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Predictive Techniques for Stock Price Movement Using Quantum-Classical Approach: A Comprehensive Review

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Abstract- This review explores the emerging field of quantum-classical hybrid approaches for predicting stock price movement. Predicting the stock price movement has been a popular topic amongst machine learning (ML) enthusiasts. However, predicting how a particular stock or stock market will perform is a difficult task, due to market dynamics, company (stock) specific dynamics, volatility, and other environmental factors. Using advanced classic machine learning techniques, such predictions have become possible, but also computationally complex. There is a need to develop a non-linear prediction model for predicting the movement of the price of a stock, in a more accurate and faster manner. We examine recent advancements in quantum computing algorithms, focusing on the potential to enhance the efficiency and accuracy of traditional prediction models. This review delves into key concepts such as quantum feature maps, variational quantum circuits, and hybrid architectures that integrate quantum and classical components. We discuss the potential advantages of quantum-enhanced techniques, for their ability to process complex financial data efficiently and unlock hidden patterns. Furthermore, we analyze the current challenges and limitations. This review aims to provide an in-depth overview of the latest quantum-classical stock price prediction, highlighting promising avenues for further research and development in this exciting field.

Keywords - Stock price prediction, quantum machine learning, quantum-classical hybrid algorithms, variational quantum circuits, quantum feature maps.

I. INTRODUCTION

Background and Context

For many years, there has been a lot of research done on forecasting changes in stock prices. Even though conventional techniques like technical analysis (chart patterns, moving averages), statistical models (e.g., ARIMA, GARCH), and fundamental analysis (company financials, industry trends) have had varied degrees of success, they frequently fail to capture the complex dynamics and non-linear relationships present in financial markets. Among these intricacies are:

High Volatility: Various factors, such as news events, economic indicators, and market sentiment, can cause stock prices to fluctuate suddenly and unpredictably.

Non-linearity: Relationships between different factors influencing stock prices are often non-linear and complex, making it difficult for linear models to capture their impact accurately.

High Dimensionality: Financial data often involves numerous variables, such as historical price data, trading volume, economic indicators, and social media sentiment, leading to high-dimensional datasets that are challenging to analyse effectively with classical methods.

A potential breakthrough is presented by the development of quantum computing [18], which uses the ideas of quantum physics to process information in ways that are essentially distinct from those of classical computers. Quantum computers can solve unsolvable problems by using fundamental quantum phenomena like superposition and entanglement and by exploring the vast solution space.

Exploring a Vast Solution Space: Quantum computers can simultaneously explore multiple possible solutions in parallel, potentially enabling them to find optimal solutions to complex optimization problems more efficiently than classical computers.

Processing Information Exponentially Faster: Certain quantum algorithms, such as Shor's algorithm for factoring large numbers and Grover's algorithm for searching unstructured databases, offer significant speedups when compared with the efficiency of the classical algorithms used for the same However, generic data search, classical machine learning [16] [17], and processing big datasets (number crunching) are not appropriate for quantum computers.[1] Quantum computing will coexist with classical computing because fully functional, practical, and generally accessible quantum computers will be available in a few years. As a complement to the cloud infrastructure, it is anticipated that an increasing number of hybrid quantum-classical architectures will be developed that will assign parts of challenging issues to a quantum computer.

Purpose of Review

As seen in Figure: 1 below, the Quantum Machine Learning approaches can be classified in the four quadrants based on the data they use (vertical axis) and the type of the algorithm (horizontal axis) used to process the data.

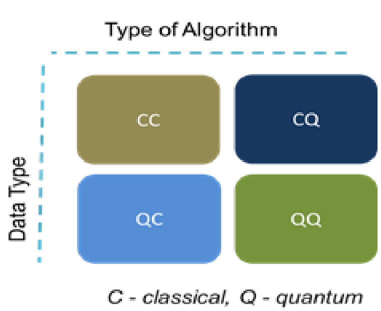

Figure 1: Quantum Machine Learning Approaches. Image adapted from Wikimedia Commons [2] (via Maria Schuld)

CC – Classical data on Classical computers, this is the conventional approach to ML some concepts are borrowed from quantum information.

