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TOPICAL REVIEW

A Review on High-Frequency Trading Forecasting Methods: Opportunity and Challenges for Quantum Based Method

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ABSTRACT High frequency trading, often known as HFT, is a subset of algorithmic trading, which is one of the most significant improvements to the trading environment in recent years. Algorithmic trading gives traders the ability to trade or receive orders within extremely brief time intervals, such as minutes or seconds based. The very nature of high-frequency trading necessitates the use of high-speed data feeds, which deliver information in real time as well as trade executions for high-frequency traders. Due to the unpredictable nature of the market, several different methods are utilised in order to forecast the HFT time series. However none of these methods have been demonstrated to be a consistently acceptable forecast tool. The majority of HFT trading is conducted using traditional arbitrage-based methods.The conventional method of forecasting using time series does not have the capability to take into account seasonality or outliers in a dataset. The HFT time series data is consistently expanding from day to day, thereby becoming big and enormous. To solve this problem, we require a model that is both more precise and less time-consuming. The purpose of this paper work is to investigate historical models, contemporary models and hypothetical future models that can be used to anticipate HFT time series. Within the domain of HFT forecasting where accuracy and productivity are of the utmost importance, it also becomes critical to investigate state-of-the-art technologies. In light of the inherent difficulties that classical computing methods encounter when confronted with the intricacies of time series data, our focus shifts to quantum computing as a prospective resolution. This undertaking is driven by the imperative to confront prevailing obstacles in the field of forecasting, including enhancing precision, managing extensive datasets and alleviating the consequences of noise and uncertainty.The progression of quantum technologies is expected to bring significant changes that will enhance the reliability, precision and scalability of forecasting methodologies. The synergy between quantum computing and HFT forecasting holds the promise of reshaping how we approach and derive insights from time-varying datasets. The exploration and use of quantum computing for HFT forecasting marks a significant stride toward overcoming current limitations.

INDEX TERMS HFT, high frequency trading, time series forecasting, machine learning, quantum computing.

I. INTRODUCTION

High frequency data, by its very definition, involves high-speed data feeds and in particular to high-frequency trading (HFT), it gives HFT traders access to real-time information and executions [1]. Traders working in banks and high frequency trading firms are responsible for HFT activities. These traders make money by purchasing and selling high frequency indexes in order to benefit from market arbitrage

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and increase their profits. When it comes to high-frequency trading, speed is the most important factor. The order book data, trade data and market data that are included in HFT data are characterised by their speed, volume and complexity [2]. Order book data is a collection of limit orders and quotations for a certain security. It offers insight into the supply and demand dynamics of the market and refers to the collection of limit orders and quotes for that security. The execution of deals is what trade data records, including the price and volume of the transaction. The bid-ask spread, volume traded and volatility are all examples of market conditions that are reflected in the data collected from the market.

HFT data is generated and analysed by traders and companies who use complex algorithms and statistical models to detect patterns and possibilities for profit in the market [3]. HFT data is used by high-frequency trading (HFT) organisations. These algorithms are frequently developed to take advantage of minute price differences and disparities that occur for only a fraction of a second. This enables traders to profit from market inefficiencies that are invisible to human traders and lasts only for a little period of time. The ability of high frequency trading firms to obtain and analyse data in real time is dependent on having high-performance computer systems and low-latency data links. HFT data is essential to the success of high frequency trading enterprises. The use of high-frequency trading (HFT) data has grown increasingly popular in the financial markets, which has resulted in controversy and increased regulatory scrutiny due to worries regarding the possible influence it may have on market stability and fairness [4], [5].

The speed with which one can react to shifts in the underlying price of an index or product is a highly crucial factor in determining whether or not they will make a profit from the deal. Having the capacity to make judgements rapidly enables traders to maintain a dominant position in the HFT trading market and get a competitive advantage in terms of price [6], [7], [8]. HFT traders are required to obtain price analysis of the underlying product or index in advance in order to aid their decision making when buying or selling in the HFT market. This is necessary in order to meet the requirements of the HFT market. It is helpful to evaluate changes in price variables over a period of time in order to have an understanding of the flow of the market and to determine the appropriate product or index on which to invest [9], [10]. HFT traders benefit from real-time information and trade executions provided by HFT. Predicting the future price of an index in advance is one of the tasks involved in forecasting. The study of time series forecasting is an important subfield of statistical modelling. It is also an important part of many other sectors, such as the economy, finance and marketing, as well as the scientific community.

Conventional forecasting methods are typically used in the trading industry for forecasting, despite the fact that these methods are vulnerable to the vast amounts of data, high volatility and constantly shifting terrain of the trading environment [11]. Forecasting HFT data using conventional methods may provide HFT traders with a number of issues, including the inability to reliably recognise patterns in vast time series, the length of time it takes to analyse the data, the amount of server resources and storage space required and the capacity to comprehend the big picture visually. Due to the advent of high speed and the ever-increasing digital processing power, algorithmic trading has become increasingly popular and demands estimation within a short period of time [12]. All these factors are making us to use a more advanced strategy, hence we can no longer rely on traditional methods of data processing and forecasting. Recent developments have seen a shift away from traditional arbitrage models and towards models based on machine language and quantum-powered forecasting. In this research, we investigate the current pattern in high-frequency trading (HFT) time series forecasting by focusing on the significant paradigm shift in the concept of time series forecasting.

This paper compiles a variety of HFT time series forecasting papers published between 2010 and the present day. First we classify those studies based on forecasting model used and then we categorise the methodologies that are utilised in those papers. In addition to this, an analysis was also carried out on high frequency data forecasting not related to trading. Following that, this paper will examine their benefits and highlight any potential omissions or errors in the text. In conclusion, a summary of the existing method and an investigation into possible future directions are presented. The purpose of this work is to present a comprehensive and methodical understanding of time series forecasting for high-frequency trading (HFT) data. This study aims to be among the pioneers in assessing time series forecasting for high frequency trading data, in contrast to other existing time series forecasting review papers, which intend to concentrate on forecasting non-trading high-frequency data, such as energy or weather. Recognizing the challenges posed by high-frequency trading (HFT) such as speed, accuracy, and efficiency which are paramount, in this paper we attempt to examine the use of quantum based method for forecasting HFT. HFT forecasting may be rethought in light of the unique characteristics of quantum computing. In order to improve the efficiency and accuracy of forecasting, we will delve further into method that is based on quantum support vector machines (SVM), where We review this method's capabilities to see if it can beat classical methods, especially in HFT.

A. ABBREVIATIONS AND ACRONYMS

The following abbreviations are used in this paper:

High-frequency trading (HFT)
Autoregressive integrated moving average (ARIMA)
Seasonal Autoregressive integrated moving average (SARIMA)
Artificial neural networks (ANN)
Support vector machines (SVM)
Convolutional neural networks (CNN)
Long short-term memory (LSTM)

Heterogeneous Autoregressive-Quantile Regression (HAR-QREG)
Smooth transition exponential smoothing (STES)
Gated recurrent units (GRU)
Support Vector Regression (SVR)
Markov Chain Monte Carlo (MCMC)
Strongly typed genetic programming (STGP)
Wavelet neural networks (WNN)
Neural networks (NN)
ANFIS (Adaptive Neuro-Fuzzy Inference System)
Quantum-behaved particle swarm optimisation (QPSO)
Deep reinforcement learning (DRL)
Root mean square relative error (RMSRE)
Root Mean Squared Error (RMSE)
Mean Squared Error (MSE)
Mean Absolute Error (MAPE)
Mean squared error (MSE)
R squared(R2)
Bitcoin (BTC)
Ethereum (ETH)
Litecoin (LTC)
Monero (XMR)
Taiwan Futures Exchange (TAIFEX)
Taiwan Stock Exchange Corporation (TSEC)
Digital Technology Group (DTG)

II. REVIEW ON HIGH FREQUENCY TIME SERIES FORECASTING STUDIES

A time series is a collection of measurements that are taken at consistent intervals of time. It is made up of a time variable that has been dated as well as a value that is accurate as of that timestamp. The process of identifying the next probable measurement based on the current time series data through the application of a forecasting model technique is what is meant by the term forecasting time series for high frequency data [13]. The rise of high frequency trading in financial markets has resulted in a major increase in the amount of attention paid to the field of research known as high frequency time series forecasting during the past several years. Growing interest in this topic can be attributed to a number of factors, including an increase in the availability of high-frequency data and the requirement in financial markets for accurate and timely predictions. There have been a great number of studies that have investigated the efficacy of various forecasting strategies for high frequency data. These techniques range from the conventional and traditional methods to the most recent hybrid methods, all of which are covered in detail in this paper.

