model are listed as follows.
(i) Input text: A tweet is provided in the form of sentence or text or tokens, for which we wish to calculate the sentiment score.
(ii) Design prompt: The input text will be converted to prompt form to instruct the model to calculate sentiment score.
(iii) API Call: The text is given as a input to the GPT-3 model using Open API to analyze the input based on the prompt framework. Then the API will helps to pass the input text as a parameter to the model.
(iv) Response generation: The model analyzes and generates a sentiment score for the text in terms of a numerical score representing the sentiment intensity.

The transformer based sentiment analysis model applies the sentiment analysis to each tweet in the dataframe and generates the sentiment scores for each tweet. Table 3 presents a few sample tweets for Apple Inc. (AAPL) with its corresponding sentiment score for a random day.

From the sentiment score of each tweet, we calculate the average sentiment score of each day. For instance, if there are p number of tweets related to a particular company in a day, then the sentiment scores of each tweet are $[x_1, x_2, \dots .., x_p]$. The average sentiment score is calculated as the ratio of the sum of the sentiment scores of each tweet to the total number of tweets. Calculation of p number of daily tweets average is presented as follows (see Eq. (1)).

$$Avgscore = \frac{(x_1 + x_2 + \cdots + x_p)}{p} = \frac{\sum_{i=1}^{p} x_i}{p} \tag{1}$$

To analyze the relationship among sentiment scores from the twitter data and the stock data of an organization, we perform fusion of one dataset into another dataset based on the date of tweet/date of stock price as a common feature. The date column is utilized to fuse the data, and the combined data frame that is produced will allow for additional analysis and insights into the potential influence of emotion on stock market activity. The fusion of two different multimodal datasets helps to efficiently analyze the impact of different textual opinions on the numerical data [30]. Thus, data preprocessing followed by fusion ensures the data quality and calculates the sentiment scores using transformers to assess the sentiment of tweets. Fusing the data facilitates the exploration of relationships between sentiment and stock market behavior.

Table 3
Sample tweets with its sentiment score.

S. No	Date	Tweet	Sentiment score
1	01/01/25	My biggest winner in 2014: Inverse volatility ETF $XIVMy biggest loser in 2014: Apple $AAPL	0.10
2	01/01/25	Prediction: $AAPL makes a huge acquisition (Similar to Beats deal; maybe $GPRO?) and begins to tap into its cash hoard	0.31
3	01/01/25	Swing trading: Up to 8.91% return in 14 days http://ow.ly/GDks0 #swingtrading #forecast #techstock $MWW $AAPL $TSLA	0.0
4	01/01/25	Had a down day of −.66%. Worst performer was $AAPL down −1.9% and best was $SBUX up 32%. #Performance #Transparency	0.02
5	01/01/25	$UNP $ORCL $QCOM $MSFT $AAPL Top scoring mega caps right now at the end of 2014 on http://GetAOM.com	0.20
6	01/01/25	RT CNBC: Earlier this month, a mysterious glitch caused $AAPL to suddenly drop 6% ≫ http://cnb.cx/1wafKRS (vi... http://ift.tt/1tpseAE)	−0.272
7	01/01/25	Investment themes: The american consumer is confident again $AAPL	0.49
8	01/01/25	Can't update my iPad because of this... Apple sued for shrinking storage space on 16 GB devices thanks to iOS 8 $AAPL	0.44
9	01/01/25	Prediction: PayPal post-spinoff and $PAY arenolongerindependentcompanies.Theyareboughtby$GOOGL $V or$MA to compete with $AAPL pay	−0.38
10	01/01/25	The week's winners and losers on Wall Street: Apple gels, Marriott jams http://aol.it/1tkWug8 $AAPL $MAR	−0.07

3.2. Designing of hybrid genetic algorithm based quantum neural networks

Quantum computing leverages quantum bits, known as qubits, which can represent both 0 and 1 simultaneously based on the principle of superposition [1,31]. This property allows quantum computers to perform complex computations in parallel, potentially providing exponential speedup for certain problems compared to classical computers. The data is presented in the form of classical bits. To train the quantum models, we need to convert the classical bits to qubits which transforms the classical information processing to quantum information processing. The classical bits of information are binary digits. Conversely, qubits are quantum counterparts that have the ability to reside in superpositions of states, simultaneously representing 0 and 1, and they can entangle with other qubits. Classical information can be encoded into the quantum state of a qubit. For instance, the classical bit 0 map to the quantum state $|0\rangle$ and 1 to the quantum state $|1\rangle$. Since qubits can exist in a superposition of states, superpositions of $|0\rangle$ and $|1\rangle$ could also be used to encode classical information. A qubit is represented as $|\phi\rangle = \sum_i a_i|i\rangle(i = 1, 2, \ldots .n)$, where i represents the computation space for n-dimensional space $\sum_i |a_i|^2 = 1$. If there is even the slightest disturbance happens, $|\phi\rangle$ collapses into possible states of $|i\rangle$ with a probability of $|a_i|^2$. For example, $(|0\rangle + |1\rangle)/\sqrt{(2)}$ represents a superposition with equal probabilities of measuring 0 or 1. The quantum simulation involving the conversion of classical bits to qubits is performed by the qiskit learn and pennylane libraries by providing the circuit size as a parameter value.

The architecture of the quantum neural network contains multiple quantum perceptrons with the optimized parameters [27]. Each perceptron contains b input and c output qubits, which result in $4^{b+c} - 1$ of complex parameters. These parameters are similar to classical weight matrices and the states are denoted by density matrices. The density matrices of input and output are considered as pure states, and hence they can be represented in terms of vector states $|\psi^{\text{in}}\rangle$, $|\psi^{\text{out}}\rangle$ and their Hermitian conjugates $\langle\psi^{\text{in}}|$, $\langle\psi^{\text{out}}|$ as follows (see Eq. (2)).

$$\rho^{\text{in}} = |\psi^{\text{in}}\rangle\langle\psi^{\text{in}}|, \quad \rho^{\text{out}} = |\psi^{\text{out}}\rangle\langle\psi^{\text{out}}| \tag{2}$$

The input layer of a quantum neural network is represented as the density input matrix, L unitary operators or hidden layers and the output layer is denoted by the density output matrix. The deep quantum neural network is presented as follows (see Eq. (3)).

$$\rho^{\text{out}} = \text{tr}_{l\in\{1,\ldots,L\}}\left[\Upsilon\left(\rho^{\text{in}} \otimes |0_{\text{out}}, 0_{\text{L}}, \ldots, 0_1\rangle\langle 0_{\text{in}}, 0_1, \ldots, 0_{\text{L}}, 0_{\text{out}}|\right)\Upsilon^{\dagger}\right] \tag{3}$$

where † represents Hermitian conjugation. Apart from the output layer, the trace is considered for every layer and $|0, \ldots, 0\rangle$ is considered as the ground state and Υ is considered as the resulting quantum circuit or unitary transformation (see Eq. (4)).

$$\Upsilon = \mathbf{U}^{\text{out}}\mathbf{U}^{\text{L}}\mathbf{U}^{\text{L-1}} \ldots \mathbf{U}^{1} \tag{4}$$

where $\{\mathbf{U}^l\}_{l=1}^{L}$ are unitary operators, i.e. they satisfy Eq. (5).

$$\mathbf{U}^l\mathbf{U}^{l^\dagger} = \mathbf{U}^{l^\dagger}\mathbf{U}^l = \mathbf{I}, \quad \forall l \tag{5}$$

Each unitary operator can be factored as the product of non-commuting unitary operators

$$\mathbf{U}^{(l)} = \prod_{j=1}^{m_l}\mathbf{U}_j^{(l)} \tag{6}$$

Each corresponding to a single unit in the lth layer. The computed network is represented as a constitution of sequence of completely positive transition maps [32].

$$\rho^{\text{out}} = \epsilon^{\text{out}} \left(\epsilon^{L} \left(\dots \epsilon^{2} \left(\epsilon^{1} \left(\rho^{\text{in}}\right)\right) \dots\right)\right) \tag{7}$$

The transition map acting on layer $l-1$ is

$$\epsilon^{l}(X^{l-1}) = tr_{l-1}\left[\prod_{j=m_l}^{1} \mathbf{U}_j^{l}(\mathbf{X}^{l-1} \otimes |0_l, \dots, 0_1, 0_{\text{in}}\rangle\langle 0_{\text{in}}, 0_1, \dots, 0_{\mathbf{L}}, 0_{\text{out}}|) \prod_{j=1}^{m_l} \mathbf{U}_j^{l^{\dagger}}\right] \tag{8}$$

where m_l is the number of units in layer l. A Genetic Algorithm (GA) is a heuristic optimization algorithm inspired by the way of natural selection and genetics, to identify the approximate solutions to optimization and search problems by mimicking the process of evolution. The representation of jth transformed quantum bit based on genetic algorithm is presented as follows Acampora et al. [33] (see Eqs. (9) and (10))

$$K_i^{js} = \frac{1}{2}(b_j(1+\beta_j^i) + a_j(1-\beta_j^i)) \tag{9}$$

$$K_i^{jc} = \frac{1}{2}(b_j(1+\alpha_j^i) + a_j(1-\alpha_j^i)) \tag{10}$$

The rotation of probability amplitudes of qubits of matrix and rotation angle size are represented as follows Singh et al. [34] (see Eqs. (11) and (12))

$$U\begin{bmatrix} sin(gene_{ij}) \\ cos(gene_{ij}) \end{bmatrix} = \begin{bmatrix} sin(\Delta\theta) & -cos(\Delta\theta) \\ cos(\Delta\theta) & sin(\Delta\theta) \end{bmatrix}\begin{bmatrix} sin(gene_{ij}) \\ cos(gene_{ij}) \end{bmatrix} = \begin{bmatrix} sin(gene_{ij}+\Delta\theta) \\ cos(gene_{ij}+\Delta\theta) \end{bmatrix} \tag{11}$$

$$\Delta\theta_{ij} = -\text{sgn}(A)\,\delta\theta_o \exp\left(-\frac{\Delta f(x_j^i - \Delta f_j min)}{\Delta f_j^{max} - \Delta f_j min}\right) \tag{12}$$

