Overview and Demonstrative Use Case of Quantum Machine Learning in Finance

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Abstract. The growing complexity and volume of financial data have posed the challenges of efficiency and accuracy for current classical machine learning. Quantum machine learning (QML) offers a promising alternative by exploiting quantum characteristics to process high-dimensional financial information more efficiently. This paper reviews key QML algorithms, i.e., quantum support vector machines, variational quantum neural networks, and quantum approximate optimization algorithms, and explores their applications in credit scoring, fraud detection, portfolio optimization, and time-series forecasting. Consequently, a high-level framework is proposed for integrating QML into financial institutions, outlining progressive stages from experimentation to infrastructure deployment. The study also explores QML challenges and limitations, including data encoding, hardware noise, and scalability, and discusses potential hybrid quantum–classical solutions for efficient implementation.

Keywords: Quantum machine learning · financial applications · credit scoring · fraud detection · portfolio optimization · time series forecast.

1 Introduction

The financial sector helps to build a country's backbone by stabilizing economic growth. Importantly, the global financial services market was recently valued at \$33.54 trillion in 2024, growing at a compound annual growth rate (CAGR) of 7.7% and has since been expected to reach \$44.93 trillion by 2028, with a projected CAGR of 7.6% [1]. The market ultimately serves as an intermediary, allowing investors to trade freely through reputable banks, financial markets, and insurance companies. Empirical studies repeatedly show that financial stability has a favourable impact on economic growth [2], [3]. A properly functioning financial system promotes capital accumulation, technical advancement, and effective resource distribution. Moreover, the financial industry faces numerous complex and challenging problems under three main categories: asset management, investment banking, and retail and corporate banking [4]. For example, some of the problems include fraud detection [5], risk management [6], portfolio optimization [7], algorithmic trading [8], credit scoring [9] as well as other specialized areas such as option pricing [10–12].

Currently, artificial intelligence (AI) and machine learning (ML) are used across almost all profitable and non-profitable industrial sectors, including telecommunications [13], healthcare [14], manufacturing [15], and social media [16]. The finance industry is no exception to this trend, however, accommodating machine learning techniques for financial scenarios presents several formidable challenges. Like any dataset, financial data faces issues with diverse and unstructured formatting and disparate sources [17], nonstationarity [18], high dimensionality [19], noise and outliers [20], missing data [21], and imbalanced classes [22,23]. Moreover, other finance-specific challenges include real-time processing requirements for high-frequency trading [24,25], complex regulatory compliance requirements [26, 27], and market microstructure noise [28]. In addition, the limitation on the precision of classical computers to run big data for long periods of time is a significant challenge.

Since financial data can involve high-dimensional data structures with intricate data patterns, new advances in quantum ML (QML) are able to provide better solutions that may help overcome these issues and others linked to the processing and representation of financial data. In particular, QML can utilize quantum computing principles like superposition and entanglement to process data [29]. This emerging domain overcomes the limits that arise with classical computing by leveraging quantum advantages in computing speed and efficiency, and further developments are envisioned to produce more potent tools that will enable the processing of large volumes of highly complex data at much faster speeds than currently achievable. Further, the combination of QML and deep learning techniques has resulted in developments for managing large-scale and high-dimensional financial datasets through quantum parallelism [19, 30] and real-time processing requirements [24]. Moreover, the utilization of QML-enhanced portfolio optimization methods [31] have been shown to help in resolving problems with market microstructure noise [28] and regulatory compliance [26]. Additionally, quantum-enhanced Monte Carlo simulations [32] can handle nonstationarity [18] and missing data [21] more efficiently. Collectively, these advancements indicate that predictions and optimizations are progressing, and consequently, less expensive through a much faster decision-making process. While real-world quantum computing hardware is in its infancy, the technology appears to have strong utility in many financial fields, such as data analysis, risk management, and strategy development.

In this study, we review the applications of QML within the field of finance, with particular emphasis on quantum-enhanced variational methods. These methods and algorithms are evaluated over a wide range of financial applications, including decision-making, classification, time series prediction, and portfolio optimization. Based on these applications, we demonstrate the efficiency of QML by presenting a practical use case.

2 An overview on Quantum Machine Learning

In recent years, AI and ML have been widely used to improve financial analyses and achieve higher profits. These technologies are now integrated in most of core activities such as credit underwriting, compliance, interaction with clients, and risk management. However, AI and ML still have difficulties in accurately predicting market dynamics, real-time data processing, and optimizing risk management portfolios under time-varying market conditions and vast amount of data. Quantum computers, endowed with supreme computational capability, are believed to give us new tools for addressing such computational problems encountered in current classical approaches.