The usage of statistical models, such as autoregressive integrated moving average (ARIMA) models and general autoregressive conditional heteroscedasticity (GARCH) models, have been investigated in the course of previous research on high frequency time series forecasting. These methods have been demonstrated to be effective in capturing the stochastic aspects of high frequency data; nevertheless, it is possible that they will struggle to capture the non-linear correlations that are present in the data [14], [15]. In addition to these methods, machine learning techniques have been an increasingly popular approach to high frequency time series forecasting. These techniques have been proved to be effective in capturing the non-linear correlations that occur in high frequency data and delivering accurate forecasts [16], [17], [18]. Models like artificial neural networks (ANN), support vector machines (SVM) and random forests, among others, are used in the machine learning techniques. The use of deep learning approaches, which are a sort of machine learning model, such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks, is one more method that has garnered a lot of interest in recent years. These approaches have shown promising results in capturing the temporal relationships and patterns in high frequency data, but they require a substantial quantity of data and computer resources to train [19], [20].

The literature as a whole argues that the level of volatility and the presence of non-linearities in the high frequency data being analysed are two of the most important factors to consider when deciding on a suitable forecasting method. Additional characteristics, such technical indications or news sentiment data, can boost the efficiency of these methods even further. However, it is important to keep in mind that high frequency time series forecasting is a difficult undertaking and that the inherent unpredictability and randomness of financial markets may restrict the accuracy of forecasts. Selecting an appropriate model for forecasting high-frequency data requires thinking about the data's frequency, trends, accuracy, scalability and interpretability. Therefore, when applying forecasting approaches to high-frequency data, researchers and practitioners need to proceed with caution and a sense of realism.

In this paper, we attempt to describe the models used for high-frequency trading time series forecasting by classifying them into four broad categories: (1) traditional models (2) machine learning-based models (3) hybrid models and (4) models that make use of quantum computing. Statistical models that use past data to make predictions about the future are the basis of conventional forecasting models. Advanced algorithms are used in machine learning forecasting models to analyse past data and foresee potential future trends. When trying to predict a time series, a hybrid model combines the best features of multiple models into a single prediction algorithm. There has also been a notable shift recently towards quantum-based forecasting models. The goal of all of these models is to provide as accurate of predictions as possible for high-frequency time series. Each of these will be supervised and evaluated in this report.

Here is an example of actual sales and forecasted sales data in graphical depiction to illustrate the sales growth in future.

A. CONVENTIONAL MODELS

Time series history on a variety of time scales, including years, can be predicted using traditional time series forecast-

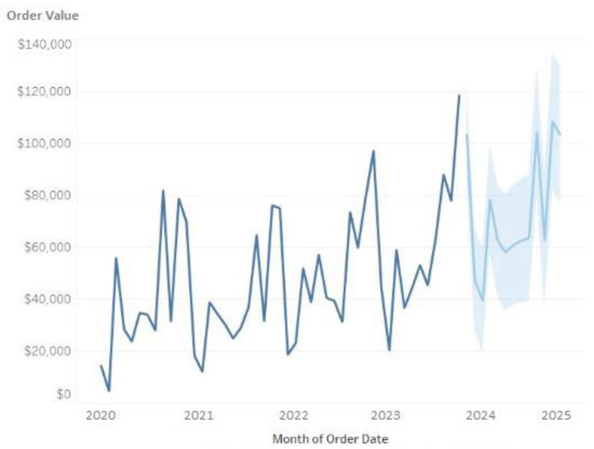

FIGURE 1. Example of actual order and forecasted order. Adapted from [14].

ing techniques [22]. Time series can be measured in years, months, days, hours, or minutes and the models use this information to generate predictions about its future values. Statistical and economic models have been created to capture the dynamics of high-frequency data and these models are used in conventional high-frequency time series forecasting. Traditional models make predictions about future time series by employing statistical methods like regression, moving averages, exponential smoothing, vector auto regression and state-space representations. The goal of traditional high-frequency time series forecasting models is to accurately predict future values by capturing the underlying dynamics of the data, such as trends, seasonality and volatility. Financial and economic forecasting, among others, have made extensive use of these models to predict high-frequency time series data.

The statistical method known as regression is the process of attempting to fit a mathematical equation to a collection of data points [56]. When predicting time series, regression models are frequently employed because of their ability to capture the linear relationship that exists between the historical observations of a time series and the variable of the forecast. The accuracy of the model is determined by determining how to estimate the model so that the sum of squared errors between the predicted values and the actual values is as small as possible. After that, one can make predictions about the values of the time series by applying the regression equation. The moving average is a technique for smoothing out time series data that works by averaging the results of a predetermined number of previous observations. Taking the average of the previous n observations is what the moving average method entails, where n is often a number with a tiny integer value, such as 3, 5, or 7. Following that, the average is utilised as the basis for the forecast for the subsequent time period. The moving average method is one that may be used to effectively uncover underlying trends in data while also helping to smooth out short-term variations in the data [57].

Time series data can be smoothed using a technique called exponential smoothing. This technique lends greater weight to more recent observations than it does to older observations. Calculating a weighted average of previous observations is required for this procedure and the weights are scaled down in a manner that is exponentially decreasing as the data get older. The smoothing parameter, whose value is normally found by a process of trial and error or optimisation is responsible for assigning the weights [58]. Exponential smoothing is useful for identifying patterns of continuity and change in the data, such as trends and seasonal patterns, but it may have trouble identifying abrupt shifts or shocks in the data. In order to model the connections between a number of different time series, vector auto regression, or VAR, models are utilised. When there are many time series that are related to one another, you can utilise them to make predictions based on high-frequency data using these models. The forecasts that are produced by VAR models are highly adaptable due to the fact that they can be made conditional on the anticipated future courses of particular variables within the model [59]. Additionally, it frequently delivers forecasts in addition to those that are generated by univariate time series models and complex theory-based simultaneous equations models.

State-space models are a versatile class of models that can be applied to a wide variety of time series data. State-space models that can be used for both filtering and forecasting are Kalman filter models [60]. The Kalman filter is predicated primarily on a mathematical algorithm that is employed for estimation based on a series of measurements. Kalman filters can be used to forecast time series data by estimating the series' future values based on their past values and other available information. The fundamental strategy is to use the Kalman filter to estimate the parameters of a time series model. The most frequent form of Kalman filter model for time series forecasting is the linear Gaussian state space model. It presupposes that a linear equation with Gaussian noise can describe the time series. It presupposes that the observations are generated by a linear function of an unobserved or latent state variable that evolves according to a Gaussian distribution over time.

Conventional models assume that the time series is stationary, which means that the statistical properties of the data, such as the mean and variance, remain constant over time and it functions accurately with relatively small data sizes. As the volume of data increases, the processing speed of conventional statistical methods slows and forecasting becomes more difficult. Size is the most essential factor to consider when selecting a forecasting model for time series forecasting [28], so it does matter when making time series forecasts. This paves the way for machine learning-based time series forecasting models. These assumptions can be classified broadly as stationary, linear and independent. Important because it enables models to make accurate predictions based on past observations if it is stationary. In conventional models, the relationship between past observations and future values of the time series is considered linear. This indicates that the change in the value of the time series in response to changes in previous observations is constant and can be modelled by a linear equation.

In conventional models, the observations in the time series are independent of one another, which means that the value of the time series at any given time does not depend on the value of the time series at any other time. The same holds true for the variance of the time series, which is considered a constant over time because the level of data variability does not change over time. Although these assumptions can be used to facilitate the modelling process, they may not always be true. Numerous real-world time series, for instance, are non-stationary, meaning their statistical properties vary over time and may exhibit nonlinear relationships between past observations and future values. In addition, many time series are dependent on one another or exhibit correlations between observations. Before applying conventional time series models to real-world data, it is crucial to thoroughly evaluate their underlying assumptions and consider alternative modelling techniques when these assumptions are not met [11]. This paper examined a number of historical studies on the use of conventional models for forecasting high-frequency time series.

The Kalman filter, a state-space model that can estimate the hidden state of a system based on noisy data, was proposed by Yan Xu for predicting the price of equities stock Changbaishan [51]. The study explains how non-linear and non-stationary dynamics make it difficult for conventional methods like autoregressive integrated moving average (ARIMA) to accurately forecast stock prices. The authors believe the Kalman filter does a better job of capturing the complicated dynamics of stock prices because it can estimate the hidden state of a system based on noisy data. Using historical stock price data from the Shanghai Stock Exchange, the research provides an empirical analysis of the proposed approach. The results demonstrate that, when it comes to predicting stock prices, the Kalman filter approach is superior to more conventional methods, especially during times of extreme volatility. In terms of prediction accuracy, the proposed Kalman filter methodology outperformed the conventional ARIMA method with a smaller mean squared error (MSE).