QQ – Quantum data encoded with states on Quantum computers, this approach is the backbone of fundamental research in Quantum Computing and is still in the experimental phase. Typically simulations are run as researchers wait for general-purpose, fault-tolerant quantum computers to be available.

CQ – Classical Data on Quantum computer. This is also called quantum-enhanced machine learning. Classical data is embedded into quantum computers using quantum circuits.

QC – Using quantum data from sources like quantum sensors and using traditional machine learning techniques on traditional computers to process it.

Using quantum algorithms to make predictions on complex systems is known as "quantum prediction" These algorithms have the potential to solve some problems far more quickly than classical algorithms, which could result in more precise and effective predictions in domains like finance. Particularly when working with huge datasets and complex variable connections.

Problem Statement and motivation for the research

Predicting stock prices with high accuracy is difficult due to many factors that can affect stock prices. These factors include politics, economic conditions, psychological factors, the company's financial performance, and the overall volatility of the market due to its dynamic and non-linear nature.

Stock price prediction accuracy is generally considered to be low with most models only achieving moderate accuracy, often not significantly better than random chance, and heavily dependent on market conditions and the specific stock being analyzed; while some advanced techniques like machine learning can improve prediction accuracy, it remains challenging to consistently predict precise future prices.

Most of the classical stock price prediction Machine Learning algorithms such as Linear Regression, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, and Long Short-Term Memory (LSTM) are analyzed for limited stocks [3]

Techniques typically used to predict stock prices are:
Technical Analysis forecasts the future direction of prices by analyzing historical market data, including price and volume.
Machine Learning uses algorithms to discover patterns in data to predict future values.
Deep Learning is used to forecast stock prices in the short term.
Statistical models like Linear Regression, Autoregressive Integrated Moving Average (ARIMA), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to model the relationship amongst the variables.

The main challenge with stock price prediction using these methods is that as per the efficient-market hypothesis, stock prices are unpredictable, and predicting the stock price is like predicting the unpredictable.

However, with the advent of the AI/ML models and classical ML models in combination or modifying the base model to incorporate the external factors or environmental variables, the accuracy can be improved [4] This is specifically true for LSTM variants that have shown considerable improvement in accuracy.

A hybrid stock prediction classical machine learning model that combined the prediction rule ensembles (PRE) approach with a deep neural network (DNN) produced a notable (5%) increase in accuracy. [5]
Similarly, Random Forest (RF) with a modified investment strategy has shown around 91.27% accuracy. [6]

A high accuracy of 93% was attained for select Vietnamese stocks using LSTM in conjunction with technical analysis of indicators including the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Simple Moving Average (SMA) [7]. However, as the number of variables or external factors increase the classical ML model becomes either too complex to be solved on the classical computer or their prediction accuracy decreases as the size of historical data increases due to overfitting.

It is promising to utilize quantum computing for modeling the stock price movement, due to its probabilistic nature and its ability to model the uncertain nature of the stock market.

The motivation for this research is to increase the accuracy and obtain a near quadratic speed up in the calculations for predicting the stock price movement. It is anticipated that the combination of classical and quantum prediction algorithms would increase accuracy and the possibility of the speed-up is greatly influenced by the successful use of quantum Monte Carlo Simulation [8]

II. RELATED WORK

Quantum Computing Basics
Superposition and entanglement, two concepts from quantum mechanics, are used in quantum computing to carry out calculations in ways that are essentially distinct from those of classical computers.
Key concepts in quantum computing include:
Qubits: Qubits are the fundamental unit of information in quantum computing, analogous to bits in classical computing. Unlike classical bits, which can only represent 0 or 1, qubits can exist in a superposition of both states simultaneously.
A single qubit is shown as, $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ and $|\psi\rangle$ denotes the qubit state
Quantum Gates: Quantum gates Similar to logic gates in traditional computing, quantum gates are operations that change the state of qubits.
Quantum Algorithms: Quantum algorithms are a collection of instructions that use quantum gates to solve certain issues.
Quantum Annealing: Quantum annealing uses quantum mechanics principles such as quantum tunnelling to determine a system's minimal energy state (global minima) quickly. It is very helpful in resolving complicated optimization issues where the

objective is to select the optimal solution from a wide range of options.