The transformation of jth quantum bit is updated based on Eqs. (9) and (10), the iteration will continue until the iteration number reaches to ceiling value or satisfy the convergence condition. Transition map can be integrated to the activation function and is represented using Eq. (7). As a cost function that quantifies how close the network output ρ^{out} is to the true output $|\psi_t^{\text{out}}\rangle$, the fidelity will be used. It is defined as

$$\mathcal{L} = \frac{1}{t_f - t_i + 1}\sum_{t=t_i}^{t_f}\langle\psi_t^{\text{out}}|\rho_t^{\text{out}}|\psi_t^{\text{out}}\rangle, \quad \mathcal{L} \in [0,1] \tag{13}$$

where t denotes a sample from the training set. The cost function ranges from 0 to 1. As the hybrid quantum neural network reaches the maximum cost function then it may equal to true output. While training, with step size η, the unitary operators are updated as follows (see Eq. (14)).

$$\mathbf{U}_j^l \rightarrow \exp\left[i\eta\mathbf{K}_j^l\right]\mathbf{U}_j^l, \quad i \equiv \sqrt{-1} \tag{14}$$

This ensures that the outcome may remain unitary. The variation of the cost function after a training iteration is represented as follows (see Eq. (15)).

$$\Delta C = \frac{\eta}{t_f - t_i + 1}\sum_{t=t_i}^{t_f}\sum_{l=1}^{L+1}\text{tr}[\sigma_t^l \Delta\epsilon^l(\rho_t^{l-1})] \tag{15}$$

where

$$\rho_t^l = \epsilon^l(\dots\epsilon^2(\epsilon^1(\rho_t^{\text{in}})\dots)) \tag{16}$$

For the layer l, the density matrix is represented as follows (see Eq. (17))

$$\sigma_t^l = \mathcal{F}^{l+1}\left(\dots\mathcal{F}^L\left(\mathcal{F}^{\text{out}}\left(|\psi_t^{\text{out}}\rangle\langle\psi_t^{\text{out}}|\right)\right)\dots\right) \tag{17}$$

For a completely positive map ϵ, the adjoint channel is represented as $\mathcal{F}$ (see Eq. (18)).

$$\mathcal{F}^l(X^{l-1}) = \text{tr}_{l-1}\left[\sum_{j=m_l}^{1}\mathbf{U}_j^{l\dagger}\left(|0_{\text{out}}, 0_L, \dots, 0_1, 0_{\text{in}}\rangle\langle 0_{\text{in}}, 0_1, \dots, 0_l| \otimes X^{l-1}\right)\prod_{j=1}^{m_l}\mathbf{U}_j^l\right] \tag{18}$$

The training phase consists of the following steps: (i) Selection of an initial unitary operator in random way (ii) Evaluation of the density matrix repeatedly (layer by layer) (iii) Computation of the parameter matrix $\mathbf{K}_j^{(l)}$ for the qubits which are unaffected by the step size η and $\mathbf{U}_j^{(l)}$ considering the trace (iv) Updation of the unitary matrix. Steps (ii) and (iii) are repeated till the cost function reaches to maximum [32]. As an outcome, for every layer l, the parameter matrix is computed. Two layers are considered at each time, which considerably optimizes the memory usage. Additionally, to ensure that quantum neural networks are computationally tractable, the matrix dimensions are scaled with the overall number of layers. We considered four layers with the optimized genetic

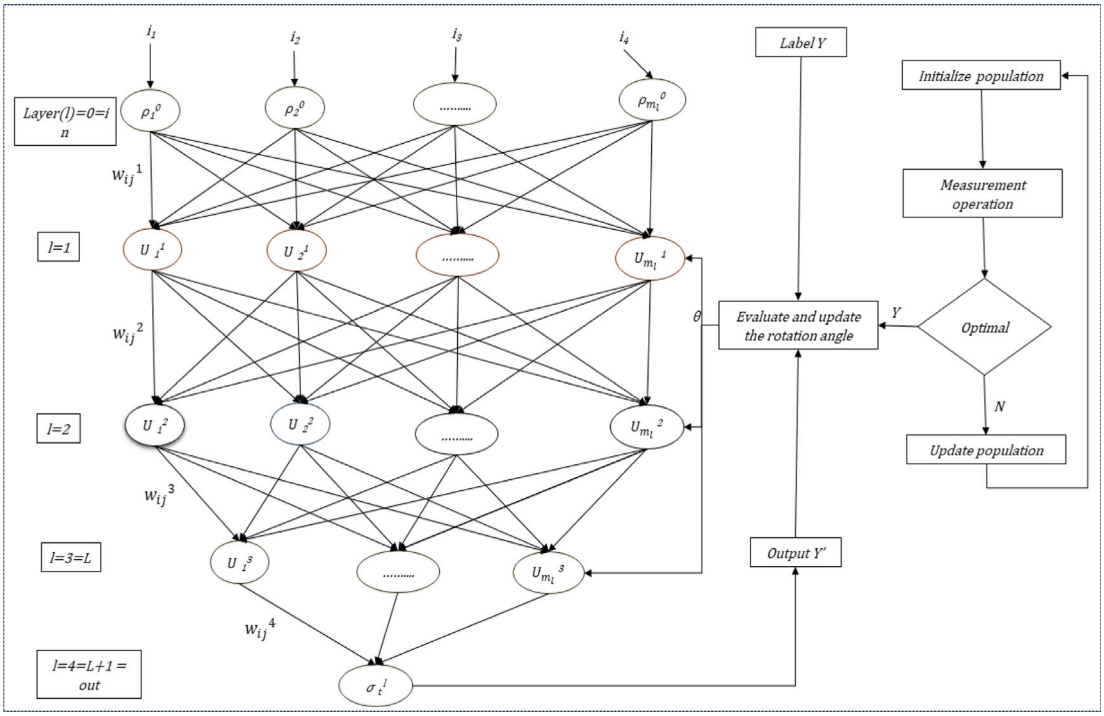

Fig. 2. Architecture of hybrid quantum neural network.

algorithm based hyperparameters to build the novel hybrid quantum neural network. The architecture of the proposed method is represented as follows (see Fig. 2).

$$\mathbf{U}_j^l, \quad j \sim p(j), \quad l \sim p(l) \tag{19}$$

$$\forall \left[\left(|\psi_t^{\text{in}}\rangle, |\psi_t^{\text{out}}\rangle \right) \in \left\{ \left(|\psi_t^{\text{in}}\rangle, |\psi_t^{\text{out}}\rangle \right) \right\}_{t=t_i}^{t_f} \right] \wedge \forall [l] \Rightarrow \rho_t^l = \text{tr}_{l-1} \epsilon^l \left(\rho_t^{l-1} \right) \tag{20}$$

$$\text{tr}_{l-1} \epsilon^l \left(\rho_t^{l-1} \right) = \text{tr}_{l-1} \left[\prod_{j=m_l}^{1} \mathbf{U}_j^l \left(\rho_t^{l-1} \otimes |0_{\text{out}}, 0_L, \ldots, 0_1\rangle\langle 0_{\text{in}}, 0_1, \ldots, 0_L, 0_{\text{out}}| \right) \prod_{j=1}^{m_l} \mathbf{U}_j^{l\dagger} \right] \tag{21}$$

$$\mathbf{U}_j^l \rightarrow \exp\left[\epsilon i \mathbf{K}_j^l \right] \mathbf{U}_j^l, \tag{22}$$

$$\mathbf{K}_j^l = \eta * \frac{2^{m}_{l-1}}{(t_f - t_i + 1)} * \sum_{t=t_i}^{t_f} \text{tr}_{\not\subset \mathbf{U}_j^l} \circ \mathbf{M}_j^l \tag{23}$$

where

$$\mathbf{M}_j^l = \left[\prod_{\alpha=j}^{1} \mathbf{U}_\alpha^l (\rho_t^{(l-1;l)}) \prod_{\alpha=1}^{j} \mathbf{U}_\alpha^{l\dagger} \cdot \prod_{\alpha=j+1}^{m_l} \mathbf{U}_\alpha^{l\dagger} (I_{l-1} \otimes \sigma_t^l) \prod_{\alpha=m_l}^{j+1} \mathbf{U}_\alpha^l \right] \tag{24}$$

$$\rho_t^{(l-1;l)} \rho_t^{l-1} \otimes |0_{\text{out}}, 0_L, \ldots, 0_1\rangle\langle 0_{\text{in}}, 0_1, \ldots, 0_L, 0_{\text{out}}| \tag{25}$$

$$\boldsymbol{\sigma}_t^l = \mathbf{F}^{l+1} \left(\ldots \mathbf{F}^{\text{out}}(|\psi^{\text{out}}(t)\rangle\langle\psi^{\text{out}}(t)|) \ldots \right) \tag{26}$$

3.3. Explainability analysis over hybrid quantum neural networks

We present the explainability analysis of hybrid quantum neural networks for predicting the stock closing price as follows. The quantum component of the proposed method is often used in the feature mapping stage, where input data is transformed to a high-dimensional quantum space. In the proposed method, the input data, such as historical stock data, is mapped to a quantum state using quantum gates and circuits. This mapping is designed to apprehend the intricate relationships and patterns within the data in a quantum representation as described in Section 3.2. Three quantum gates are considered in our work, so that the possible

Table 4
Number of tweets considered for each stock after data preprocessing.

