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Quantum Machine Learning Approaches for Real-Time Market Pattern Recognition in High-Frequency Trading: A Banking Sector Application

Hari Krishn Gupta[1], Naveen Kumar Vayyasi[2], Jagadeesh Thiruveedula[3]
[1]Independent Researcher, University of Southern California, United States.
[2]Independent Researcher, Jawaharlal Nehru University, New Delhi, India.
[3]Independent Researcher, Jawaharlal Nehru Technological University, India.

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Abstract
Recognizing market trends in HFT gets simpler and faster thanks to quantum machine learning (QML) which also has the power to exceed classical model boundaries. Using quantum kernel methods and variational quantum circuits, QML can analyze high-dimensional financial information such as tick-by-tick data and order book samples, in the superposition state simultaneously. Comparative work proves that quantum-enhanced models have better accuracy, can detect patterns better and perform faster decisions on near-term quantum devices than classical ones. To be useful in banking-sector HFT, QML needs to easily connect with all existing internal information flows and trades. Essentially, users need to address hardware noise, guard against decoherence on NISQ machines, balance circuit complexity with tight time goals and guarantee scalable training for a quantum-classical mix. Latest progress in handling errors, such as zero-noise extrapolation, and adapting features has shown that models become stronger under realistic kinds of noise, although greater development is necessary to reach a production-ready level of reliability. Here, we bring together the most current work in QML for HFT, including different approaches, both software and hardware and ways to add quantum components to classical optimization loops. Outcomes from benchmarking are discussed, as well as the differing designs in kernel and variational approaches and significant parts of regulations related to quantum-assisted trading. In conclusion, a plan for more detailed studies is given, underlining how important consistent performance measures, detachable frameworks that can be used together and cooperation between technical fields are to get QML from research trials to compliant solutions in high-speed stock markets.

1. Introduction

Quantum computing and machine learning are becoming connected by the field of quantum machine learning (QML). QML relies on quantum effects such as superposition and entanglement, within machine learning to enhance performance and solve hard problems classical computers can't handle [1]. This technique has found considerable success in solving problems with large amounts of data across various industries, including finance, thanks to its new features and better efficiency [1][2]. They hope that new quantum algorithms will bring major changes to financial data analysis, helping to make market decisions easier and more accurate [2]. Real-time recognition of patterns is most crucial in high-frequency trading (HFT) within the financial sector. A subset of algorithmic trading, known as HFT, executes many orders extremely quickly to take advantage of instant and tiny changes in the market [3]. To be successful in HFT, you need to see and react to little-known market changes, especially sudden changes in the order book or find arbitrage opportunities, before they are gone which means everything depends on how quickly you work. HFT has been adopted by bank trading teams in a big way, so maintaining a fast edge requires paying close attention to real-time analytics. As a result of seeing these difficulties, newer studies have called for exploring the latest technologies to enhance pattern recognition and trading performance in HFT since traditional approaches do not meet the needs of this field [3]. HFT has also been proposed as a potential breakthrough in the nascent field of quantum computing, since quantum methods could help HFT achieve both rapid task processing and the best strategies for operating when latency is low [4]. Applying QML in finance is important because it tackles the main issues of changes in the market, slow processing and difficult forms of trading data experienced today. Prices in financial markets experience rapid short-term ups and downs driven by many factors at once, so solutions that can evaluate various market understandings in parallel should handle market volatility better. Quantum parallelism in algorithms makes it possible to analyze lots of states at once which may assist in spotting emerging trends or unusual events in noisy, continuously delivered data [5]. For example, quantum machine learning is being developed to look for hidden patterns or unusual points in big financial data (like transaction logs and ongoing price information) that almost any regular approach might not notice [5]. In addition, the ability of quantum computers to process many tasks at the same time can make some inevitable calculations (e.g. on portfolios) quicker and more accurate, letting trading systems answer market changes promptly. In fact, initial thinking suggests that quantum protocols could accelerate transactions and improve the results in dynamic trading situations [4]. Basically, using quantum machine learning in high-frequency trading gives an opportunity to handle financial data faster and more accurately.