Based on the GARCH and asymmetric models of the GARCH family, Salamat et al. [26] developed a model for predicting the volatility of crypto currencies. This model can be found here. This study looked at the global secondary price indices of eight different cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), XPR, XLM, NEO and Monero (XMR). The GARCH model and its numerous offshoots, such as the EGARCH, TGARCH and PGARCH, were the subjects of our investigation for this particular paper. These models are able to reflect the volatility clustering and leverage effects that are observed in the returns of bitcoin while also allowing for asymmetric responses to shocks. The results for an explicit collection of currencies over the full period revealed proof of the volatile nature of crypto money, showing that PGARCH is a better-fitting model with student's t distribution. These results were found by looking at the entire period. A better GARCH fitted model has been found by the utilisation of an effective error distribution measurement approach and the high rate of volatility that has been observed in the pricing of cryptocurrencies has been identified. It is a benchmark that investors in crypto currencies can use to evaluate the effect of both positive and negative shocks on the value of their holdings [27].

An ARIMA model was utilised to make projections regarding the price of Netflix shares over the next five years [23]. The author of the paper begins by providing an overview of the ARIMA model and its utilisation in time series forecasting. Next, the author discusses the modification of the model, an experiment and the findings of the experiment. The daily stock price data from Netflix over a period of five years has been evaluated using three distinct ARIMA models, including a conventional ARIMA model and two more specialised techniques. The analysis was carried out using ARIMA. The degree to which the model was able to produce accurate forecasts was one of the key focuses of the study. We were able to make accurate predictions on the performance of the stock market by applying an ARIMA model to time series data. If this modification is not made, the ARIMA model is susceptible to the same difficulties that are encountered in conventional time series forecasting, such as having difficulty coping with intricate data and having to perform lengthy computations. The study was helpful in describing the ARIMA model and how some changes improved the findings, however it is essential to bear in mind that classical models may struggle with big data sets and require more time to analyse. Although the study was helpful in explaining the ARIMA model and how some modifications improved the findings, it is necessary to remember that classical models.

An innovative method for modelling VaR that combines the heterogeneous autoregressive-quantile regression (HAR-QREG) model, which is a state-of-the-art model for modelling volatility dynamics with a jump component which captures the impact of unexpected events on asset prices [54]. This model is known as the heterogeneous autoregressive-quantile regression (HAR-QREG) model. The author applies this method to high-frequency financial data and demonstrates that it is effective in enhancing VaR measures and forecasts by showing how it works with those data. The empirical findings of the research indicate that the proposed model performs better in terms of VaR forecasting accuracy than a number of benchmark models, including the HAR and GARCH models. The research also demonstrates that the model is resistant to alterations in the distributional assumptions of the underlying asset returns and is able to capture the dynamics of extreme events like financial crises. These findings are presented in the study. In general, the purpose of this paper is to present a novel strategy for modelling VaR that takes into account both the volatility dynamics and the jump components. If implemented, this strategy has the potential to improve VaR measures and forecasts. The research makes a contribution to the existing body of literature on high-frequency financial modelling and sheds light on the various practical applications of VaR modelling in the financial industry.

Smooth transition exponential smoothing (STES) models, which feature a smooth transition function was introduced as a novel method for forecasting high-frequency currency exchange rate volatility [61]. Smooth transition exponential smoothing models feature a smooth transition function across distinct regimes. With the use of a comparison between the daily changes in value of the Malaysian ringgit and those of the US dollar, this study offers an empirical evaluation of the technique. According to the findings of the study, traditional methods of forecasting, such as the ARCH and GARCH models, cannot be relied upon to accurately predict high-frequency changes in the value of currencies. The authors argue that the complicated dynamics of exchange rate volatility can be more accurately modelled using STES models since these models allow for non-linear links to be made between the variables being studied. The findings shed light on the potential advantages of using STES models in forecasting high-frequency exchange rate volatility and show that STES models perform better than traditional models, especially during periods of extreme volatility. The findings also show that STES models are superior to traditional models in terms of their ability to predict high-frequency exchange rate volatility.

B. MACHINE LEARNING MODELS

The recent trend tend to focus more on machine learning techniques for forecasting mainly due to ever growing size of data [28]. The problem of voluminous and dimensional of the time series data arises as data grows and as a consequence, time series analysis based on learning-based techniques are required. There are several machine learning methods used for time series forecasting. Machine learning algorithms are designed to learn from patterns in data and make predictions based on those patterns. As a result, they can often produce more accurate forecasts than traditional statistical methods. Machine learning algorithms also are capable of handling complex, high-dimensional data with many variables, making them well-suited to time series forecasting tasks that involve large and diverse data sets [17]. They can adapt to changing conditions over time, making them useful for forecasting tasks where the underlying patterns in the data may shift or change over time. Machine learning algorithm can automate the process of time series forecasting, reducing the need for manual intervention and allowing for more efficient and timely forecasting. There are several machine learning methods commonly used for time series forecasting discussed in this paper such as neural network, support vector regression, ensemble and bayesian methods.

In order to model time series data and derive predictions, neural network-based methods employ artificial neural networks. Long short-term memory networks, gated recurrent units (GRU) and recurrent neural networks are a few examples. Artificial neural network-based deep learning models, on the other hand, are built to discover hidden relationships within data by way of a hierarchical representation of features. Time series forecasting has seen a rise in the use of deep learning models, a form of machine learning model. They differ from traditional models in that they may be adjusted to different situations and make less assumptions about the origin of the data. This enables them to describe nonlinearities and interactions between variables, two phenomena that might be challenging to portray using more traditional approaches [62]. The goal of these models is to eliminate the need for human intervention in feature engineering by automatically learning features from the input data.

Time series forecasting challenges are ideal for Support Vector Regression (SVR). SVR is used for time series forecasting on the premise that the past time series data can be viewed as input features, while the desired future time series values may be viewed as output targets. The connections between the input and output variables can be linear or nonlinear; SVR can handle either. It can be used for time series forecasting, stock price prediction and other regression applications and it shines when working with high-dimensional data [63]. The Support Vector Machine (SVM) algorithm forms the basis for SVR, which locates the optimal hyperplane for data separation while reducing the prediction error. Because of its efficiency in dealing with high-dimensional data, SVMs are well-suited for complicated datasets with numerous features, including HFT, making them a potent machine learning tool. SVMs are resistant to noisy data because, rather than trying to fit a model to the data, they seek to determine the optimal decision boundary that splits the data into multiple groups [64]. For an illustration of the SVM classification process, see the diagram below.

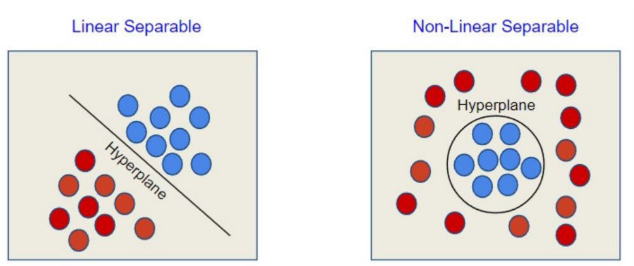

FIGURE 2. Support vector machine classification. Adapted from [17].

The ensemble technique is yet another type of machine learning that can be used to forecast time series. When making predictions using ensemble methods, numerous models are combined into one model, which can lead to overfitting. This is especially true if the individual models that make up the ensemble are very complicated or were trained using an excessive amount of data. The creation of a single, more accurate forecast requires the use of ensemble methods for time series, which include merging several forecasts derived from a variety of models or algorithms. The capacity of ensemble methods to recognise a wide variety of recurring patterns in the data is one of the most significant benefits offered by these techniques. On the other hand, achieving adequate diversity among the models that make up an ensemble might be challenging at times [65]. Techniques such as bagging and boosting can help to generate variety by selecting different subsets of the data or by altering the weights of the data points. Nevertheless, it is essential to ensure that the diversity that is achieved is meaningful and not merely the result of random variation.