Stock_Name	Number of tweets after preprocessing
Apple (AAPL)	1 417 557
Amazon (AMZN)	715 527
Google (GOOG)	389 998
Google-L (GOOG-L)	326 384
Microsoft (MSFT)	373 222
Tesla (TSLA)	1 094 031

number of quantum circuits can be computed using $X^3 * Y^3 * Z$, where X is the number of unique single qubit gates, Y is the number of different kinds of two qubit gates, and Z is the number of different kinds of three qubit gates. This expression takes into consideration of the permutations that can be obtained by combining single qubit, two qubit, and three qubit gates within a three qubit quantum system. Each type of single qubit gate can be independently applied to each qubit, resulting in X^3 possible number of configurations. In a similar way, each of these configurations can then be combined with each type of two qubit gate, yielding Y^3 number of possibilities. Furthermore, the addition of three qubit gates introduces a new layer of complexity, with Z number of potential configurations. When combined, these parameters yield $X^3 * Y^3 * Z$ number of unique quantum circuits, illustrating the wide variety of circuit possibilities for design available in a three-qubit quantum system.

Quantum feature mapping techniques, such as quantum embeddings or quantum kernels, are employed to encrypt the data into a quantum state. The quantum representation obtained from the feature mapping stage is then fed into a classical neural network model. This model typically contains multiple layers of classical neurons, such as convolutional or dense layers, which can process the quantum encoded data. The classical network learns from the relationships among the target variable and the quantum-encoded features. The hybrid quantum neural network is trained with labeled data, where the historical stock market price data, tweets sentiments data and the corresponding stock closing price values are considered as training examples. In order to lower the specified loss function, the genetic algorithm is used during training to optimize the parameters of both the classical neural network layers and the quantum feature mapping.

The outcomes of hybrid quantum neural networks are analyzed with Shapley analysis for providing explanations over the predictions of the proposed method and analyzing the interpretability of features. Utilizing Shapley analysis methods such as Shapley Heatmap Analysis, Waterfall Analysis, Cohort Plot Analysis, and Mean Value Analysis enhances the interpretability of outcomes produced by the proposed hybrid quantum neural network. Shapley Heatmap Analysis visually represents the quantum and neural network-driven contributions of individual features to prediction outcomes, offering insights into feature importance. Waterfall Analysis dissects the cumulative impact of features on predictions, unveiling the hierarchical structure of feature importance within the proposed method. Cohort Plot Analysis segments data into cohorts based on feature characteristics, revealing patterns and anomalies in feature interactions across different subsets of observations. Mean Value Analysis computes average Shapley values for each feature, providing an overview of feature importance and aiding in the identification of key drivers within the feature space. Collectively, these Shapley analysis methods facilitate comprehensive explanations of hybrid quantum neural network predictions and insightful analyses of feature interpretability, empowering practitioners to understand and trust the decision-making processes of hybrid quantum neural networks.

4. Results and validation

The proposed methodology is executed on the Google Colab environment using NVIDIA-SMI version 535.104.05, CUDA version 12.2 and hardware accelerator T4 GPU. In our work, we used two different datasets to anticipate the stock closing price. The dataset 1 that we used for our experiments contains more than 4 million unique tweets on six different organizations (Apple, Amazon, Google, Google-L, Microsoft, and Tesla). The dataset 2 that we used in our experiments contains the historical stock prices of the six organizations which are represented in the dataset 1. These datasets are publicly available at https://www.kaggle.com/datasets/omermetinn/tweets-about-the-top-companies-from-2015-to-2020.

The features of the dataset 1 are *tweet id*, *author details of tweet posted*, *post date*, *text of tweet and comments*, *total number of likes for tweet*, and *number of retweets*. The dataset 2 contains historical stock price data from the year 2015 to 2020. The features of the dataset 2 are stock prices of *open*, *high*, *low*, *close*, *volume*, *dividend*, and *stock splits*. In our work, we fused the average daily tweets sentiment score (*avgScore*) from the tweet dataset into the stock price dataset.

As part of data preprocessing, we removed the words which are not useful to find the emotion of the tweet, such as alphanumeric characters, punctuation, numbers, stop words, hashtags, URLs and also removed the words whose length is equal to one. After removing these words, we performed stemming and lemmatization on the words. The number of tweets considered for each stock after preprocessing is given as follows (see Table 4).

We input the data to the transformer sentiment analyzer after preprocessing the data. The analyzer is able to find the sentiment score for each tweet. From the tweets score, we computed the average sentiment score for everyday and fused this average sentiment score data with the stock price data.

In our work, we use a comprehensive simulation setup designed to explore how changes in the key parameters influence the performance of the model. By systematically adjusting these parameters and analyzing their effects, we aim to gain valuable

Table 5
Hybrid quantum neural network parameters.

Parameter	Parameter value
L (number of hidden layers)	4
η (Step size)	0.5
τ_{max}(Strides and number of networks)	20
Number of epochs	50
Δ (Window size)	2
Population size	50
Mutation probability	0.1
Quantum bits (n-dimensional space)	3
Initial value of step length	0.01π

insights into the underlying dynamics of the system and extract optimal operating conditions. Using Google Colab environment, we implemented our hybrid quantum neural network model to perform the future stock price prediction. Table 5 lists the parameters used to implement the hybrid quantum neural network.

This preprocessed data is split into 70% for training and 30% for testing the proposed model. The training data is trained with the proposed hybrid quantum neural networks to analyze the variations and stock movements accurately. The trained hybrid quantum neural network is evaluated on the test dataset. The actual stock closing price and the predicted stock closing price values for the six different organizations are illustrated as follows (see Fig. 3).

The proposed hybrid quantum neural network is evaluated with the performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) (see Table 6). These are commonly used metrics in evaluating the performance of regression models, including time series forecasting.

Mean Squared Error (MSE) measures the average squared difference between the actual and predicted values. It penalizes large errors more heavily than small errors. A lower MSE indicates better performance, as it signifies that the model's predictions are closer to the actual values on average. Thus, minimizing MSE is often a primary goal in regression model optimization.

Root Mean Squared Error (RMSE) is the square root of MSE, providing a measure of the average magnitude of errors in the same units as the target variable. Like MSE, lower RMSE values indicate better model performance, with the added benefit of being easily interpretable in the same units as the target variable. RMSE is particularly useful for understanding the typical size of prediction errors.

Mean Absolute Error (MAE) measures the average absolute difference between the actual and predicted values. It provides a more robust measure of error compared to MSE, as it is less sensitive to outliers. Similarly to MSE and RMSE, lower MAE values indicate better model performance. MAE is especially useful when outliers are present or when errors of a consistent size are undesirable.

R-squared (R^2) represents the proportion of variance in the dependent variable that is explained by the independent variables in the model. A higher R^2 value suggests that the model provides a better explanation of the variability in the target variable. R^2 is valuable for assessing the overall goodness-of-fit of the model and comparing different models' performance. The mathematical notations of these metrics are presented as follows (see Table 6).

MSE, RMSE, MAE, and R^2 are chosen as evaluation metrics because they provide comprehensive insights into different aspects of model performance, including accuracy, precision, robustness to outliers, and overall explanatory power. By considering these metrics together, analysts can assess the effectiveness of the proposed solution in accurately forecasting time series data and make informed decisions about model selection and optimization.

In all these metrics, y_i represents the actual value, $\bar{y}_i$ represents the predicted value, and n represents the number of data points. The selection of evaluation metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 (coefficient of determination) for assessing the performance of hybrid quantum neural network offers tailored advantages within this unique framework. MSE, RMSE, and MAE provide a detailed view of prediction errors, focusing on both large errors and average magnitude, essential for a comprehensive analysis of hybrid quantum neural network performance across various datasets. Additionally, RMSE and MAE, being less influenced by outliers, adapt well to the probabilistic nature of quantum operations, accurately reflecting performance in quantum computing environments. R^2 serves as a valuable indicator of how well hybrid quantum neural networks align their predictions with actual data, offering insights into the model's ability to leverage complex quantum relationships and providing a quantum-specific measure of fitness and predictive power. Moreover, RMSE and MAE's interpretability within the quantum domain enhances generalization, making them applicable to a broad spectrum of quantum computing tasks. By using established metrics, hybrid quantum neural network performance assessment aligns with quantum computing standards, ensuring consistency, comparability across studies, and enhancing credibility and reproducibility within the quantum machine learning field. In summary, leveraging these evaluation metrics enables a nuanced assessment of prediction accuracy, robustness, interpretability, and alignment with quantum computing standards, facilitating a comprehensive evaluation of hybrid quantum neural network performance in quantum computing applications.