Unlike classical computers that store information in the form of binary values (0 or 1), quantum computers store information in the form of quantum bits (qubits) which can exist in a superposition of 0 and 1. Therefore, complex financial datasets can be represented by fewer qubits compared to classical bits, allowing for more compact data representation. Moreover, the state of one qubit can influence the others, regardless of physical distance, due to entanglement. Quantum computation can perform computational tasks exponentially faster than their classical counterpart, as has been shown in famous problems such as integer prime factoring or searching unsorted databases [33–35]. This significant improvement boosts the attention, development, and use of quantum computing. Moreover, its application operates in a high-dimensional Hilbert space which can handle the increasing complexity of data currently compiled in the financial field and offers better efficiency for common ML tasks, such as unstructured search and solving linear equation systems. Additionally, quantum embedding techniques can also provide a method for encoding large amounts of data within several qubits [36], which classical techniques typically struggle with. At the moment, financial institutions can make use of high-speed simulation tools, such as IBM's Qiskit and Xanadu's Pennylane, or attempt to access current cloud-based quantum computers.

Table 1 compares commonly employed QML algorithms with their classical counterparts. While the quantum algorithms can, in principle, provide noticable speedup and efficient high-dimensional data encoding, the current state of noisy hardware has resulted in difficult algorithm implementation and unimpressive efficiency. Moreover, not all algorithms are suitable for this "quantum conversion" process, which leads to challenges in exploring quantum-enhanced algorithms. Overall, the current challenges with quantum hardware, the lack of highly trained personnel, and the true efficiency of quantum algorithms must be addressed before the full advantage of QML in the financial sector can be realized.

Table 1: Comparison of QML algorithms and their classical counterparts.

Algorithm	Classical Version	Quantum Version	Advantages of Quantum Version	Challenges
Support Vector Machine (SVM) [37]	Finds the hyperplane that maximizes the margin between classes.	Classifies data by quantum kernels with classes represented by qubits' measurement.	Exponentially faster kernel evaluation and optimization steps.	Quantum noise and error issues, requirement for efficient quantum mapping.
Neural Networks (NNs) [38]	Uses multi-layer perceptron to form networks with trainable weights.	Uses quantum gates and qubits to process data with weights encoded by parameterized gates.	Richer feature representation and exponential speed-up.	Requirement for efficient gradient calculation in quantum domain and entanglement schemes.
Convolutional Neural Networks (CNNs) [39]	Employs convolutional layers to extract features from structured data.	Represents convolution and pooling layers by quantum circuits.	More efficient high-dimensional data process and feature extraction.	Limited scalability due to quantum hardware constraints, resource-intensive encoding.
K-means Clustering [40]	Clusters unlabeled data using distance metrics and iterative optimization.	Uses quantum computing for distance and nearest-neighbor calculations.	Quadratic speed-up in distance calculation and iteration.	Hardware-intensive implementation, requirement for classical preprocessing.

3 Quantum Machine Learning for Finance Applications

3.1 Classification

Classification is a fundamental ML task that categorizes inputs into predetermined discrete labels or classes. In finance, this technique is integral to automating and enhancing the accuracy of decision-making tasks such as credit scoring, fraud detection or risk assessment [41–43]. However, these determining processes are computationally expensive, especially with high-dimensional data. To address these challenges, quantum computing is being explored as a solution for its parallelism which can significantly accelerate the classification process through its superior encoding and processing of complex, multidimensional data. [29]. This has been evidenced by the utility of quantum SVM (QSVM) in [44], where a $O(\log NM)$ time complexity was demonstrated in both training and classification stages due to the handling of inner products (N is the size of the input vectors and M is the number of training examples) [45].

Based on the importance of classification in financial applications, credit scoring stands out as a critical use case. This process is important for financial institutions to evaluate the creditworthiness of loan applicants. Currently, most credit scoring models rely heavily on historical data, such as customer demographics, their behavior, and macro economics. As not all of the collected information is relevant for precise learning, feature selection is essential in the development process by identifying and retaining only the most meaningful data. In recent work [46], a quantum-optimization-based feature selection algorithm called VarQFS was applied to a German credit risk data set from the UCI Machine Learning Repository to construct a predictive model with 20 and 59 input features (qubits). The model was implemented using quantum hardware and compared to a tensor-network-based numerical simulation. The results showed that the quantum approach can yield remarkable accuracy, thanks to their scheme of feature selection techniques, which outperform those currently used in industry [46]. Another novel credit scoring model of small and medium-sized enterprises has been developed in [47] by incorporating quantum layers into a traditional neural network. This hybrid model achieves a notable training time, requiring significantly fewer epochs in comparison to its classical counterpart for a similar predictive accuracy.