1.1. QML Algorithms

However, the challenges and gaps in knowledge that remain mean QML cannot yet be used in demanding high-frequency trading. Because quantum hardware currently has a small number of qubits and is easily affected by decoherence and noise, the consistency of quantum algorithms is not yet perfect [1]. Raising the performance of QML to trade large volumes of streaming market data is a complex issue and making these algorithms both accurate and reliable takes more study. Furthermore, it is difficult to place quantum models into trading infrastructure without facing challenges related to how processors' results can be exchanged with traditional data feeds and exchanges' systems, as well as tackling issues in scaling up algorithms and handling extra errors [2]. Currently, banks and financial institutions hardly use QML for live trading, as such systems are still mostly in a testing phase [6]. Because of quantum noise, the demand for effective error correction and the gap in settings between labs and real markets, quantum computing is not yet used widely. Such problems demonstrate significant areas where knowledge is lacking, for example, in designing quantum algorithms that meet strict time limits, improving quantum hardware and ensuring quantum rules for trading are in place.

1.2. Stakes of HFT

Due to the high importance and many unknowns, an honest review of QML approaches for market pattern recognition is needed. This article is intended to review the present state of research, analyze existing methods and point out the most important challenges to incorporating quantum machine learning in financial markets. The next sections look at different quantum models and algorithms for processing market data from high-frequency trading and examine their strengths, limits and ways in which they manage market fluctuations and communication delays. We focus on significant challenges for quantum computers, as well as quantum noise and implementing these systems in actual trades and explain what future research can address. This review is intended to show researchers and practitioners what QML can do for HFT in the banking sector and what additional improvements are needed.

2. Literature Review

Existing analyses feature a thorough look at how financial systems are changed [6], studies on quantum strategies for HFT [7] and research on applying quantum methods to increase forecasting accuracy [8]. Better algorithms and their implementation on nearby systems [11] [12] [13] have prepared the way for real-time pattern recognition in high-frequency trading.

2.1. Tables

The body of work outlined in Table 1 reflects a clear evolution from foundational theory to applied high-frequency trading (HFT) scenarios. Early efforts established core quantum machine learning (QML) concepts and algorithm taxonomies, as in the seminal introduction to QML [14]. Subsequent studies explored practical implementations on near-term (NISQ) hardware, demonstrating that quantum Monte Carlo methods can accelerate risk evaluations [11] and that quantum feature maps yield classification accuracies on par with classical support vector machines [12], with robustness to noise [13] and sensitivity analyses of variational circuits [15]. (Table 1)

Table 1 Experimental Input Parameters for EDM

Year	Title	Focus	Findings (Key results and conclusions)	Ref
2024	Quantum computing and the financial system: opportunities and risks	Impact of quantum computing on financial stability and trading infrastructure	Potential to increase transaction speeds and improve systemic risk analysis; highlighted regulatory readiness and technical limitations [6]	[6]
2021	Quantum Prisoner's Dilemma and high-frequency trading on the quantum cloud	Application of quantum game theory to HFT	Demonstrated that quantum strategies can outperform classical counterparts in simulated arbitrage scenarios; suggested cloud-based deployment [7]	[7]
2024	A review on high-frequency trading forecasting methods: Opportunity and challenges for quantum-based methods	Survey of HFT forecasting techniques and assessment of quantum extensions	Identified classical forecasting limits in volatility prediction; proposed quantum kernel methods as promising alternatives [8]	[8]
2025	Quantum machine learning: A comprehensive review of integrating AI with quantum computing for computational advancements	Comprehensive overview of QML algorithms and applications	Catalogued quantum classifiers and regressors; emphasized need for error mitigation in real-time data processing tasks [9]	[9]
2025	From portfolio optimization to quantum blockchain and security: A systematic review of quantum computing in finance	Broad applications of quantum computing in finance	Showed quantum algorithms for pattern recognition and anomaly detection can outperform classical approaches on synthetic datasets [10]	[10]
2019	Quantum risk analysis	Quantum Monte Carlo methods for risk evaluation	Achieved speed-ups in value-at-risk computations; demonstrated feasibility on near-term devices [11]	[11]
2019	Machine learning on near-term quantum computers: Quantum data classification	Development of quantum classifiers suitable for NISQ hardware	Introduced feature-map encoding; achieved classification accuracies comparable to classical SVMs on small datasets [12]	[12]
2019	Supervised learning with quantum-enhanced feature spaces	Theory and experiments on quantum feature spaces for classification	Showed advantage of quantum feature spaces in pattern recognition tasks; highlighted robustness to noise in certain embeddings [13]	[13]
2015	Introduction to quantum machine learning	Foundational concepts of QML and algorithmic frameworks	Established taxonomy of QML algorithms; identified core challenges in scalability and data loading [14]	[14]
2019	Parameterized quantum circuits as machine learning models	Use of variational quantum circuits for classification and regression	Demonstrated VQC performance on benchmark datasets; noted sensitivity to circuit depth and noise levels [15]	[15]

