Quantum Machine Learning Architectures for Stock Market Forecasting, Anomaly Detection, and Pattern Recognition in Financial Time Series

Tugan Başaran
Özyeğin University

***Abstract*—Financial markets generate complex, high-dimensional time series characterized by nonlinearity, noise, and structural uncertainty, posing persistent challenges for classical machine learning and statistical forecasting models. This paper examines quantum machine learning (QML) architectures for stock market forecasting, anomaly detection, and pattern recognition in financial time series. By leveraging quantum phenomena such as superposition, entanglement, and quantum-enhanced feature spaces, QML models offer new computational paradigms for capturing intricate market dynamics and latent structures. The study synthesizes recent advances in quantum neural networks, variational quantum circuits, and hybrid quantum–classical models, evaluating their applicability to predictive modeling and risk-sensitive detection tasks in finance. The paper argues that QML architectures have the potential to complement classical approaches by improving representational capacity and scalability for complex financial data, while also outlining current technical limitations and research directions necessary for practical deployment.**

Forecasting financial markets and identifying meaningful patterns within stock price movements have long been central objectives in quantitative finance. Financial time series are inherently noisy, non-stationary, and influenced by a multitude of interacting economic, behavioral, and geopolitical factors [5]. These characteristics challenge traditional econometric models, which often rely on linear assumptions and stable statistical properties. While advances in classical machine learning and deep learning have significantly improved predictive performance, they remain constrained by issues such as overfitting, limited interpretability, and computational scalability when applied to high-dimensional financial data [9].

Digital Object Identifier 10.62802/0c086y54
Date of publication 07 02 2026; date of current version 07 02 2026

In recent years, the convergence of quantum computing and machine learning has introduced novel computational frameworks capable of addressing some of these limitations. Quantum machine learning integrates principles from quantum information science with learning algorithms, enabling new ways of encoding, processing, and analyzing data [4]. In the context of financial markets, QML architectures offer the promise of enhanced feature representation and more efficient exploration of complex state spaces, which are critical for tasks such as stock market forecasting, anomaly detection, and pattern recognition [7].

Stock market forecasting requires models that can capture subtle temporal dependencies and nonlinear interactions across multiple assets and time horizons. Classical recurrent and transformer-based architectures have demonstrated strong performance, yet they often require extensive computational resources and large training datasets [3]. Quantum-enhanced models, particularly hybrid quantum–classical architectures, introduce alternative mechanisms for representing correlations and temporal structures through quantum states and parameterized circuits [6]. These models may provide richer representations of financial dynamics, especially in regimes where classical feature spaces struggle to separate signal from noise.

Anomaly detection in financial time series is equally critical, particularly for risk management, fraud detection, and market surveillance. Sudden regime shifts, extreme volatility, and rare events can have significant financial consequences if not identified in a timely manner [9]. Quantum machine learning approaches offer potential advantages in detecting such anomalies by exploiting quantum distance measures and high-dimensional Hilbert spaces, which can amplify distinctions between normal and abnormal market behavior. This capability is particularly relevant in environments where anomalies are subtle and embedded within large volumes of data (Zhang et al., 2025).

Pattern recognition represents a foundational task underpinning both forecasting and anomaly detection. Identifying recurring structures, trends, and market micro-patterns is essential for developing trading strategies and understanding market behavior. Quantum kernel methods and variational circuits enable the mapping of classical financial data into quantum feature spaces where complex patterns may become more linearly separable [11]. This shift challenges conventional assumptions about feature engineering and opens new directions for discovering latent structures in financial time series.

Despite their theoretical promise, quantum machine learning architectures face significant practical challenges. Current quantum hardware remains limited by noise, qubit coherence times, and scalability constraints [2]. As a result, most applications in finance rely on hybrid approaches that combine classical preprocessing and optimization with quantum subroutines. Understanding how to design architectures that balance quantum advantage with practical feasibility is therefore essential for meaningful progress in this field [1].

This paper explores the application of quantum machine learning architectures to financial time series analysis, with a focus on stock market forecasting, anomaly detection, and pattern recognition. It reviews the theoretical foundations of QML, examines representative architectures and algorithms, and evaluates their relevance to financial modeling tasks. By situating quantum machine learning within the broader landscape of computational finance, this study aims to clarify both the opportunities and limitations of QML as a next-generation tool for financial analytics. Ultimately, the paper argues that while quantum machine learning is unlikely to replace classical methods in the near term, it represents a powerful complementary paradigm with the potential to reshape how complex financial systems are modeled and understood.

REFERENCES

1. Andreas, A., Mavromoustakis, C. X., Mastorakis, G., Bourdena, A., & Markakis, E. (2025). Quantum Computing in Semantic Communications: Overcoming Optimization Challenges With High-Dimensional Hilbert Spaces. IEEE Access.
2. Awschalom, D. D., Bernien, H., Hanson, R., Oliver, W. D., & Vučković, J. (2025). Challenges and opportunities for quantum information hardware. Science, 390(6777), 1004-1010.
3. Ghribi, F., & Hamdaoui, F. (2025). Innovative deep learning architectures for medical image diagnosis: a comprehensive review of convolutional, recurrent, and transformer models. The Visual Computer, 41(13), 11603-11628.
4. Ramya, R., Kumar, P., Dhanasekaran, D., Kumar, R. S., & Sharavan, S. A. (2025). A review of quantum communication and information networks with

advanced cryptographic applications using machine learning, deep learning techniques. Franklin Open, 10, 100223.

5. Sakib, M., Mustajab, S., & Alam, M. (2025). Ensemble deep learning techniques for time series analysis: a comprehensive review, applications, open issues, challenges, and future directions. Cluster Computing, 28(1), 73.
6. Tomal, S. M., Shafin, A. A., Bhattacharjee, D., Amin, M. D., & Shahir, R. S. (2025). Quantum-enhanced attention mechanism in NLP: A hybrid classical-quantum approach. arXiv preprint arXiv:2501.15630.
7. Tomar, S., Tripathi, R., & Kumar, S. (2025). Comprehensive survey of qml: from data analysis to algorithmic advancements. arXiv preprint arXiv:2501.09528.
8. Wang, L., An, S., Dong, Z., Dong, X., & Li, J. (2025). Early warning of regime switching in a financial time series: A heteroskedastic network model. Plos one, 20(10), e0333734.
9. Wang, Y., Wei, W., Liu, Z., Liu, J., Lv, Y., & Li, X. (2025). Interpretable machine learning framework for corporate financialization prediction: A SHAP-based analysis of high-dimensional data. Mathematics, 13(15), 2526.
10. Zhang, H., Jia, X., Chen, C., Bachani, S., Goel, J. K., Tarun, M., ... & Anyanwu, E. C. (2025). Deep learning-based real-time data quality assessment and anomaly detection for large-scale distributed data streams. International Journal of Medical and All Body Health Research, 6(1), 01-11.
11. Zhou, J. (2025). Quantum finance: Exploring the implications of quantum computing on financial models. Computational Economics, 1-30.