In addition to credit scoring, fraud and anomaly detection across various financial activities is also essential for financial institutions to prevent losses. In [48], QSVM shows that it can be useful for cybersecurity, which prevents fraud at the first place. The quantum circuits themselves act as a kernel function to translate classical data into a quantum state. In most of quantum feature map methods, they appear advantageous compared to the classical equivalent [48]. Additionally, QML models including QSVM, quantum NNs (QNNs), and variational quantum circuits (VQCs) have been investigated to enhance the performance of detection activities and have exhibited promising results with massive financial transaction datasets [49]. Another novel approach which has been studied for detecting financial fraud is quantum graph neural networks (QGNNs), which has recently been applied to a real-world dataset in [50] with preliminary results greatly outperforming classical GNNs.

3.2 Time Series Forecast

In finance, predicting market trends is crucial, as even slight improvements in predictive power can yield huge benefits. There are two primary approaches to analyzing and forecasting asset values: fundamental analysis and technical analysis. Fundamental analysis evaluates the intrinsic value of an asset by examining economic indicators, revenue, profit margins, and industry outlook, but may overlook short-term volatility. On the other hand, technical analysis relies on historical signals to identify trends and predict future values, making it a key method in time-series forecasting [51, 52]. Time-series data consists of sequential observations recorded at regular intervals, capturing trends and fluctuations over time. It can be categorized into univariate (tracking a single variable, like stock prices) and multivariate data (considering multiple variables, such as stock prices, trading volume, and interest rates). While univariate time series data analyses suffer from limited information and difficulties in capturing underlying patterns, multivariate data analyses expect more complex tasks since the interaction between variables causes both intra-dependencies (within one variable) and inter-dependencies (across variables) that affect the analysis performance.

To date, financial time-series prediction has been a difficult field of study because of its nonlinear, dynamic, and chaotic behavior. To date, deep learning models have been proposed as a method to alleviate these problems. For example, the recurrent neural networks (RNNs) architecture of long short-term memory (LSTM) neural networks, which were proposed in 1997 [53], are the most popular approach due to successes in modeling the relationships between sequential data in a deep and layered hierarchy [54, 55]. Importantly, its predictive power has been proven to surpass that of the traditional auto-regressive statistical methods [56]. In terms of quantum computation, the equivalents of NNs and LSTM are QNNs and quantum LSTM (QLSTM), respectively, which behave in nearly the same manner as their classical counterparts but are constructed using quantum circuits. For instance, hybrid-QNN models were proposed in [57] to forecast both univariate time series (Mackey-Glass time series and USD-to-euro currency exchange rate) and multivariate time series (Lorenz attractor and the carbon dioxide concentration from Box-Jenkins gas furnace time series). By using the Pennylane simulator lighting.qubit and the Pytorch package, the experiments incorporated VQCs with specific encoding schemes and optimization methods which achieved a highly competitive result compared to multi-layer perceptron (MLP), CNNs, and LSTM for the same number of trainable parameters [57]. Moreover, an implementation of QNN on 24 securities based on a QuantumLeap system was introduced in [58], and demonstrated high accuracy and efficiency in both regression and extrapolation regimes. This system consists of 3 components associated with each time stride to parallelize the learning process: i) an encoder that transforms each sliding window of financial time series into a sequence of density matrices, ii) a deep quantum network that predicts the density matrix of the next trading day, and iii) a classical-based network that measures the daily maximum price (high) of the security from the output density matrix. In [59], researchers also used parametrized quantum circuits to form QNNs for stock price signals forecasting. This research indicated two benefits that QNNs outperform classical bi-directional LSTM (BiLSTM); QNNs can be trained much faster and require fewer features in scenarios of lower noise levels. In some cases, QNNs have even outperformed BiLSTM when dealing with higher noise, which is a challenge frequently encountered in financial data analysis [59].

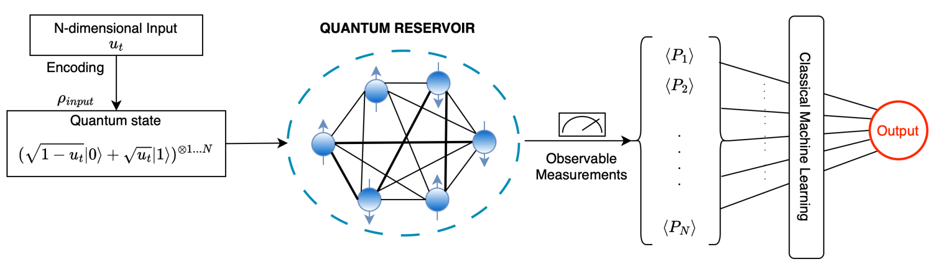

Fig. 1: In QRC an N-dimensional input u_t is fed to a spin by setting its state to $|\psi_{u_t}\rangle = \sqrt{1-u_t}\,|0\rangle + \sqrt{u_t}\,|1\rangle$. After free time evolution, the readout node values are obtained as the expected value of observable measurement. Those expected values are then fed into classical ML for training before generating the predicted output.