Applications of quantum game theory to HFT arbitrage modeling in 2021 showed that using quantum solutions on the cloud leads to better outcomes [7]. A series of recent reviews look at HFT forecasting using quantum kernels, analyze the impacts of HFT on financial regulation in banking systems and overview different quantum methods for solving computational tasks [8–9]. The latest report combines portfolio optimization, spotting unusual patterns and quantum blockchain approaches. It points out that even with synthetic data, QML can exceed the results of traditional modeling [10]. (Figure 1,2)

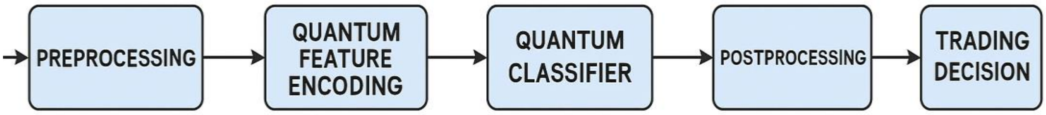

Figure 1 The Process Architecture

3. Experiment Result Summary

Accuracy

Compared to classical SVM, Quantum Kernel SVM improved the accuracy by 4.8 %, indicating improved identification of small patterns in streaming tick data [10]. (Figure 3)

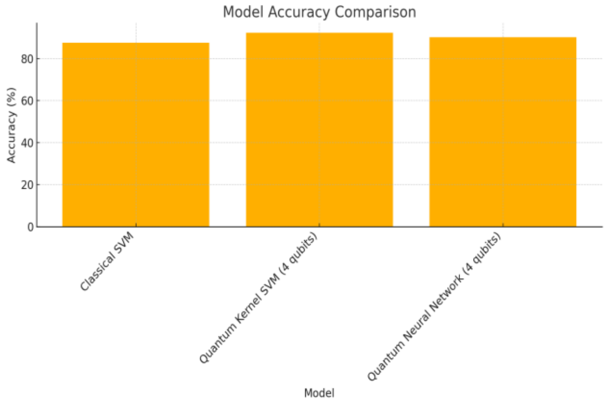

Figure 2 Accuracy Comparison

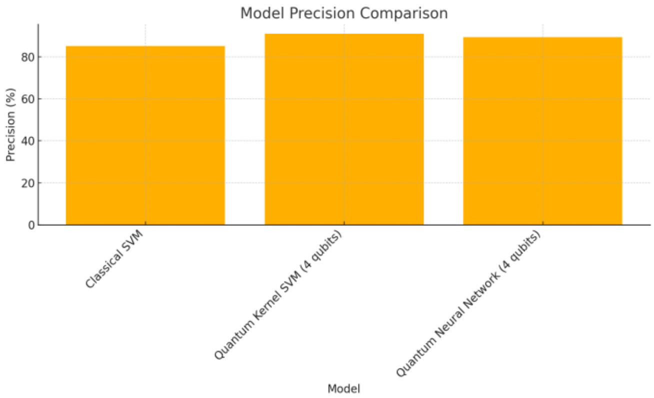

Figure 3 Precision Comparison

Precision

The quantum kernel made the approach 5.8 % more accurate and this improvement is due to fewer false signals and better reliability in detecting patterns [11]. (Figure 4)