Literature Survey

The advantages of both quantum and classical computers are combined in quantum-classical hybrid techniques. When it comes to predicting stock prices, these hybrid models usually include:

Quantum Feature Maps (QFMs): QFMs are a way to transform classical data into quantum states so that quantum algorithms can process it.

Variational Quantum Circuits (VQCs): Parameterized quantum circuits, or VQCs, can be trained to carry out certain functions like regression or classification.

Hybrid Architectures: These architectures integrate quantum and classical components, often using classical computers to pre-process data, optimize parameters, and post-process results.

Quantum Feature Maps

In order to encode classical data into quantum states, quantum feature maps are essential. Numerous kinds of quantum feature maps have been suggested, such as:

Angle Encoding: This method encodes classical data into the parameters of quantum gates, such as rotation angles.Amplitude Encoding: This technique converts classical data into quantum state amplitudes.

Data Encoding: This method directly encodes classical data into the state of the quantum system.

One such study [9] highlights how quantum data embedding might improve classical machine learning models and stresses the significance of balancing computational costs and performance gains.

Variational Quantum Circuits

VQCs are parameterized quantum circuits that can be trained to perform specific tasks. The parameters of the VQC are optimized using classical optimization algorithms, such as gradient descent. VQCs have shown promise in a variety of applications, including machine learning and quantum chemistry.

Generic VQC as shown in Figure:2, typically includes encoding circuit, responsible for transforming the classical input, a variational circuit as learning component with training parameters and finally measurements to extract information from the VQC. A framework leveraging deep reinforcement learning to construct quantum machine learning models tailored for specific task can be explored [10]

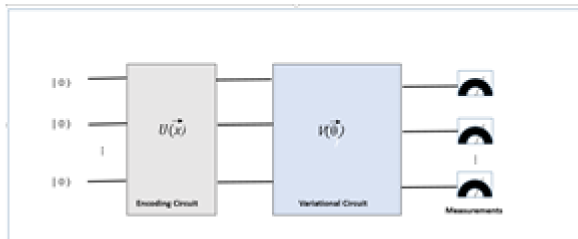

Figure 2: Generic Variational Quantum Circuits Image adapted from Creative Commons via [10]

Hybrid Architectures

Hybrid architectures combine quantum and conventional components to maximize their respective strengths. A popular approach is to use a classical computer to pre-process data, extract pertinent features, and then feed the data to a quantum circuit for further processing. The results from the quantum circuit can then be post-processed by a classical computer to generate predictions. Some of the hybrid architectures are elaborated in applications and case studies.

Applications and Case Studies

A number of research teams have investigated the use of hybrid quantum-classical methods for stock price forecasting. Among the noteworthy instances are:

Quantum Support Vector Machines (QSVM): QSVM is a quantum-enhanced version of the classical SVM algorithm. It has been shown to outperform classical SVM on certain datasets.

However significant improvement over classical SVM is not seen on diverse datasets. Use of quantum annealing for dimension reduction (feature selection) for stock market indicators, instead of popular principal component analysis (PCA) has shown promising result in both classical and quantum approaches [11]

Quantum Neural Networks (QNN): QNNs are quantum-enhanced versions of classical neural networks. They have the potential to learn complex patterns and make more accurate predictions than classical neural networks. Many researches have tried to build quantum circuits with gates or features inspired by neural computing such as quron (quantum equivalent of classical neuron), quantum perceptron and interacting qudots. However these approaches lacks coherence and need further exploration and studies [12]

Hybrid Quantum-Classical Models: These models combine quantum and classical components to create more powerful predictive models. For instance, in a hybrid model, financial data features may be extracted using a quantum circuit and then sent to a classical neural network for prediction. In a simulated noiseless environment about 9% prediction accuracy improvement is shown by a hybrid approach, Quantum Long Short-Term Memory (QLSTM) when compared with its classic counterpart LSTM [13].