The proposed method is evaluated and compared with the existing models across the six different organizations (see Table 7). The existing algorithms including Deep Long Short Term Memory [35], Ensemble Deep RVFL [26], Ensemble Deep ESN [36], Quantum Decision Tree [37], Quantum Support Vector Machine [38], Quantum Deep Artificial Neural Networks [1], Quantum Leap [27] are compared with the proposed methodology.

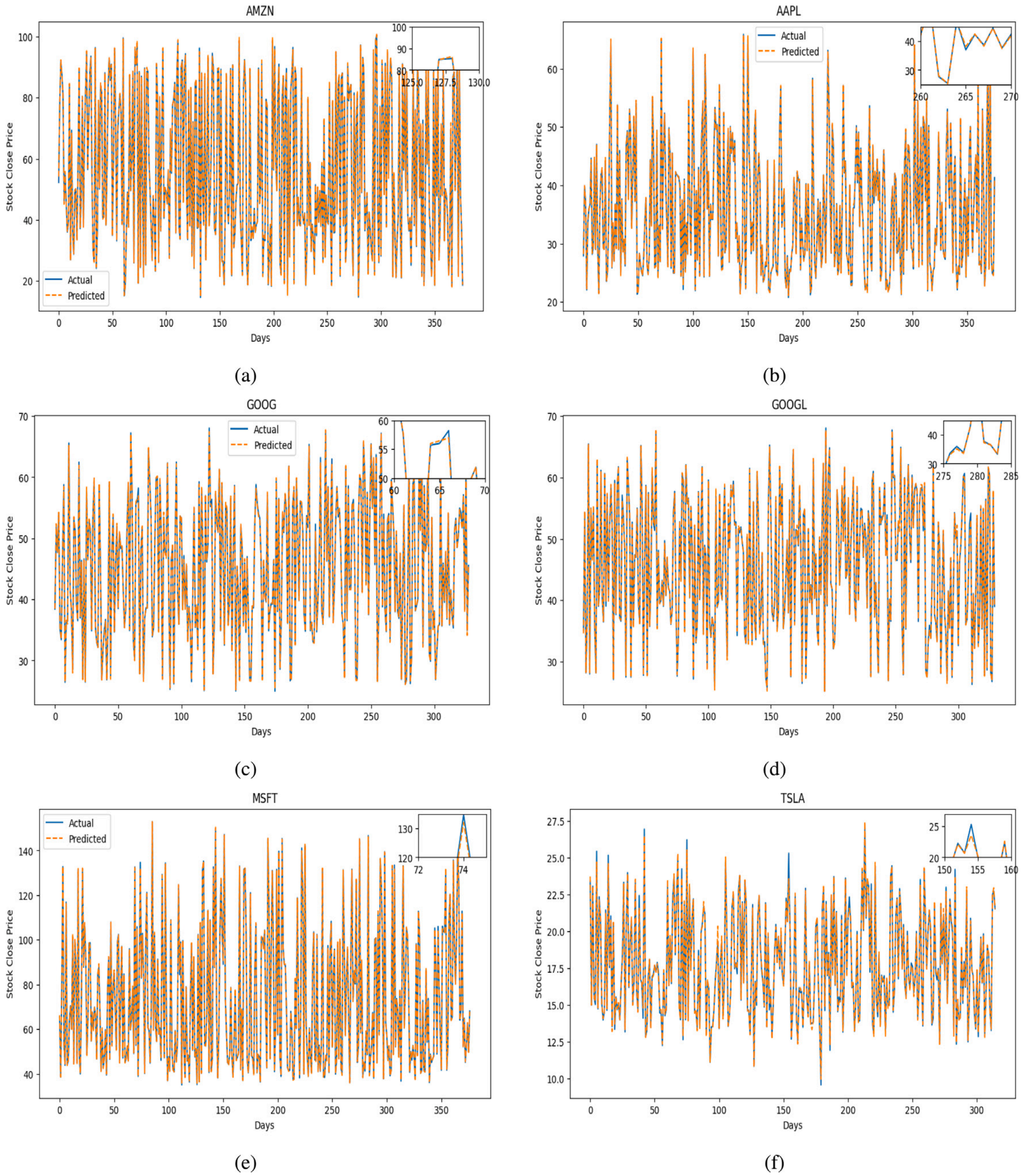

Fig. 3. Comparison of actual vs. predicted values by hybrid quantum neural networks. (a) Amazon. (b) Apple. (c) Google. (d) Google-L. (e) Microsoft. (f) Tesla.

Table 6
Evaluation metrics.

Metric	Equation
MSE	$\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert$
R^2	$1-\frac{SS_{\text{res}}}{SS_{\text{tot}}}$

Table 7
Comparison of proposed model outcomes with existing models.

Company	Model	MSE	RMSE	MAE	R^2
Apple (AAPL)	Deep LSTM	8.24	2.87	3.01	91.44
	Ensemble Deep RVFL	7.48	2.73	2.42	91.98
	Ensemble Deep ESN	5.26	2.29	1.77	93.16
	Quantum Decision Tree	2.84	1.68	1.42	95.84
	Quantum SVM	3.71	1.92	1.94	93.71
	Quantum Deep ANN	1.44	1.20	1.52	94.92
	Quantum Leap	0.98	0.99	1.02	96.18
	Proposed model	**0.42**	**0.64**	**0.48**	**99.27**
Amazon (AMZN)	Deep LSTM	3.04	1.74	1.44	91.96
	Ensemble Deep RVFL	2.91	1.70	1.32	94.18
	Ensemble Deep ESN	2.44	1.56	1.20	95.14
	Quantum Decision Tree	1.08	1.03	0.89	96.46
	Quantum SVM	1.87	1.36	1.12	97.29
	Quantum Deep ANN	0.96	1.16	0.92	97.64
	Quantum Leap	0.67	0.81	0.59	98.21
	Proposed model	**0.31**	**0.55**	**0.35**	**99.95**
Google (GOOG)	Deep LSTM	5.48	2.34	1.31	96.14
	Ensemble Deep RVFL	6.01	2.45	1.38	95.97
	Ensemble Deep ESN	5.52	2.35	1.30	96.38
	Quantum Decision Tree	0.87	0.93	0.78	99.18
	Quantum SVM	0.58	0.76	0.69	99.47
	Quantum Deep ANN	0.36	0.60	0.52	99.52
	Quantum Leap	0.34	0.58	0.51	99.49
	Proposed model	**0.09**	**0.30**	**0.23**	**99.93**
Google_L (GOOG_L)	Deep LSTM	15.92	3.98	3.45	92.41
	Ensemble Deep RVFL	12.12	3.48	3.11	92.10
	Ensemble Deep ESN	13.28	3.64	3.25	93.28
	Quantum Decision Tree	5.68	2.38	2.61	94.57
	Quantum SVM	9.47	3.07	3.27	93.48
	Quantum Deep ANN	2.56	1.61	1.21	93.96
	Quantum Leap	1.16	1.07	0.94	97.48
	Proposed model	**0.11**	**0.33**	**0.23**	**99.89**
Microsoft (MSFT)	Deep LSTM	15.01	3.87	3.30	91.98
	Ensemble Deep RVFL	12.78	3.57	3.11	93.65
	Ensemble Deep ESN	9.49	3.08	2.92	94.12
	Quantum Decision Tree	4.27	2.06	1.24	97.59
	Quantum SVM	2.31	1.51	1.19	99.12
	Quantum Deep ANN	1.96	1.42	0.79	99.27
	Quantum Leap	1.80	1.34	0.72	99.29
	Proposed model	**0.32**	**0.56**	**0.39**	**99.96**
Tesla (TSLA)	Deep LSTM	8.12	2.84	1.86	91.42
	Ensemble Deep RVFL	5.48	2.34	1.64	93.91
	Ensemble Deep ESN	6.24	2.49	1.51	94.85
	Quantum Decision Tree	2.27	1.50	1.04	97.21
	Quantum SVM	3.19	1.78	1.59	96.89
	Quantum Deep ANN	2.89	1.72	1.51	97.12
	Quantum Leap	2.12	1.45	1.39	97.93
	Proposed model	**0.38**	**0.61**	**0.41**	**99.15**

The results illustrate that the proposed methodology accurately predicts the future closing values of the stocks across all datasets with an accuracy rate of better than 99 percent (see Table 7). The proposed method outperforms SOTA models due to its ability of effective feature representation, adaptability and flexibility, parallel processing and complex decision boundaries. The proposed approach integrates the advantages of multiple computational paradigms (quantum computing, neural networks, and genetic algorithms) while minimizing the drawbacks of each one separately. The proposed method accurately identifies the complex relationships and patterns in data through the combination of neural networks and quantum computing principles. Quantum computing principles, such as superposition and entanglement, offer computational advantages over classical approaches by enabling parallel processing of information. The proposed methodology leverages the quantum principles to explore a larger solution space more efficiently and to analyze and process data more quickly. This parallelism can significantly speed up inference and training, leading to faster convergence. The neural network component of the proposed approach is able to efficiently intricate the complex relationships in tasks where the decision boundary is highly nonlinear or complex. This capability makes them well-suited for tasks where traditional approaches may fail to capture the underlying relations or patterns accurately. Genetic algorithms are known for their ability to optimize and adapt solutions over multiple iterations. By incorporating genetic algorithms into the training process, the proposed methodology updates their parameters and structure, leading to improved performance. This adaptability gives them an edge over fixed-structure approaches like Quantum Support Vector Machines or Quantum Decision Trees. Overall,

Table 8
Feature importance from Shap mean value analysis.