The modelling and forecasting of time series data can be done with the help of Bayesian statistics when using Bayesian methodologies. Bayesian structural time series models and Gaussian process regression models are two examples of models in this category. When the previous knowledge or belief regarding a parameter or hypothesis is uncertain and when new data might help update existing beliefs, Bayesian methods are valuable. Bayesian methods were developed by the Bayesians. Bayesian methods are particularly effective in complex models, where the estimation of the parameters can be challenging or if there is a limited amount of data [66]. [Citation needed] Bayesian methods are particularly useful in complex models. Bayesian methods include the likes of Bayesian regression, Bayesian hierarchical modelling, Bayesian networks and Markov Chain Monte Carlo (MCMC) approaches, to name a few examples of Bayesian methods. The application of Bayesian approaches can be found in many different sectors, including the social sciences, engineering, medicine and finance. Only a few studies from the past on the use of machine learning techniques to the forecasting of high-frequency time series were looked at.

Using the Generative Adversarial Nets approach [34], Zhou et al. made an attempt to forecast the price of the stock market based on high-frequency data. The Generative Adversarial Nets method generates image patches with the help of random noise. Although this method has been shown to be effective for video forecasting and semantic segmentation, the owner of the business tried to use it to predict the stock of China CSI 300 for the year 2016, using information obtained from the Wind Financial Terminal. The discriminative performance of the generative adversarial network model was significantly higher than that of other models. This model executes complex operations on a one-dimensional input sequence in order to determine whether or not the sequence originates from the dataset and to produce a probability of forecast based on previous stock. The accuracy level of the measurement was determined based on the root mean square relative error (RMSRE). Through the use of this model, the forecast error loss was brought down to a minimum.

A study on forecasting financial markets using HFT data in 2019 proposed the use of strongly typed genetic programming (STGP) for forecasting financial markets by applying high-frequency trading data from the S&P 500 index and comparing the results with a number of benchmark models, such as neural networks, decision trees and support vector regression [53]. The empirical findings of the study indicate that the suggested STGP approach is superior to the benchmark models in terms of both the accuracy of its forecasts and the performance it achieves in trading. It was found that the performance of the model improves when it is trained on longer time series data, which indicates that STGP is capable of capturing long-term interdependence in financial markets. The paper, in its entirety, presents a novel method for forecasting financial markets by utilising STGP and highlights the potential of evolutionary computation techniques in the financial industry. The research makes a contribution to the existing body of literature on high-frequency trading and sheds light on the ways in which machine learning and evolutionary computation approaches might be practically applied in the context of financial markets.

Another study was done on rice movement in Taiwan proposed the use of autonomous and self-evolving forecasting models [52]. The purpose of this work is to predict price fluctuations in high-frequency trading using a self-evolving forecasting model that is based on an advanced version of GA. The model is intended to acquire knowledge from previously collected data and to adjust to the ever-shifting conditions of the market over time. The author suggests encoding model parameters and baseline rules with binary strings instead of traditional text. The empirical findings of the research indicate that the suggested self-evolving forecasting model performs better than numerous benchmark models with regard to both the accuracy of its forecasts and the trading performance it achieves. According to the findings of the study, the performance of the model also improves over time as it adjusts to the shifting conditions of the market. Overall, the research presents an innovative method for predicting price movement in high-frequency trading (HFT) by making use of autonomous self-evolving forecasting models. This method has the potential to increase the accuracy and efficiency of trading decisions.

An examination on a various machine language models were conducted with the purpose of determining how accurately they could forecast stock prices [13]. In order to determine the benefits and drawbacks of various machine language models, such as SVM, LSTM and Random Forest, among others, they are compared to one another. Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAPE) and R squared(R2) were the metrics upon which the measurement was performed. In the comparative study that was conducted, the SVM approach was shown to perform very well. This may be due to the fact that the SVM approach can handle complicated data; nevertheless, the SVM approach was discovered to be time demanding when it came to its implementation. In the survey, both the benefits and drawbacks of each algorithm are analysed and examples of research that has used these algorithms to make stock price predictions are provided. It also discusses the difficulties and unresolved issues associated with predicting stock prices, such as the problem of poor data quality and the difficulty of accurately reflecting the intricate correlations that exist between the various market variables.

In a research done recently, the difficulties associated with modelling high-frequency stock trading data were analysed. The research also explores some novel strategies to overcome these difficulties by applying novel modelling strategies to high-frequency trading data of Dow Jones 30 component stocks [64]. It emphasises the significance of using high-frequency data for modelling and analysis of stock prices. Additionally, it also suggests the utilisation of machine learning algorithms such as artificial neural networks and support vector machines in order to model the intricate relationships that exist between stock prices and other variables, such as trading volume and market volatility. The unique approach to modelling volatility that has been offered, which uses a combination of support vector machines and wavelet analysis, is a strategy that could potentially provide more accurate findings compared to the standard approaches that have been used. The traders and investors who want to get the most out of their investments could find it helpful to optimise their trading tactics with the help of genetic algorithms.

C. HYBRID MODELS

The hybrid technique uses the most advantageous aspects of both traditional and modern forecasting practises and combines them into a single model. It could be a combination of more than one conventional method, or it could be a method of machine learning, or it could be both. The core concept behind the combination is that it makes up for the shortcomings of one strategy by capitalising on the advantages offered by the other. There is no presumption made to the effect that the data are linear or stationary. The data are handled as though they were living things, constantly shifting and progressing. Due to high volatility, complexity, irregularity and noise, time series forecasting in the real world is a far cry from being able to be done using a simple forecasting model. In addition to this, it is uncommon for practical time series to be completely linear or nonlinear. They frequently include both linear and nonlinear patterns in their structure.

A hybrid model was presented as a solution to the problem in forecasting high-frequency time series for stock market [47]. An autoregressive integrated moving average (ARIMA) model and a neural network model have been combined in the model that has been suggested in order to increase the accuracy of stock price predictions at high frequencies. The ARIMA model is used to capture the short-term trends in the data, while the neural network model is used to capture the long-term patterns and interactions between the many market variables. Both models can be found here. An empirical investigation on the prediction of stock prices in the Brazilian stock market is presented in this paper. The study demonstrates that the suggested hybrid model beats both the ARIMA model and the neural network model alone in terms of the accuracy of forecasting. In addition, the research demonstrates that the model may be utilised to produce profitable trading signals when it is combined with a straightforward trading strategy. The overall results of the study indicate that the high-frequency stock market forecasting hybrid model that was proposed is a promising technique and the study provides empirical proof for its usefulness.

There was another new method for forecasting high-frequency volatility on large indices was identified [55]. In the beginning of that study, an overview of the difficulties that are connected with forecasting high-frequency volatility is presented. These difficulties include the influence of noise as well as the difficulty of capturing non-linear patterns. Then a new method for forecasting volatility was presented which make use of an innovative strategy for feature extraction that is founded on the Hilbert-Huang transform as well as an artificial neural network model for making predictions. The suggested method is assessed using historical data from the SP 500 index and it is demonstrated to perform better in terms of forecasting accuracy than a number of benchmark models. In this paper, the applicability of the method in trading strategies is proved by establishing a volatility-based trading strategy that is capable of generating consistent profits over a five-year period. In general,this study emphasises the need of correct volatility forecasting in trading and provides a new strategy that can be implemented to improve trading strategies on large indices.

On another study, a hybrid method was suggested for the purpose of anticipating the direction in which crude oil prices will move using various time frames, dynamic temporal warping and genetic algorithm [50]. In order to increase the accuracy of forecasting the direction in which crude oil prices will move, the method that has been developed combines the study of several periods, dynamic temporal warping and genetic algorithms. The multiple time frames analysis considers a variety of time scopes and trends within the data, whereas the dynamic time warping technique is utilised to align and compare several time series in order to locate patterns that are comparable. In order to enhance the predictive accuracy of the model, the genetic algorithm is utilised to perform optimisations on the feature selection as well as the model parameters. In this research, an empirical analysis on the prediction of the direction in which the price of crude oil would move is presented. The study demonstrates that the suggested hybrid method beats numerous benchmark models in terms of the accuracy of its forecasting. According to the findings of the study, the approach can also be utilised to generate profitable trading signals when it is combined with a straightforward trading strategy.

A study on evaluating the forecasting ability of wavelet neural networks (WNNs) with other topologies of neural networks (NN) on data sets pertaining to financial markets were done [73]. WNNs are a subcategory of NNs that employ wavelet transforms as a means of doing data preprocessing and the extraction of features that make it simpler for neural networks to acquire new information. The research covers the training and testing of a variety of NN models on several financial market data sets. These models include feed forward neural networks, radial basis function neural networks, recurrent neural networks and WNNs. Several measures of accuracy, such as mean absolute error, mean squared error and root mean squared error, are utilised in the process of determining which models perform the best. The results of the study then identify the most effective NN topology and preprocessing technique for financial market forecasting. The hybrid approach led to an increase in forecasting performance compared to classical NN; however, it is important to note that this difference is dependent on the respective data set.