In general, QLSTM outperformed other classical models in simulated environment. However, this advantage of improved prediction accuracy was lost when the QLSTM was run on actual quantum hardware. This shows that quantum circuits have not yet reached full functionality for practical applications and inference. In terms of prediction accuracy, noisy simulators often outperforms the real quantum computers as simulators use a simplified noise models, while in real world actual noise on quantum machine can be complex. With progress in classical ML techniques, more hybrid or quantum inspired models are expected to be studied, especially for unlocking their combined predictive power.

Limitations and Challenges

Although quantum computing holds potential for stock price prediction, there are still a number of limitations and constraints that needs to be addressed:

Hardware Limitations: Due to their restricted qubit counts and error rates, current quantum computers are still in their infancy

Algorithm Development: The development of robust and efficient quantum algorithms for financial applications is still in progress

Data Preparation: Preparing financial data for quantum algorithms can be challenging, as it often requires specialized techniques.

Interpretability: Understanding the results of quantum-based models can be difficult, as the underlying mechanisms are often complex.

Future Direction

Despite the current challenges, the potential of quantum-classical hybrid approaches for stock price prediction is significant. Future research directions include:

Developing more efficient and robust quantum algorithms for financial applications.

Improving the scalability and accuracy of quantum computers.

Exploring new hybrid architectures that combine quantum and classical components more effectively.

Developing methods for interpreting and explaining the results of quantum-based models

Combining classical computing advancements such as AI agentic design patterns and leveraging the recent advancement in logical qubits and qubit virtualization [14] and quantum error correction [15]

III. FURTHER STUDY AND CONCLUSION

In one such ongoing study related to the use of quantum-classic approach to predict the stock price movements, authors are developing a hybrid quantum classical computer model that is multi-layered, modular, and aims to increase the accuracy of stock price movement predictions. A logical architecture of proposed hybrid model is shown in Figure: 3

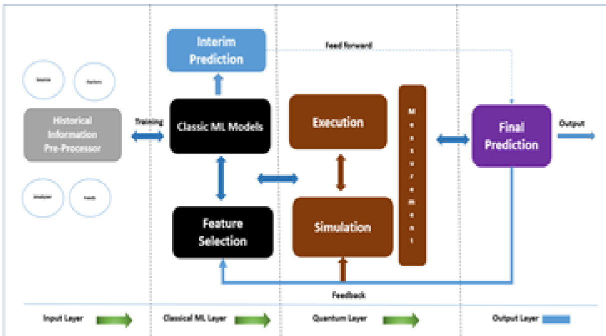

Figure 3: Logical architecture diagram of proposed hybrid quantum classical approach [16]

Input Layer: This layer will act as a data provider for both training and actual prediction use by interacting with various sources for financial and related information

Classical ML Layer: This layer is typical used for initial analysis, reducing dimensionality of the datasets provided by the input layer. This layer will provide interim prediction. The strength of classical computing, especially time series analysis and number crunching will be leveraged in this layer.

Quantum Layer: Output from the classical layer will be fed into the Quantum Layer for modeling and simulation. Once the simulation and measurements shows positive results, a run on quantum hardware will be conducted.

Output Layer: Output layer presents the prediction outcome to the end user/upstream systems. This layer implements Human-In-The-Loop (HITL) and feedback in the hybrid model.

The authors anticipate that the proposed multi-layer, quantum-classical hybrid approach to stock price prediction will significantly increase accuracy compared to traditional methods.

In summary, this study advances knowledge of application of quantum computing in the financial industry and lays the groundwork for upcoming studies on financial analysis and decision-making specifically for the stock price movement using quantum technology.

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