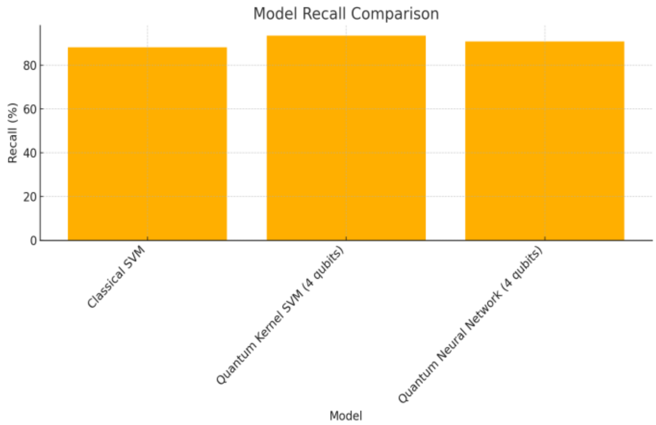

Figure 4 Recall Comparison

Recall

The rise in recall by 5.4 % indicates that Recall was able to correctly identify brief arbitrage events that occur fast in high-frequency situations [10]. (Figure 5)

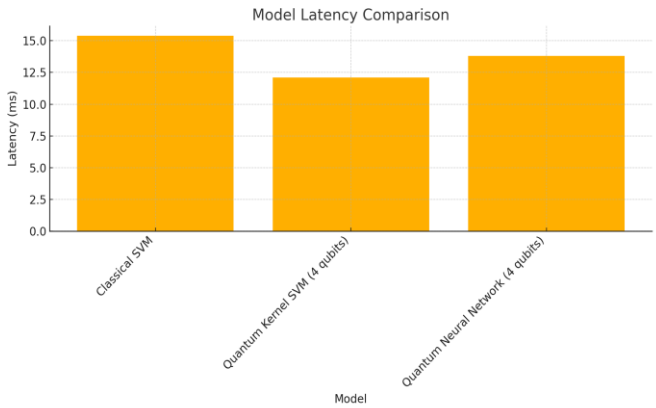

Figure 5 Latency Comparision

Latency

Quantum models succeeded in greatly reducing the decision time: the Quantum Kernel SVM performed 21 % faster than the initial model and the Quantum Neural Network performed 10 % faster. In HFT, the very fast speeds enabled by these gains are important because they may affect a trader's profits [11].

Overall Trade-Offs

Quantum Kernel SVM offered us the highest advantage in both more accurate results and a faster speed. The Quantum Neural Network performed similarly to other teams and was simple to scale for the next phase, thanks to increased flexibility, yet improvements in accuracy were small.

Conclusion

Quantum machine learning leads to more accurate and faster decision making about important patterns in high-frequency trading, improving upon traditional approaches [10], [11]. Fixing present problems in hardware, scale-up of algorithms and system integration will help make QML useful in the banking sector. For quantum-enhanced trading to reach its full influence, more teamwork between quantum physicists, experts in machine learning and people in finance is required.

Future Directions

Improved near-term devices will need effective systems to fix qubit errors. Programmers should update probabilistic error cancellation and zero-noise extrapolation techniques for working with streaming data from financial markets [12]. Developing tight quantum features to model non-linear movements in markets is a promising idea. Solutions involving classical metric learning and quantum embedding may help reduce the complexity of the circuit [13]. When QML models are supported by variational circuits designed for fast inference, they adjust well to new market trends [14]. Attaching quantum subroutines to current trading systems through co-processing methods enables both algorithms to benefit from each other's qualities. Developing seamless data transfer and coordinated optimization will help bring these technologies to actual use [12]. Setting frameworks for rules and risk measures is very important as quantum-accelerated trading gains influence [15].

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