A model that combines an incremental learning algorithm with a deep neural network was introduced with the objective to provide real-time stock prediction while maintaining a low level of computational complexity [49]. The incremental learning approach allows for the model parameters to be updated by making use of new data samples without the need to retrain the complete model. This helps to lower the computing cost and improves the effectiveness of the process of making predictions. The deep neural network is put to use to create accurate forecasts and to grasp the complexities of the relationships that exist between the various market variables. An empirical investigation on the prediction of stock prices on the Indian stock market is presented in this work. The study demonstrates that the suggested model beats numerous benchmark models in terms of forecasting accuracy and computational efficiency. In addition, the research demonstrates that the model may be utilised to produce profitable trading signals when it is combined with a straightforward trading strategy.

D. QUANTUM MODELS

Richard Feynman suggested a machine that would simulate the behavior of quantum system which operates based on quantum mechanical principles [29]. Quantum computing performs calculations based on qubits, it provides a superposition state instead of 0's and 1's. Superposition means existence in multiple states at the same time. In classical computing, bits are like transistors which corresponds to the states 0 or 1. In qubits, they are treated as electrons, 0 or 1, or both. This approach outlay classical computer parallel processing with sequential processing with significant speed of simulations and decreases the chance of error rate [28]. Quantum approach translate classical data points into quantum state data points where quantum feature map transforms data into higher dimensional for easier & faster processing [35]. It also gives the opportunity to process exponentially more data compared to classical computers. Quantum computing approach is applied either with conventional model or with machine learning model or to a hybrid model. The injection of quantum approach exponentially increase the speed of time series computation thus enables a large processing of time series data within short period of time in comparison to classical computation. Quantum computing able to perform complex simulation and solve complex problems [26]. Following diagram shows the feature of quantum computer model.

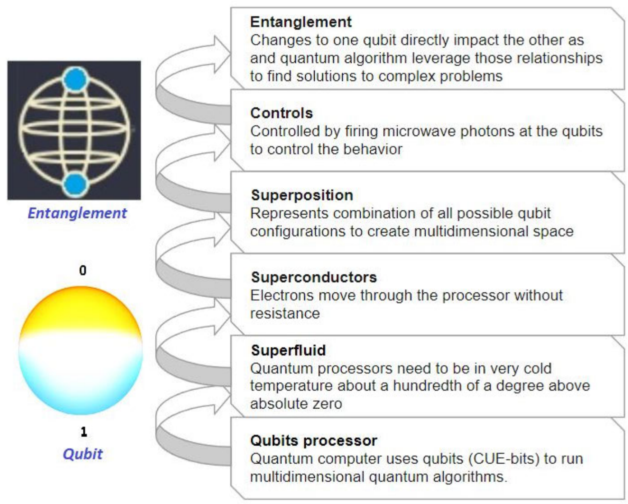

FIGURE 3. Quantum computer model. Adapted from [35].

Large organizations like Google, IBM and Microsoft, as well as newer companies like Rigetti, D-Wave and Xanadu, have all developed their very own quantum computing systems. A software development kit, often known as an SDK, is currently accessible for use by the general public. Using this SDK, one can experiment with quantum computers by using simulators. To this day, applications of quantum computing can be seen in a variety of business sectors. Quantum computing has been responsible for the discovery of new small-molecule medicines [32], which are used in the medical business. The use of quantum computing can make it easier to crack asymmetric encryption and cryptography, both of which are important aspects of the cybersecurity business [33]. In the field of finance, a full software suite has been developed to solve quantitative financial and macroeconomic simulation problems [34]. Quantum computing has also been utilised in the field of logistics, namely in the process of determining the shortest route via an intricate road network and simulating distribution networks in order to bring optimisation to energy flow. Quantum computing has been of assistance in the field of physics research and development [35], particularly in the study of atomic physics and high-energy physics.

Many investigations have been carried out in relation to the time series forecasting capabilities of quantum computing. Among them, the ANFIS (Adaptive Neuro-Fuzzy Inference System) networks with quantum-behaved particle swarm optimisation (QPSO) was utilised for the foreign exchange forecasting of the four key currency pairs EUR/USD, USD/JPY, GBP/USD and USD/CHF [69]. ANFIS networks are a sort of neural network that build a hybrid system for prediction and inference by combining fuzzy logic and neural network techniques. This type of network is known as an ANFIS network. A subtype of particle swarm optimisation known as QPSO makes use of ideas from quantum mechanics in order to make the optimisation process more effective. Investigation into the feasibility of using ANFIS networks in conjunction with QPSO for financial forecasting was carried out. The authors of this paper compare the performance of ANFIS networks with QPSO to the performance of other optimisation algorithms such as genetic algorithms to show that ANFIS networks with QPSO achived good results where it was found to be highly efficient for forecasting in financial markets, particularly in the Forex market. This paper was published in the journal Frontiers in Financial Engineering.

In another recent quantum related research, a study on quantum particle swarm optimization algorithm with the truncated mean stabilization strategy was published [75]. This study introduces a novel method for particle swarm optimization that incorporates principles from quantum computing, notably utilizing a technique known as the truncated mean stabilization strategy. The author suggest a quantum particle swarm optimization method that is anticipated to integrate notions from quantum computing to improve the exploration and exploitation abilities of the optimization process. Quantum-inspired optimization techniques utilize principles derived from quantum physics to create algorithms that are more efficient in addressing optimization problems. To evaluate the performance of the method, one could use criteria such as convergence speed, solution quality and scalability. The paper offers insights on the use of quantum computing principles to optimization problems. Quantum information processing involves multiple domains, such as quantum algorithms, quantum communication, among others. This study makes a valuable contribution to the expanding domain of quantum-inspired optimization algorithms and offers valuable insights into the possible benefits of employing quantum computing approaches for tackling intricate optimization problems.

Another related study was done on using quantum algorithm for K-nearest neighbor classification tasks, utilizing a divide-and-conquer approach [76]. K-nearest neighbor is a widely used supervised machine learning method employed for classification applications. The algorithm operates by identifying the K-nearest neighbors of a given query point in the feature space and then assigning the label that appears most frequently among these neighbors to the query point. The divide-and-conquer approach is a problem-solving technique that involves breaking down an issue into smaller sub problems and solving them recursively. The author suggest a quantum adaptation of the KNN algorithm that leverages concepts from quantum computing to achieve more efficient classification jobs in comparison to classical algorithms. Quantum computing has the ability to perform multiple calculations simultaneously and achieve a significant increase in computational performance for specific workloads, which makes it a compelling option for machine learning. This paper enhances the field of quantum machine learning by presenting a new quantum algorithm for K-nearest neighbor classification tasks. The technique utilizes a divide-and-conquer approach to enhance efficiency and scalability.

Similarly, real-world trading data from the Shanghai Stock Exchange was used in conjunction with a cutting-edge deep reinforcement learning (DRL) framework that makes use of quantum computing techniques [71]. This allowed for the prediction and monitoring of the profit and loss associated with the trading strategy. In this particular investigation, the profit and loss limits were positioned at a variety of quantum price tiers and the trading strategy was modified according to whether or not the profit and loss were contained inside these tiers. The DRL framework makes use of a neural network in order to discover the most effective trading strategy by analysing data from the market's past. The neural network is taught using a combination of supervised learning and reinforcement learning. It is designed to react to changing market conditions in real time and this is accomplished through the training process. According to the findings, this method used in the trading system is superior to others in terms of both the returns it generates and the management of the risks it exposes investors to.

Another investigation was carried out on data sets consisting of univariate financial time series by employing fuzzy logic in conjunction with quantum. It combines fuzzy time series forecasting with a fast forward quantum optimisation algorithm and it was evaluated using three different data sets, namely the daily average of Taipei, the index for the Taiwan Futures Exchange (TAIFEX) and the weighted index for the Taiwan Stock Exchange Corporation (TSEC). Fuzzy logic makes use of fuzzy linguistic variables for forecastingand the fast forward quantum optimisation technique assists in locating the best possible solution for the selection of universe discourse and the uncertainty in time series [36]. The calculation was based on the mean value of the absolute percentage inaccuracy (MAPE). The findings of the experiment indicate that the fast forward fuzzy quantum algorithm outperforms other optimisation algorithms in the sense that it enhances the performance of fuzzy quantum time series modelling while using a significantly reduced amount of CPU time.

In a research for the Mackey-Glass time series prediction investigated the application of hybrid quantum-classical recurrent neural networks for time series prediction [67].