Company/Attributes	High	Low	Open	Volume	Dividends	Stock splits	Avg score
APPLE (AAPL)	*All/Pos_High*	*All/Pos_High*	*All/Pos_High*	*Neu_High*	*Neu_Low*	*Neu_Low*	*Neu_High*
AMAZON (AMZN)	*All*	*All*	*All*	*Neu_Low*	*Neu_Low*	*Neu_Low*	*Neu_Med*
GOOGLE (GOOG)	*All*	*All*	*All/Neg_Low*	*Neu_High*	*Neu_Low*	*Neu_Low*	*Neu_Med*
GOOGLE-L (GOOG-L)	*All/Pos_High*	*All/Pos_High*	*Pos & Neg*	*Neu_Low*	*Neu_Low*	*Neu_Low*	*Neu_Med*
MICROSOFT (MSFT)	*Pos&Neg/Pos_High*	*Pos&Neg/Pos_High*	*All/Pos_High*	*Neu_Low*	*Neu_Low*	*Neu_Low*	*Neu_Low*
TESLA (TSLA)	*All/Pos_High*	*All*	*Neu/Neg_High*	*Neu_Low*	*Neu_Low*	*Neu_Low*	*Neu_Med*

the integration of quantum computing, neural networks, and genetic algorithms in the proposed methodology gives a versatile and powerful framework for tackling a wide range of machine learning tasks, leading to improved accuracy compared to deep LSTM, deep ensemble methods, or various other quantum machine learning models.

4.1. Explainability analysis for stock prediction

A crucial graphical depiction of Shapley values for model interpretability is the Shapley heat map. We take the Shapley values — a value of prediction among the supplied features — from the Shapley analysis. The value represents the difference between the expected outcome and predicted outcome. Features which are contributing high will have higher Shapley values whereas features which are contributing less will have less Shapley values. The Shapley heat map for the six organizations are shown as follows (see Fig. 4). In Fig. 4(a), we have grouped the instances of similar importance values. The features *Low*, *High* and *Open* could influence the predictions in positive (red colored) or negative (blue colored) or neutral (white colored) way. Based on their intensity levels, the thickness of the feature is presented. For every instance contained in the test data, the *avgScore* is depicted in white, indicating that the feature would not affect the outcome of the prediction. For each of the six groups, we can find the same observation. These plots allow us to draw the conclusion that the sentiment score of tweets has no bearing on the forecast of stock price.

Waterfall plots are the models of explainability analysis, which is used to represent the explanations for the individual outcome. Here, we considered a data sample to explain the influence of features towards the outcomes. The waterfall plot begins by depicting expected value as a result. In this graph, the color red denotes the contribution of positive features to the anticipated outcome, while the color blue denotes the contribution of negative features. The value of each feature for the sample under consideration is shown by the gray text before the feature name. The Waterfall plots based on the proposed hybrid quantum neural networks for the six different organizations are presented as follows (see Fig. 5). For instance, in Fig. 5(a), the average predicted closing price of a stock E[f(x)] is 54.072 and the predicted stock closing price f(x) is 35.998. The features *Low*, *High*, and *Open* influence the average predicted value by −7.74, −6.06, and −4.25 respectively. The feature *avgScore* influence the average predicted value by 0.02 negatively. The remaining features *volume*, *Stock Splits*, and *Dividends* influence the average predicted value by −0.01, +0 and +0 respectively. Thus, we observe that the average predicted value is only little impacted by the *avgScore* among all of these factors for Amazon. We can see a comparable influence on all other organizations regarding the *avgScore*.

The cohort Shapley plots display the Shapley values of explainable analysis for each feature present in the cohort. The plots are represented as a horizontal bar chart or heatmap, where each feature is represented as a cell or bar. The length of the cell represents the impact or magnitude of its Shapley value. Features that have a greater impact on the cohort's outcomes will have longer bars or more intense colors (see Fig. 6). The feature *Low* is having significant contribution for Amazon, Apple and Google-L and the feature *High* is having the significant contribution for Google, Microsoft and Tesla. The plot represents the importance of features in a sequence manner. For Amazon, *Low* is the most significant feature and *Dividends* is the least significant feature. From the plots, we observe that the *avgScore* is having the feature importance ranging from +0.01 to +0.05 for all organizations. Thus, the feature *avgScore* is not contributing to predict the closing price of stock.

Shap mean value analysis interprets to find how the variables influence the predicted outcomes. We use the Shap mean value analysis to visualize the influence of the features on the stock price prediction (see Fig. 7). For the stock price prediction of these six distinct organizations, the feature importance is represented in Table 8 and we observe how each feature is contributed towards the outcomes. In Table 8, the variable *All* represents that the feature is contributed positively, negatively and neutral way. *Pos* represents that the feature is contributed positively and *Neg* represents that the feature is contributed negatively. *Pos_High* represents that the feature is contributed positively with higher coefficients and *Pos_Low* represents that the feature is contributed positively with lower coefficients. Similarly, features with *Neg_High* and *Neg_Low* indicate that these features contributed negatively with high and low coefficients respectively. *Neu_High* represents that the feature contributed with high coefficients with no impact and *Neu_Low* represents that the feature contributed with low coefficients with no impact and *Neu_med* represents that the feature contributed with both positive and negative coefficients with no impact. From the Shap mean value analysis, we observe that the features *Low*, *High* and *Open* are contributing to a greater extent in the prediction of the closing price of a stock more accurately. The remaining features *avgScore*, *Dividends*, *Stock Splits* and *Volume* are not contributed towards the outcomes. Thus, we observe that the tweets do not influence stock price to a greater extent in this case study.

In our research, we applied different models within the realm of explainable artificial intelligence (XAI) to determine the role of individual attributes to our outcomes. In particular, we employed approaches like Shapely heat map analysis (see Fig. 4), waterfall modeling (see Fig. 5), cohort analysis (see Fig. 6), and Shapley mean value analysis (see Fig. 7). Our major focus lays