4 Use case: Quantum Reservoir Computing for Stock Volatility Prediction

To demonstrate the potential of QML in real-world financial data, we explore quantum reservoir computing (QRC) for predicting daily stock volatility of S&P500 index, collected from NASDAQ. The volatility is defined as the standard deviation of the daily log return over a given time period t. In this work, we set the time period of observing volatility to 5 days to maintain consistency with other works of [60] and [61]. Acknowledging volatility enables investors to devise schemes for managing risks and optimizing portfolio, however, estimation of volatility is challenging due to nonlinear and highly temporally variable collected data.

Classical reservoir computing (RC) employs a dynamical system to execute temporal information processing tasks. Typically, the goal of this task is to learn a function that transforms an input sequence to a target output sequence for the purpose of time series forecasting [62]. The key idea is to transform input sequences into higher-dimensional representations via a reservoir in order to enrich the extracted feature before being optimized by a simple learning algorithm to minimize the error between predicted value and target output. In comparison to the RNN approach, RC is much simpler as it only requires adjustment of a few parameters in the output layer. On the other hand, the crucial role of feature extraction is left to the reservoir dynamics, so the design of reservoir is very important and vital to the success of the algorithm.

In terms of quantum computing, instead of working with classical data, QRC deals with quantum data whose states are derived from classical inputs. Consequently, inputs from classical datasets are required to be encoded into quantum states, which are ordinarily conducted by angle encoding. The enrichment process of the RC model is then governed by a time-dependent unitary matrix which behaves as the classical reservoir and evolves the system. The useful information from the quantum state will then be extracted through operator measurements that are subsequently fed into a classical ML model for training, as illustrated in Fig. 1. In general, the measured result is the average value of many iterations to assure reliability of noisy quantum computers.

In order to test QRC performance after model training, we conducted an out-of-sample test using daily stock price spanning from 08 March 2022 to 05 March 2025. The forecasting accuracy was assessed using mean absolute error (MAE) and root mean square error (RMSE). Results indicated that QRC achieved a MAE of 0.0016 and an RMSE of 0.0025, demonstrating high accuracy in daily S&P500 stock return volatility prediction. Furthermore, as shown in Fig. 2, the predicted value from QRC can closely match actual volatility with minimal deviation. These results highlight the strong predictive capability of QRC in financial forecasting, underscoring its potential for broader quantum machine learning applications in finance. The input dataset also contains the value of volatility and the corresponding dates only, which proves the ability to effectively recognize the underlying patterns of QRC.

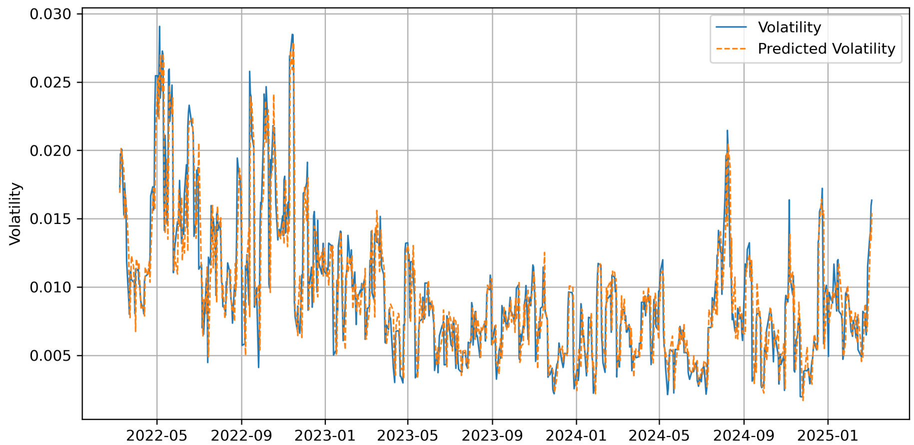

Fig. 2: Performance of QRC on predicting daily S&P500 volatility.

5 Conclusion

QML is a promising technique for handling high dimensional, complex data with high accuracy and speed. In this paper, we provided a review of the financial applications of QML, specifically in subfields including credit scoring, fraud detection, time-series forecast, and portfolio optimization. Alongside the emergence of commercial quantum computers, these studies have showcased the potential and competitive benefits of QML models compared to classical methods in terms of speed, accuracy, and complexity handling. A specific use case of QRC for volatility prediction has also been demonstrated to highlight those advantages further. In summation, the widespread use of QML within the finance sector is crucial, not only to address current challenges but also to aim toward stable economic development.

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