According to the research, time series prediction is a difficult topic in a variety of sectors, including economics, finance and others, where making accurate forecasts of future trends can be extremely important. The Mackey-Glass time series is a benchmark dataset that is frequently utilised for the purpose of time series prediction in decision making. The next thing they do is describe how hybrid quantum-classical recurrent neural networks can be used to predict time series. The paper presents experimental results on several datasets to demonstrate the effectiveness of hybrid quantum-classical recurrent neural networks for time series prediction. Additionally, the paper proposes a novel architecture based on stacked Long Short-Term Memory layers and a variational quantum layer. In addition, the paper demonstrates the effectiveness of hybrid quantum-classical recurrent neural networks for time series prediction. The authors make a performance comparison between hybrid quantum-classical recurrent neural networks and classical recurrent neural networks and they demonstrate that hybrid quantum-classical recurrent neural networks are capable of achieving higher levels of accuracy than classical recurrent neural networks.

E. HIGH FREQUENCY TIME SERIES FORECASTING IN NON TRADING DOMAIN

While high frequency time series forecasting sees widespread application in the financial markets for trading purposes, it also has applications outside of finance in fields as diverse as energy, manufacturing, healthcare and transportation. High-frequency time series forecasting has applications in the energy sector, including load forecasting, distribution optimisation and cost minimization. Predicting equipment breakdowns, maintenance needs and bottlenecks in production are all areas where high-frequency time series forecasting can be useful in manufacturing. Using this information, production schedules can be improved and downtime minimised. Predicting patient outcomes and spotting trends in vital signs and illness progression are two areas where high frequency time series forecasting can be useful in healthcare. This can help in early disease detection and subsequent therapy. High-frequency time series forecasting has applications in transportation, including traffic prediction, route optimisation and arrival time estimation. This has the potential to speed up processes and cut down on wasted time spent travelling.

In other fields outside trading, the modelling strategies that are used in trading can also be utilised successfully. For example, in the field of healthcare, it may be necessary to take into account the effect that external factors like the weather, seasonality and public holidays have on the number of patients. On the other hand, in the field of energy production, it may be necessary to take into account production constraints, maintenance schedules and technical failures. The availability of a substantial quantity of historical data with which to train the forecasting model is essential to the accomplishment of accurate high-frequency time series forecasting. In addition to this, it is essential to select an appropriate modelling approach that takes into consideration the one-of-a-kind properties of the time series that is the subject of the forecast [46]. In general, high-frequency time series forecasting has the potential to be an effective tool in non-trading areas, assisting companies in improving the quality of their judgements and the efficiency of their operations. In this research, we studied a few high frequency time series forecasting studies that were carried out in non-Trading domains. This was done so that we could gain an understanding of how time series forecasting is carried out in other domains, as well as the results of such work.

Accurate forecasting models for wind power generation were the goal of the study "SARIMA model-based short-term forecasting of wind power using wind speed time series data" [24]. Accurate wind power forecasting is critical for the effective and reliable functioning of power systems, as wind power generation is a key renewable energy source. The research utilised high-frequency (10-minute) wind speed data collected from a wind farm in South Korea. The information was gathered over the course of three years, from 2013 to 2015 and then split into two distinct datasets for training and evaluation purposes. In order to predict wind power generation using the wind speed data, a SARIMA model was constructed for this study. The seasonal patterns in the data were captured by using an autoregressive integrated moving average (SARIMA) model, which also contained seasonal differencing. The study revealed that the SARIMA model could predict wind power output up to 12 hours in advance with a MAPE of less than 5.

A study on electricity consumption prediction was done where a novel approach that combines deep learning with ARIMAX-GARCH models was introduced to enhance the accuracy of electricity consumption forecasts [25]. Deep learning is known for its ability to capture complex patterns in data, while ARIMAX-GARCH models are widely used in time series analysis. By integrating these two methods, the study seeks to improve the precision and reliability of electricity consumption predictions. A comparison was made between the performance of the proposed models and many other models such as wavelet transform,long short-term memory and random forest in the UK energy market. The comparison was based on a 24-hour ahead forecasting horizon, using a sample rate of 30 minutes, and was conducted during two separate seasons. According to the forecast results, hybrid model surpasses the present approaches in terms of performance. The hybrid approach is designed to leverage the strengths of both models, ultimately offering a more robust forecasting solution for electricity consumption.

In 2016, attempt to model solar power by utilising quantum SVM in the context of utilising machine learning method on a quantum computer was done [37]. SVM model applied to solar power dataset of Digital Technology Group (DTG) Weather station in Cambridge University, where this data was converted to quantum state for training reasons, then support vector hyper plane formation was carried out after that. The author utilised a quantum algorithm in order to find solutions to the linear equations. Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and R2 error were used in the calculation to establish the level of precision associated with the measurement. It provides a global optimum at the level of 70 percent training size, which is provided as the results on estimated errors for several different training size datasets. An SVM quantum technique for prediction was developed by the author. With this technique, the quantum algorithm typically has a tendency to have an exponential speedup in contrast to the classical SVM.

A quantum algorithm that is based on a quantum autoencoder was proposed to forecast cloud workloads [68]. The quantum autoencoder is a compressed representation of the workload by being trained on previous cloud data workload. This representation of the workload is then used to make predictions about future workload demand. The authors demonstrate the usefulness of their approach by presenting the results of experiments conducted on a dataset taken from the real world. They show that the quantum autoencoder can achieve better accuracy with 91.6

Research on developing strategies for the prediction of breast cancer using machine learning was carried out [70]. The author of the study stated that early detection of breast cancer can enhance patient outcomes and that machine learning can be used to develop prediction models that can assist in early detection and early detection of breast cancer. The purpose of this work is to discuss the application of machine learning approaches to the forecasting of breast cancer. Several different approaches to machine learning, including decision trees, k-nearest neighbours, support vector machines and artificial neural networks, were utilised in this specific inquiry. The authors analyse the effectiveness of these machine learning algorithms by making use of a wide array of performance metrics such as accuracy, sensitivity and specificity. After this, we compared the performance of the machine learning approaches to that of a clinical decision support system and demonstrated that the random forest machine learning strategy provided more accurate results than the clinical decision support system did.

In addition to that, in the recent research on quantum–classical generative adversarial networks for image generation via learning discrete distribution, an intriguing method was presented by using hybrid quantum-classical generative adversarial networks (GANs) with the objective of increasing image production [48]. This paper intends to learn discrete distributions in an effective manner by utilizing different computer paradigms, including quantum computing and classical computing. In addition to this, the benefits of the suggested method was highlighted in comparison to conventional GANs in terms of both efficiency and performance. When it comes to generative modeling, particularly with GANs, one of the most prominent challenges is effectively learning discrete distributions. Discrete distributions are quite prevalent because the values of each pixel are often discrete. Through the utilization of the hybrid quantum-classical framework, these discrete distributions was learned in an effective manner. It produced superior outcomes in terms of picture quality and training speed by utilizing quantum computing techniques in conjunction with classical methods.

Another approach that integrates quantum computing into convolutional neural networks (CNNs) using variational quantum circuits was recently introduced.The proposed method combines quantum computing principles with convolutional neural networks (CNNs) through the utilization of variational quantum circuits [74].The authors suggest a QCNN architecture which is a modified version of regular CNNs designed to utilize quantum computing principles. These circuits consist of adjustable parameters that are tuned to minimize a specific cost function, usually using methods such as gradient descent. Within the framework of the quantum convolutional neural network, it is highly probable that variational quantum circuits play a pivotal role in the process of learning, allowing the model to dynamically adjust and enhance its performance as time progresses.The quantum convolutional neural network seeks to investigate potential enhancements in performance and efficiency by integrating quantum principles. This article offers a comprehensive understanding of how the principles of quantum computing can be applied or achieved via optical devices. The research aims to investigate the potential linkages between quantum computing and optical communication technologies, with a focus on utilizing the distinct features of light for computation. This study signifies a captivating convergence of quantum computing and deep learning, with potential ramifications for future progress in image processing and beyond.

Forecasting high frequency trading (HFT) data is not the same as forecasting high frequency data that is not related to trading. There are numerous key differences. High-frequency trading (HFT) data is often characterised by a very high frequency and volume of incoming financial market data. This means that there are much more data points to examine compared to high-frequency data that is not associated with trading. High frequency data that does not involve trading is often measured in minutes, hours, or days, but high frequency data that does involve trading is typically measured in millisecondss. This indicates that forecasting HFT data requires more sophisticated and specialised methods for evaluating and processing highly volatile and subject to unexpected changes, which makes forecasting more tough. These methods are required because forecasting HFT data is more difficult. Because of the high frequency and volume of data, even relatively minor shifts in market circumstances have the potential to have a major effect on the pricing and the number of trades. Because of this, the models used for forecasting need to be able to quickly adjust to the ever-shifting conditions of the market and produce predictions in real time.