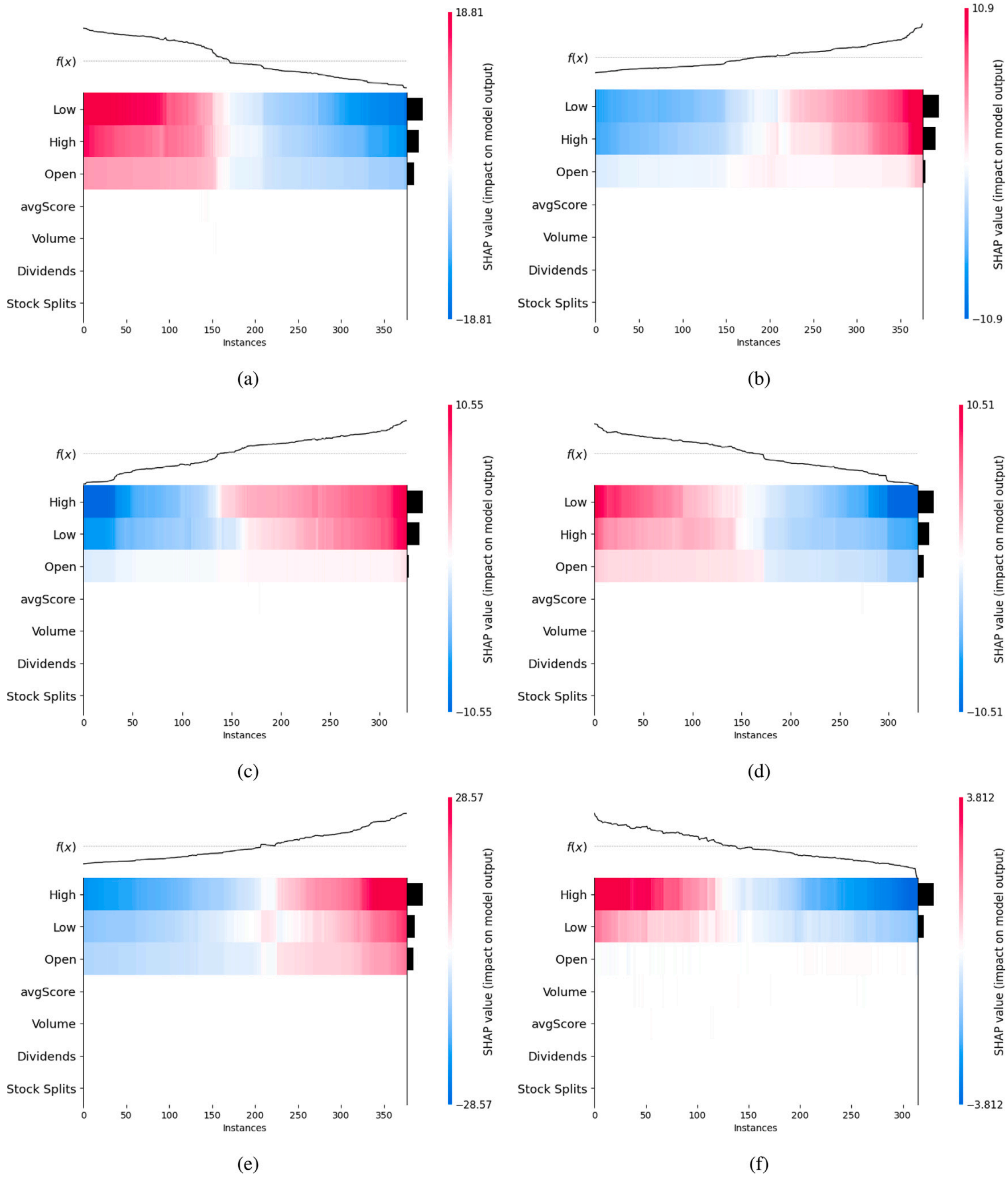

Fig. 4. Shapely heat matrix for six different organization (a) Amazon. (b) Apple. (c) Google. (d) Google-L. (e) Microsoft. (f) Tesla.

in understanding the influence of average sentiment scores on these stock price prediction outcomes. Remarkably, in contrast to our initial expectations, XAI methods illustrate that the sentiment scores taken from the tweets had no obvious impact on the predictions of stock price. This observation underscores the nuanced nature of attribute contributions within our model, suggesting that factors beyond sentiment play a more significant role in determining the outcomes of the stock price prediction.

4.2. Statistical analysis

Statistical analysis provides valuable insights into the relationships between variables, aiding in understanding complex phenomena such as stock market dynamics. A widely used measure for quantifying the strength and direction of the linear relationship

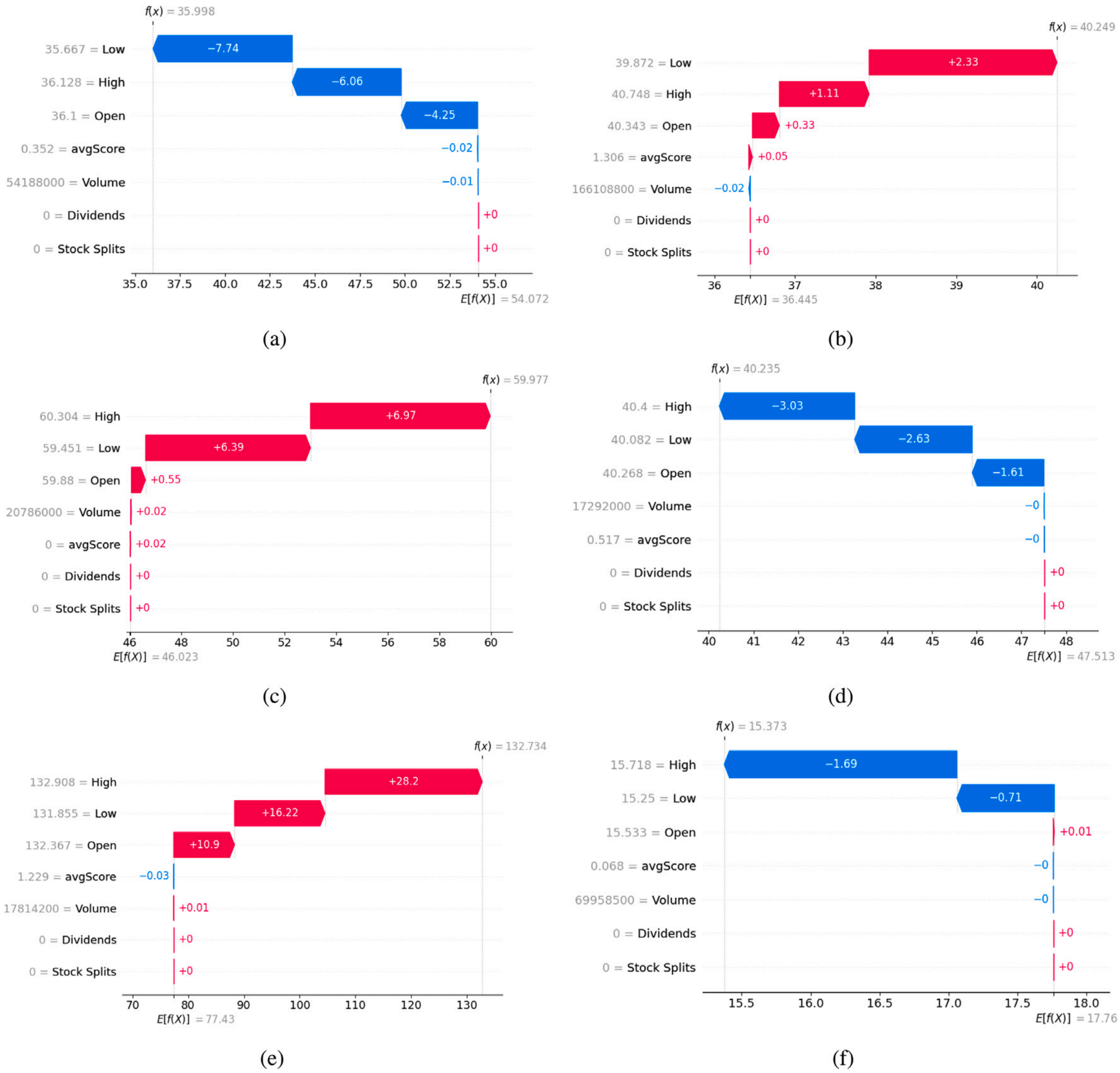

Fig. 5. Shapley waterfall plots of hybrid quantum neural networks predictions (a) Amazon. (b) Apple. (c) Google. (d) Google-L. (e) Microsoft. (f) Tesla.

between two variables is the Pearson correlation coefficient (PCC). The PCC ranges from −1 to 1, where −1 represents a perfect negative linear relationship, 1 represents a perfect positive linear relationship, and 0 represents no linear relationship. In our study, we examined the potential connection between average tweet sentiment scores and stock prices, yielding a PCC coefficient of 0.003. This result suggests a negligible linear relationship between the two variables. Additionally, the associated p-value, a measure of the probability of obtaining the observed correlation coefficient if the true correlation in the population is zero, was found to be 0.12. With a p-value above the conventional significance level of 0.05, the analysis indicates that the observed correlation is not statistically significant. Consequently, based on this analysis, it appears that there is no meaningful association between average tweet sentiment scores and stock prices.

Spearman's Rank Correlation (SRC), also known as Spearman's rho, is considered as a non-parametric measure for the linear association between the variables. We estimate the SRC between the trade volume and the volume of tweets (see Table 9). The SRC and its associated p-value is computed for all organizations. From these computed values, we observe that the p-value for Microsoft exceeds the predetermined threshold value of 0.05, indicating that the considered features (trade volume and tweet volume) are not statistically significant. The remaining all dataset attributes are statistically significant.

Further, we conducted Friedman and Nemenyi tests [39] to assess the performance of the models. The Friedman test checks if there are statistically significant differences among multiple related groups and the Nemenyi test is a pairwise comparison test to determine which groups differ significantly from each other.

To perform the Friedman test we need to (i) Compute the average rank for each model across all datasets. (ii) Calculate the Friedman statistic. (iii) Determine if the Friedman statistic is significant. The average rank of each model across all datasets are listed in Table 10.

Fig. 6. Shap cohort plots of hybrid quantum neural networks predictions. (a) Amazon. (b) Apple. (c) Google. (d) Google-L. (e) Microsoft. (f) Tesla.

The Friedman statistic follows a chi-squared distribution with k-1 degrees of freedom. For $k = 8$ models and $\alpha = 0.05$, the critical value of the Friedman statistic is approximately 14.06 (from the chi-squared distribution table). Since our computed Friedman statistic (23.451) is greater than the critical value, we can reject the null hypothesis and conclude that there are significant differences among the models. Further, we proceed with the Nemenyi test to determine which models differ significantly from each other.

To conduct the Nemenyi test, we compute the critical difference (CD) value, which represents the minimum mean rank difference required for two models to be considered significantly different. Then, we compare the mean ranks of each pair of models to the CD value. For 95% confidence level and $k = 8$, the critical value from the Studentized range distribution table is approximately 2.56 and the computed CD value is 2.40. Hence, we compare the mean ranks of each pair of models to the CD value. The comparison of mean rank difference and CD value significance is presented in Table 11.

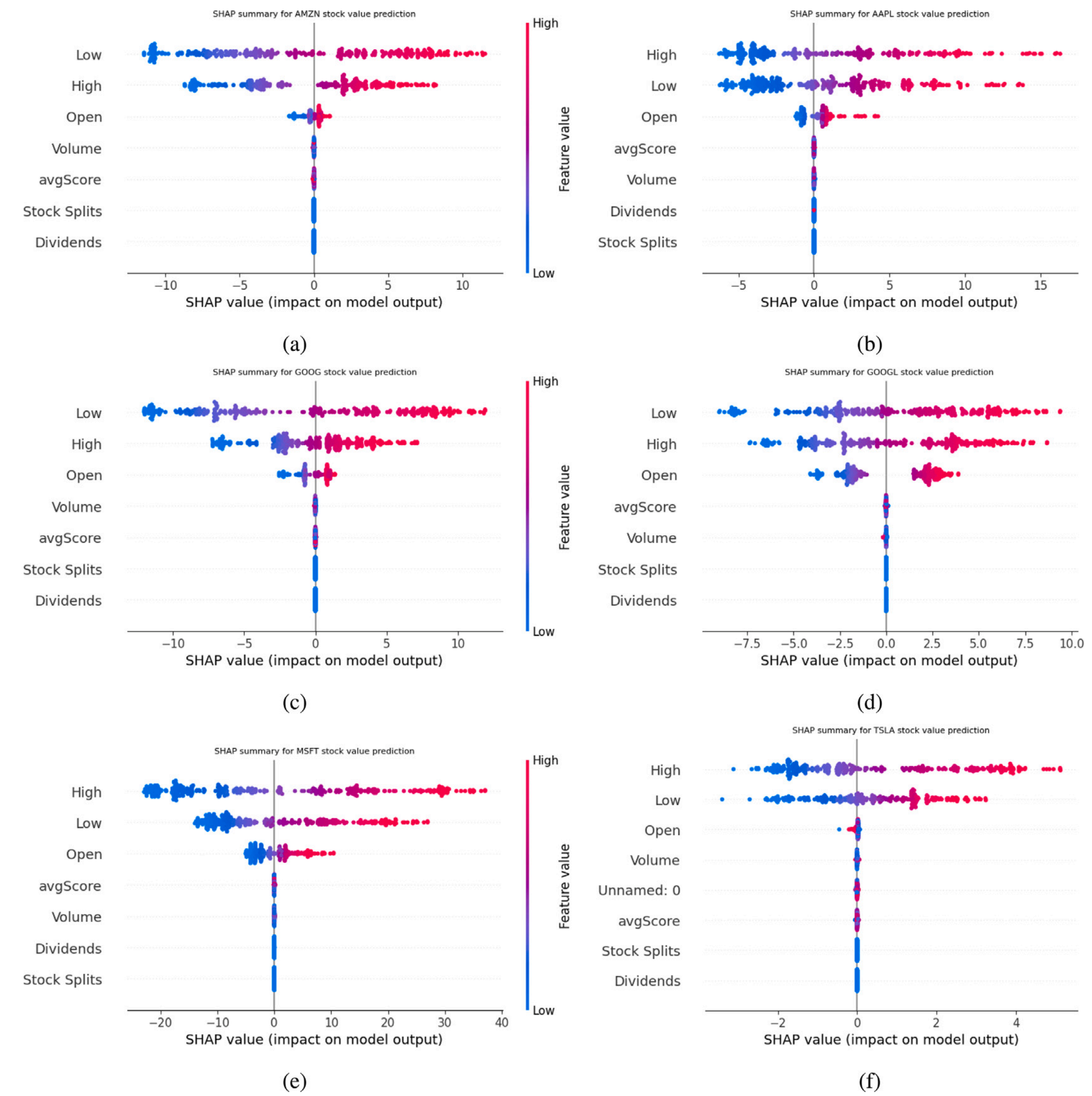

Fig. 7. Shap mean value analysis of hybrid quantum neural networks predictions. (a) Amazon. (b) Apple. (c) Google. (d) Google-L. (e) Microsoft. (f) Tesla.

Table 9
SRC and p-values.

Company name	SRC	Relation type	p-value	Significant
Apple (AAPL)	0.39	Medium correlation	$0.26e^{-5}$	Y
Amazon (AMZN)	0.21	Small correlation	$0.72e^{-5}$	Y
Google (GOOG)	0.23	Small correlation	$0.07e^{-3}$	Y
Google-L (GOOG-L)	0.33	Medium correlation	$0.24e^{-4}$	Y
Microsoft (MSFT)	0.03	No correlation	0.29	N
Tesla (TSLA)	0.59	Strong correlation	$0.39e^{-8}$	Y

From the comparison, we observe that Deep LSTM, Ensemble Deep RVFL, Ensemble Deep ESN, Quantum Decision Tree, Quantum SVM, Quantum Deep ANN, and Quantum Leap exhibit significantly higher mean rank differences compared to the proposed method. The significant differences suggest that, on average, these models perform less accurate than the proposed method across the datasets and the proposed method consistently outperforms these models in terms of mean rank across multiple datasets. Therefore, based on the analysis, the proposed method stands out as a robust and effective approach compared to the other models. The comparison of CD diagram for all the models is presented in Fig. 8.

Table 10
Average rank of each model using Friedman test.

Model	Average rank
Deep LSTM	7.66
Ensemble Deep RVFL	6.83
Ensemble Deep ESN	6.5
Quantum Decision Tree	4.16
Quantum SVM	4.66
Quantum Deep ANN	3.16
Quantum Leap	2.0
Proposed Method	1.0

Table 11
Significance of every model with the proposed method using Friedman and Nemenyi test.

Model	Mean rank difference	Significant (CD < Mean rank difference)
Deep LSTM	5.67	Yes
Ensemble Deep RVFL	4.82	Yes
Ensemble Deep ESN	3.00	Yes
Quantum Decision Tree	4.33	Yes
Quantum SVM	3.83	Yes
Quantum Deep ANN	3.00	Yes
Quantum Leap	2.67	Yes

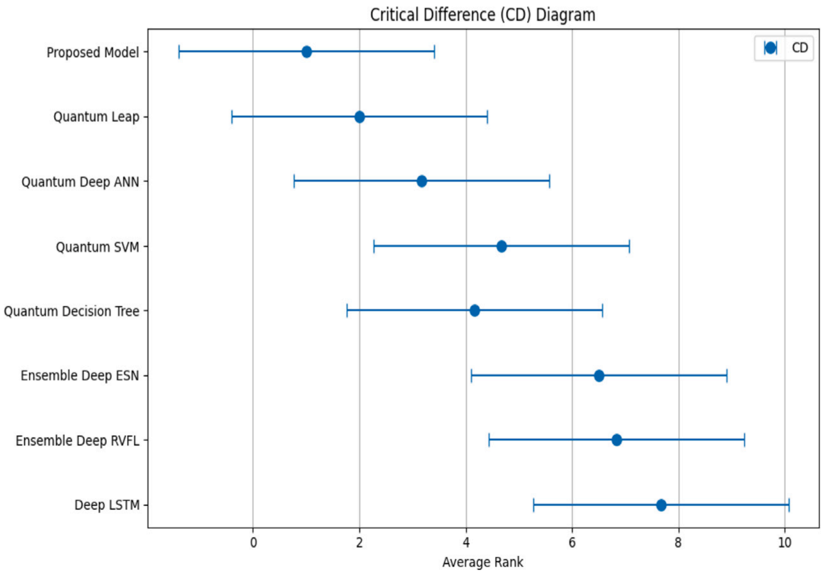

Fig. 8. Comparison of critical difference.

4.3. Ablation studies

We performed ablation studies to demonstrate the significance of various components in the proposed methodology. As part of the ablation study, we remove the specific components from the proposed methodology and we evaluate performance of the model. The outcomes are represented as follows (see Table 12). In Table 12, *w/o sentiment score* represents that we have not introduced the average sentiment score into technical indicators, *w/o hyperparameters embedding* represents that we have not included the tuned hyperparameters, *w/o QNN layer 1* represents the model without the first hidden layer, *w/o QNN layer 2* represents the model without the second hidden layer, and *w/o QNN layer 3* represents the model without the third hidden layer.

Based on the outcomes of the ablation study, we observe that the proposed methodology outperforms compared to the ablation models. Furthermore, we conclude that the tweets did not significantly influence the outcome prediction.

5. Conclusion and future work

Stock market data is very complex and generally hard for understanding the variations. In this study, we proposed explainable hybrid quantum neural networks to analyze the influence of tweets on stock price. We used historical stock price data and tweets for

Table 12
Ablation studies.