The market dynamics of high frequency trading data are distinct from those of high frequency data used for purposes other than trading. The factors that drive high frequency trading data, such as bid-ask spreads, order book dynamics and market liquidity, can be more complex than the ones that influence high frequency data that is not related to trading. HFT trading data is frequently influenced by these factors. This necessitates the development of forecasting models that are capable of capturing these subtleties and making accurate predictions based on the intricate workings of the market. In general, forecasting HFT data calls for the application of specialist methods and models that are able to deal with the volatility and complicated market dynamics of this sort of data. Although there are some parallels between forecasting high-frequency trading data and forecasting high-frequency non-trading data, accurate forecasting of high-frequency trading data requires more particular customised methodologies due to the unique characteristics of high-frequency trading data.

III. DISCUSSION

Not only in HFT, but also in a great number of other domains, forecasting models have been helpful in predicting future time series. Forecasting based on time series has found use in a wide variety of applications, particularly in the fields of finance, medicine, meteorology and economics [38]. We have looked at a small number of earlier predicting studies that were conducted in various domains. The similar forecasting models that were discussed before can be used here, with the caveat that some customisation or selection of model is required depending on the type of data and predicting that needs to be done. It has also been noticed that time series forecasting models with employment of hybrid and quantum computing approach have been applied in these non-trading based high frequency data, which will be described more below. A high level summary of various previous papers analysed on high frequency time series forecasting is provided below. These papers were utilised in order to gain an understanding of the forecasting of high frequency trading data in order to comprehend its methodology along with its general results and observations.

In spite of the fact that we examined a variety of studies on forecasting, for the purpose of this particular paper, we attempt to review trading-based high frequency data. 1985 saw the introduction of electronic trading on the Nasdaq, which paved the way for the development of high frequency trading [1]. There has been a clear evolutionary trend in the adoption of new technologies as a result of competition, innovation and regulation [39], which has led to the development of high-frequency trading (HFT), which is a natural progression of the securities markets. It is only the following step that has been taken as a direct response to the ever-increasing need for quickness from investors [40]. The nature of HFT data is one of volatility and the vast majority of HFT trading is conducted using traditional arbitrage-based approaches [41]. In order to make the most effective choices for their companies, the HFT traders struggle to comprehend the overall direction of the HFT index prices or the changes that occur over time. When it comes to high-frequency trading, it is essential to have results that are both precise and quick in order to facilitate trading activities in general.

The detection of outliers and seasonality for the HFT index is essential for time series forecasting in order to prevent erroneous forecasting and the overfitting of forecast models [42]. The presence of non-linearity in data is indicated by phenomena such as outliers and seasonality. The advent of the era of big data has resulted in the continuous production of enormous non-linear time series data that obey numerous distribution patterns. This has resulted in increased difficulty for time series forecasting algorithms [43]. Every every day, the New York Stock Exchange records one terabyte's worth of data pertaining to trading [44]. The enormous amounts of trading data that are handled on a daily basis force us to make use of a technique that is superior, given that traditional forecasting demands more resources. According to the publications that were looked at before, time series forecasting in HFT is completely reliant on the accuracy of the forecast model as well as the forecasting time criticality [44]. In the absence of these parameters, it is possible that the index predicting will be inaccurate, which may result in an underestimate or an overestimate of the index forecasting.

Forecasting in high-frequency trading can no longer be done in basic ways, thanks to newly emerging machine language methods that are now gaining traction for forecasting. Although these methods can be used for the time being, it is possible that machine learning alone will not be sufficient to meet the forecasting needs of high-frequency trading in the future. Because the HFT data will be more dynamic, large and constantly growing in the future, incorporating a quantum method into machine learning may prove to be the most effective strategy for meeting the forecasting requirements of the HFT industry. Quantum machine learning, also known as QML, is a relatively new topic of research that blends quantum computing and machine learning strategies with the goal of enhancing the effectiveness and precision of learning algorithms. Within the realm of finance, the application of QML has the ability to bring about a sea change in the manner in which we analyse financial data, build trading strategies and make forecasts.

Pistoia presented an overview of the current state of QML in finance in 2021 and discussed the potential applications of this technology as well as the obstacles that may arise from its use [45]. He highlights the potential benefits of QML for the financial industry, such as the ability to handle vast and complicated datasets, enhanced risk managementand faster and more accurate predictions. We also looked at some of the obstacles that must be overcome in order to put QML into practise, such as the requirement to have access to quantum hardware and specialised knowledge. An overview of some of the current research in QML for finance was included in the same report. This research included applications in portfolio optimisation, credit risk analysis and algorithmic trading. The study, taken as a whole, gives a complete overview of the potential uses and limitations of QML in finance, underlining the necessity for future research and development in this subject. Although though QML is still in its infancy in terms of its development, it shows great promise for the future of finance and has the ability to revolutionise the way in which we conduct financial research and make decisions.

IV. SUPPORT VECTOR MACHINE MODEL WITH QUANTUM APPROACH

According to the findings of the investigation presented earlier, SVM is typically an excellent model to use when it comes to making forecasts. The support vector machine model is a strategy that uses machine language to build a hyperplane via a kernel, which then modifies the data in order to determine the ideal boundary for forecasting [45]. This method is successful even when applied to data with a large dimension. Data encoding in higher dimensional space is typically how the separation for the boundary is carried out in conventional practise.

The kernel matrix is constructed by employing explicit equation calculation to build the connections between the data points. In contrast, calculations in the quantum technique are performed using qubits. In this method, the probability of an object's state is not simply represented as 1s or 0s, but rather as superpositions of those two states. A quantum system's qubit is characterised by the Hilbert space, which allows the qubit's state to take on any value of the form's possible combinations. When compared to traditional computers, this opens up the possibility of processing an extremely large amount of data.

The SVM Quantum model is shown here in the form of a graphical depiction.

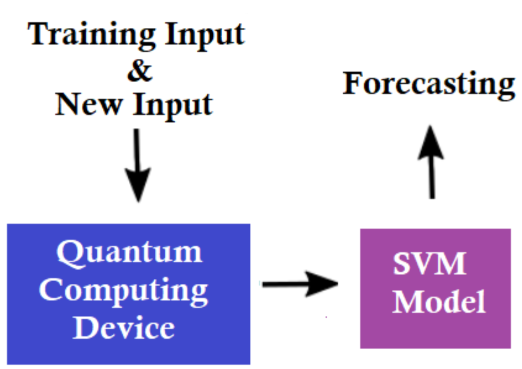

FIGURE 4. SVM model with quantum approach. Adapted from [30].

As a result of the fact that the quantum technology performs calculations based on qubits, this strategy outlays traditional computer processing with a significant improvement in the rate at which simulations can be performed and a reduction in the possibility that mistakes would be made. The technique in which the data is processed and the data points are calculated is, in general, the most important difference that can be found between the conventional SVM approach and the quantum SVM approach. When applying a quantum technique to an SVM model, the initial phase in the process is label classification, which is followed by subsequent steps.

After the labels of the data points have been classified, the next step is to transfer classical data points into quantum state data points using the quantum feature map, which converts the data into higher dimensions so that it can be processed more easily and quickly [30]. After that, we have to make an estimation of the hyperplane by using the kernel. We are able to compute the kernel by utilising quantum data points. The calculation and processing of support vector machine kernels will be improved with the application of quantum computing. A precise calculation of the quantum kernel function is absolutely necessary in order to improve results [31].

When integrated with quantum computing, SVMs have the potential to deliver a number of benefits that are not available to traditional SVMs. Quantum computers are capable of completing specific computations far quicker than classical computers. For instance, quantum computers can utilise Grover's method to search an unsorted database with a speedup that is proportional to the square root of the number of items in the database. This can significantly improve the efficiency of the search. Calculations using SVM on huge datasets can be sped up significantly as a result of this. Quantum computing enables more sophisticated calculations and the exploration of a broader feature space, both of which can contribute to an improvement in the accuracy of support vector machines (SVMs). This can be especially helpful for datasets that have a large number of features and intricate patterns.

Quantum support vector machines have the potential to scale better than their traditional equivalents, particularly for enormous datasets. This is as a result of the fact that quantum computers are able to utilise quantum parallelism to carry out multiple calculations at the same time, which has led to this result. In addition to this, quantum secure virtual computers have the ability to give more privacy by enabling the processing of data in an encrypted form. This, in turn, minimises the likelihood of data breaches taking place.