Company name	Evaluation metrics	w/o sentiment score	w/o parameters embedding	w/o QNN layer 1	w/o QNN layer 2	w/o QNN layer 3
Apple (AAPL)	MSE	0.46	13.22	12.48	15.27	11.17
	RMSE	0.67	3.63	3.53	3.90	3.34
	MAE	0.50	11.03	15.14	19.29	16.46
	(R^2)	98.62	82.17	88.74	86.21	89.12
Amazon (AMZN)	MSE	0.42	14.28	10.15	12.24	14.14
	RMSE	0.64	3.77	3.18	3.49	3.76
	MAE	0.64	2.12	1.95	2.48	2.62
	(R^2)	98.81	81.21	86.12	88.45	87.98
Google (GOOG)	MSE	0.19	21.48	28.82	34.47	29.93
	RMSE	0.43	4.63	5.36	5.87	5.47
	MAE	0.63	8.25	9.14	10.27	9.74
	(R^2)	98.96	79.96	82.14	81.17	83.19
Google-L (GOOG-L)	MSE	0.26	16.28	22.17	31.10	24.29
	RMSE	0.50	4.03	4.70	5.57	4.92
	MAE	0.55	8.11	12.19	19.46	14.81
	(R^2)	97.24	84.71	82.26	72.14	81.72
Microsoft (MSFT)	MSE	0.41	11.35	12.14	18.78	9.14
	RMSE	0.64	3.36	3.48	4.33	3.02
	MAE	0.83	2.14	3.01	2.87	3.44
	(R^2)	99.14	91.27	90.37	92.96	91.45
Tesla (TSLA)	MSE	0.34	10.48	11.69	19.41	9.89
	RMSE	0.58	3.23	3.14	4.40	3.14
	MAE	0.71	3.19	2.48	1.96	2.93
	(R^2)	98.94	89.92	87.21	91.17	92.24

5 calendar years of six different organizations. The accuracy of the proposed model is more than 99% on all six different data sets. Thus, the proposed hybrid quantum neural networks analyze the stock movements in an effective way and optimize the number of computations as compared to the classical machine learning/deep learning paradigms. Based on the explainability analysis, we observed that the attributes *open*, *high*, and *low* contribute to a greater extent to arrive at decisions of the proposed hybrid quantum neural network and the daily average tweet sentiment score did not influence the stock variations. However, it is essential to interpret these findings within the context of broader market dynamics and consider other factors that may influence stock price movements. Although the proposed explainable hybrid quantum neural networks predict the stock closing price in an efficient and accurate manner, the calculation of the daily average sentiment score from the tweet datasets is very complex and time consuming for the dataset having more than four million tweets. While X (Twitter) can be a valuable source of data for establishing certain assertions or trends, it is not the only source available. Depending on the nature of the assertion or the type of data needed, we can explore various other sources, including news articles and other online forums and social media communities. As a future avenue of exploration, further research may focus on developing sophisticated algorithms that leverage Bayesian optimization for ensemble compositions, potentially leading to effective forecasting performance across diverse and evolving datasets.

Code availability

(software application or custom code) Custom code developed.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Manoranjan Gandhudi reports financial support was provided by Conde Nast India Private Limited. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data is publicly available.

References

[1] Liu G, Ma W. A quantum artificial neural network for stock closing price prediction. Inform Sci 2022;598:75–85.
[2] Yıldırım DC, Toroslu IH, Fiore U. Forecasting directional movement of forex data using LSTM with technical and macroeconomic indicators. Financ Innov 2021;7:1–36.
[3] Wu D, Ma X, Olson DL. Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. Decis Support Syst 2022;159:113814.
[4] Liu W, Yang Z, Cao Y, Huo J. Discovering the influences of the patent innovations on the stock market. Inf Process Manage 2022;59(3):102908.
[5] Yuan F, Zhan H. Stock market investment behavior based on behavioral finance based on data fusion algorithm. IETE J Res 2022;1–7.
[6] Xu H, Cao D, Li S. A self-regulated generative adversarial network for stock price movement prediction based on the historical price and tweets. Knowl-Based Syst 2022;247:108712.
[7] Ni H, Wang S, Cheng P. A hybrid approach for stock trend prediction based on tweets embedding and historical prices. World Wide Web 2021;24:849–68.
[8] Chiong R, Fan Z, Hu Z, Dhakal S. A novel ensemble learning approach for stock market prediction based on sentiment analysis and the sliding window method. IEEE Trans Comput Soc Syst 2022.
[9] Chaudhari K, Thakkar A. Data fusion with factored quantization for stock trend prediction using neural networks. Inf Process Manage 2023;60(3):103293.
[10] Yan X, Yang H, Yu Z, Zhang S, Zheng X. Portfolio optimization: A return-on-equity network analysis. IEEE Trans Comput Soc Syst 2023.
[11] Ma Y, Han R, Wang W. Portfolio optimization with return prediction using deep learning and machine learning. Expert Syst Appl 2021;165:113973.
[12] Liu J, Lim KH, Wood KL, Huang W, Guo C, Huang H-L. Hybrid quantum-classical convolutional neural networks. Sci China Phys Mech Astron 2021;64(9):290311.
[13] Adadi A, Berrada M. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE access 2018;6:52138–60.
[14] Omrani N, Rivieccio G, Fiore U, Schiavone F, Agreda SG. To trust or not to trust? An assessment of trust in AI-based systems: Concerns, ethics and contexts. Technol Forecast Soc Change 2022;181:121763.
[15] Kumar IE, Venkatasubramanian S, Scheidegger C, Friedler S. Problems with Shapley-value-based explanations as feature importance measures. In: International conference on machine learning. PMLR; 2020, p. 5491–500.
[16] Li Y, Pan Y. A novel ensemble deep learning model for stock prediction based on stock prices and news. Int J Data Sci Anal 2022;1–11.
[17] Carta S, Corriga A, Ferreira A, Podda AS, Recupero DR. A multi-layer and multi-ensemble stock trader using deep learning and deep reinforcement learning. Appl Intell 2021;51:889–905.
[18] Swathi T, Kasiviswanath N, Rao AA. An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis. Appl Intell 2022;52(12):13675–88.
[19] Li X, Wu P, Wang W. Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong. Inf Process Manage 2020;57(5):102212.
[20] Rezaei H, Faaljou H, Mansourfar G. Stock price prediction using deep learning and frequency decomposition. Expert Syst Appl 2021;169:114332.
[21] Long J, Chen Z, He W, Wu T, Ren J. An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An application in Chinese stock exchange market. Appl Soft Comput 2020;91:106205.
[22] Leow EKW, Nguyen BP, Chua MCH. Robo-advisor using genetic algorithm and BERT sentiments from tweets for hybrid portfolio optimisation. Expert Syst Appl 2021;179:115060.
[23] Fiok K, Karwowski W, Gutierrez E, Wilamowski M. Analysis of sentiment in tweets addressed to a single domain-specific Twitter account: Comparison of model performance and explainability of predictions. Expert Syst Appl 2021;186:115771.
[24] Xu H, Chai L, Luo Z, Li S. Stock movement predictive network via incorporative attention mechanisms based on tweet and historical prices. Neurocomputing 2020;418:326–39.
[25] Liu H, Zhao T, Wang S, Li X. A stock rank prediction method combining industry attributes and price data of stocks. Inf Process Manage 2023;60(4):103358.
[26] Shi Q, Katuwal R, Suganthan PN, Tanveer M. Random vector functional link neural network based ensemble deep learning. Pattern Recognit 2021;117:107978.
[27] Paquet E, Soleymani F. QuantumLeap: Hybrid quantum neural network for financial predictions. Expert Syst Appl 2022;195:116583.
[28] Liu H, Long Z. An improved deep learning model for predicting stock market price time series. Digit Signal Process 2020;102:102741.
[29] Leippold M. Sentiment spin: Attacking financial sentiment with GPT-3. Finance Res Lett 2023;103957.
[30] Li L, Zhu F, Sun H, Hu Y, Yang Y, Jin D. Multi-source information fusion and deep-learning-based characteristics measurement for exploring the effects of peer engagement on stock price synchronicity. Inf Fusion 2021;69:1–21.
[31] Pira L, Ferrie C. An invitation to distributed quantum neural networks. Quantum Mach Intell 2023;5(2):1–24.
[32] Beer K, Bondarenko D, Farrelly T, Osborne TJ, Salzmann R, Scheiermann D, Wolf R. Training deep quantum neural networks. Nat Commun 2020;11(1):808.
[33] Acampora G, Chiatto A, Vitiello A. Genetic algorithms as classical optimizer for the quantum approximate optimization algorithm. Appl Soft Comput 2023;142:110296.
[34] Singh AK, Saxena D, Kumar J, Gupta V. A quantum approach towards the adaptive prediction of cloud workloads. IEEE Trans Parallel Distrib Syst 2021;32(12):2893–905.
[35] Sagheer A, Kotb M. Time series forecasting of petroleum production using deep LSTM recurrent networks. Neurocomputing 2019;323:203–13.
[36] Gao R, Li R, Hu M, Suganthan PN, Yuen KF. Dynamic ensemble deep echo state network for significant wave height forecasting. Appl Energy 2023;329:120261.
[37] Beigi S, Taghavi L. Quantum speedup based on classical decision trees. Quantum 2020;4:241.
[38] Anguita D, Ridella S, Rivieccio F, Zunino R. Quantum optimization for training support vector machines. Neural Netw 2003;16(5–6):763–70.
[39] Pereira DG, Afonso A, Medeiros FM. Overview of Friedman's test and post-hoc analysis. Comm Statist Simulation Comput 2015;44(10):2636–53.