Quantum SVMs also enables novel applications that were previously impossible to accomplish with traditional SVMs. For instance, quantum support vector machines (SVMs) can be put to use to classify quantum states. This capability has the potential to have significant implications for quantum computing as well as quantum information processing. It is important to keep in mind that quantum computing is still in its infant phases of development; nonetheless, if the science behind quantum computing continues to grow, it is possible that in the future there will be more applications of SVMs that use quantum computing.

TABLE 1. **II.III Summary table showing previous HFT forecasting studies.**

Forecasting Model Category	Author	Title	Method and Dataset
Conventional	Xu, Y. and Zhang, G., 2015 [51]	Application of Kalman Filter in the Prediction of Stock Price	Kalman filter using Changbaishan index stock price
Conventional	Salamat, S., et al, 2020 [26]	Modeling cryptocurrencies volatility using GARCH models: A comparison based on normal and student's T-Error distribution	GARCH, EGARCH, TGARCH, PGARCH using crypto currencies volatility (BTC, ETH, LTC, XPR, XLM, NEO, DASH and XMR)
Conventional	Tan, Y.F., et al , 2021 [21]	Exploring Time-Series Forecasting Models for Dynamic Pricing in Digital Signage Advertising	ARIMA using Netflix stock price
Conventional	Huang, J., et al, 2022 [54]	A high-frequency approach to VaR measures and forecasts based on the HAR-QREG model with jumps	HAR-QREG using Shangai Stock Exchange Composite Index price
Conventional	Jen Sim, H., et al, 2022 [61]	Forecasting the High Frequency Exchange Rate Volatility With Smooth Transition Exponential Smoothing	STES using exchange rate data for the Malaysian ringgit and the US dollar
Machine Learning	Zhou, X., et al, 2018 [34]	Stock Market Prediction on High-Frequency Data using Generative Adversarial Nets	Generative Adversarial Nets using China CSI 300 weighted index price
Machine Learning	Manahov, V., Zhang, H, 2019 [53]	Forecasting Financial Markets Using High-Frequency Trading Data: Examination with Strongly Typed Genetic Programming	Strongly Typed Genetic Programming using E-Mini SP 500
Machine Learning	Feng Huang, C., et al, 2020 [52]	Autonomous self-evolving forecasting models for price movement in high frequency trading	Genetic Algorithm using Taiwan index high frequency data
Machine Learning	Harikrishnan. R., et al, 2021 [13]	Machine Learning Based Model to Predict Stock Prices: A Survey	SVM, LSTM, Random Forest etc using various base stock price dataset
Machine Learning	Zhang X, et al, 2023 [64]	Novel modelling strategies for high-frequency stock trading data	Neural networks and SVM using Dow Jones 30 component stocks
Hybrid	Araújo, R., et al, 2015 [47]	A hybrid model for high-frequency stock market forecasting	ARIMA with Neural Network using Brazilian Stock market price
Hybrid	Liu, F. et al, 2017 [55]	Forecasting and trading high frequency volatility on large indices	Hilbert-Huang transform, Recurrent Neural Network (RNN) and combined using SP 500 index price, liquid SPY ETF, VIX, VXX ETN index
Hybrid	Deng, S., et al, 2019 [50]	A hybrid method for crude oil price direction forecasting using multiple timeframes dynamic time wrapping and genetic algorithm	Mulltiple timeframes analysis, dynamic time warping with genetic algorithm using crude oil price
Hybrid	Vogl, M, et al, 2022 [73]	Forecasting performance of wavelet neural networks and other neural network topologies: A comparative study based on financial market data sets	Neural network with Wavelet function using MSCI World index
Hybrid	Singh, T., et al, 2022 [49]	An efficient real-time stock prediction exploiting incremental learning and deep learning	Incremental learning and deep learning using Nifty-50 stocks (India NSE) price
Quantum	Bhageri, A., et al, 2014 [69]	Financial forecasting using ANFIS networks with Quantum-behaved Particle Swarm Optimization	ANFIS with quantum-behaved particle swarm optimization using EUR/USD, USD/JPY, GBP/USD and USD/CHF Fx rate
Quantum	Lee, R., 2019 [72]	Quantum Finance Intelligent Forecast and Trading Systems	AI, Machine learning with Quantum using various exchange stock price
Quantum	Qiu, Y., et al, 2021 [71]	QF-TraderNet: Intraday Trading via Deep Reinforcement With Quantum Price Levels Based Profit-And-Loss Control	Deep reinforcement learning (DRL) with Quantum Approach using Shanghai Stock Exchange price
Quantum	Singh, P., 2021 [36]	A Fuzzy-Quantum Time series forecasting model	Fuzzy logic with quantum using Taipei, Taiwan Futures Exchange (TAIFEX) index and Taiwan Stock Exchange Corporation (TSEC) weighted index
Quantum	A. Ceschini, et al, 2022 [67]	Hybrid Quantum-Classical Recurrent Neural Networks for Time Series Prediction	Quantum-classical recurrent neural network using Mackey-Glass time series

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The difference between the conventional SVM model and the quantum SVM model is illustrated in the diagram that can be found below.

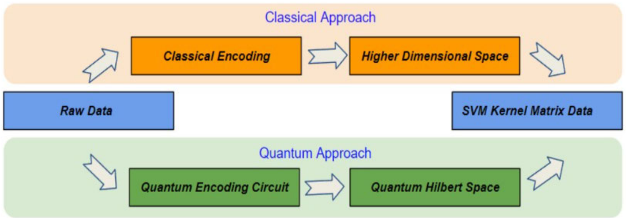

FIGURE 5. **Classical SVM vs quantum SVM. Adapted from [31].**

V. CONCLUSION

Different forecasting techniques are combined in hybrid methods in order to capitalise on the strengths of each particular technique while mitigating the limitations of each technique. Hybrid methods are designed to enhance the reliability and precision of forecasts by incorporating a number of different approaches. With the goal of improving the capabilities of traditional forecasting models, particularly with regard to the management of the ever-increasing volume of data, hybrid approaches have been presented as a potential answer. By utilising a variety of different approaches, these algorithms are able to increase the accuracy and efficiency of their predictions.

High-frequency trading involves executing a large number of transactions in a very short time frame, relying heavily on rapid data processing and accurate predictions. HFT forecasting models face challenges in processing vast amounts of data within tight time constraints. As data volumes increase, conventional forecasting models may struggle to maintain performance, leading to the exploration of alternative approaches like hybrid methods. In HFT, accurate time series forecasting is essential for making informed trading decisions. The precision of forecast models and the timeliness of predictions are critical factors that impact trading outcomes. A slight delay or inaccuracy in prediction can result in significant financial losses, therefore HFT models must strike a balance between accuracy and speed to stay competitive in fast-paced markets.

SVM is a powerful machine learning algorithm known for its ability to handle complex datasets and capture nonlinear relationships. In the context of forecasting, SVM offers advantages such as robustness against overfitting and flexibility in modeling diverse data patterns. However, its performance may degrade when dealing with large datasets due to computational constraints. To address the limitations of SVM in handling large datasets, researchers propose hybridizing SVM with other techniques, including quantum computing. Quantum computing offers the potential for exponential speedup and enhanced computational power, which could complement SVM's capabilities and improve its performance on big data. By integrating quantum computing into hybrid forecasting models, researchers aim to achieve more accurate and efficient predictions, particularly in HFT applications.

The shift from conventional time series forecasting methods to machine learning-based approaches and eventually to quantum computing is expected to occur in the near future. The application of the rules of quantum mechanics to carry out complex calculations at astonishingly fast rates has the potential to revolutionise predicting. Quantum computing has the potential to revolutionise forecasting. The application of the rules of quantum mechanics to carry out complex calculations at astonishingly fast rates has the potential to revolutionise predicting. However, in order to fully utilise the possibilities of quantum computing for forecasting, additional research and development is required. This involves the process of transforming time series data into a format that is compatible with quantum processing.

In summary, it is crucial to utilise innovative approaches, such as integrating hybrid techniques and quantum computing, to address the challenges faced by traditional forecasting models, particularly in high-frequency trading environments. Quantum computing notably has the potential to revolutionise HFT forecasting by offering exciting new possibilities. Quantum computing will usher in a new era of HFT forecasting analysis. These advancements have the potential to significantly enhance the accuracy, efficiency and timeliness of time series forecasting, ultimately resulting in better decision making within financial markets.

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