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*Original Article*

# Stock Market Forecasting Using Quantum Computing Simulation and News Based Sentiment Analysis

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***Abstract*** - *Stock market forecasting is challenging due to high volatility, non-linearity, and the strong influence of external information such as financial news. Traditional forecasting models mainly rely on historical price data and often fail to respond effectively to sentiment-driven market fluctuations. To address this limitation, this paper proposes a hybrid stock market forecasting framework that integrates historical stock price indicators, news-based sentiment analysis, and quantum computing simulation. Financial news articles are processed to extract sentiment scores representing investor mood, which are combined with normalized price features to form a unified dataset. The combined features are analyzed using a Variational Quantum Classifier implemented through quantum simulation. Experimental results show that incorporating sentiment information improves prediction stability and accuracy compared to price-only models, demonstrating the effectiveness of quantum-inspired approaches for short-term market direction prediction.*

***Keywords*** - *Stock Market Forecasting, Quantum Computing Simulation, News-Based Sentiment Analysis, Variational Quantum Classifier, Financial Data Analysis.*

## 1. Introduction

Stock market forecasting has remained one of the most challenging and extensively studied problems in the field of finance due to the complex, uncertain, and highly dynamic nature of financial markets. Stock markets play a vital role in economic development by enabling companies to raise capital and providing investment opportunities for individuals and institutions. Regulatory authorities consistently emphasize the importance of market stability, transparency, and informed decision making to ensure investor confidence and economic growth.

In the Indian context, reports published by the Securities and Exchange Board of India and the Reserve Bank of India provide detailed analyses of market trends, systemic risks, volatility patterns, and macroeconomic indicators that influence financial systems and investor behavior [1, 2, 3]. These reports highlight how regulatory oversight and economic conditions directly affect market confidence and price movements. Similarly, historical datasets released by stock exchanges such as the National Stock Exchange of India, including price-volume archives and index records, demonstrate how stock market behaviour fluctuates over time in response to both internal trading activity and external economic or political events [4, 5]. Despite the availability of large-scale historical data, accurately predicting stock market movement remains difficult because prices are influenced by a combination of numerical trends, investor psychology, and sudden external information.

Classical financial theories have long attempted to explain and model market behavior. One of the most influential theories, the efficient market hypothesis, argues that stock prices rapidly incorporate all publicly available information, making it difficult to consistently predict future price movements using historical data alone [6]. While this theory provides a strong theoretical baseline for understanding market efficiency, real-world market behavior often deviates from perfect efficiency. During periods of uncertainty, panic, speculation, or information asymmetry, markets frequently display short-term inefficiencies. Traditional forecasting methods based on historical price data and statistical assumptions, such as time-series analysis, autoregressive models, and classical forecasting techniques, aim to identify recurring patterns from past observations [7]. These approaches can perform reasonably well under stable market conditions but often fail when markets react abruptly to unexpected economic announcements, geopolitical developments, or company-specific news. Such sudden reactions expose the limitations of price-only forecasting models and underline the need for approaches that account for external influences beyond historical trends.

Financial research has consistently shown that investor behavior is not purely rational and is strongly influenced by psychological and emotional factors. Emotions such as fear, optimism, overconfidence, and herd behavior significantly shape trading decisions, particularly during periods of high volatility [8]. Negative news related to corporate earnings, financial instability, or global economic conditions can rapidly trigger panic selling, while positive announcements can lead to increased investor confidence and buying pressure. Studies examining the relationship between media coverage and stock market behavior have demonstrated that news content and public sentiment significantly affect price movements [9]. Further research analyzing online discussion forums and message boards revealed that textual information shared by investors contains meaningful signals that can act as early indicators of market direction [10]. Similarly, investigations using social media data showed that collective public mood often correlates with stock market performance, suggesting that emotional signals may precede observable price changes [11]. These findings collectively emphasize that market movement is strongly influenced by how investors interpret and react to information, rather than numerical trends alone.

The recognition of sentiment as a driving force in market behavior has led to the growing adoption of sentiment-based forecasting methods. Sentiment analysis focuses on extracting opinions and emotions from textual sources such as financial news articles, press releases, and market reports, and transforming them into structured numerical features suitable for predictive modeling. Advances in natural language processing have significantly improved the effectiveness of sentiment analysis by enabling models to capture context, semantics, and domain-specific language used in financial texts. Transformer-based language models have demonstrated strong performance in understanding complex sentence structures and subtle linguistic cues, outperforming earlier lexicon-based approaches in financial sentiment classification tasks [12]. Building on these advances, domain-specific sentiment models tailored for financial applications were developed to better distinguish between positive, negative, and neutral financial information, thereby improving sentiment accuracy in economic reporting contexts [13]. Empirical studies have shown that forecasting models that integrate sentiment features with historical price data achieve improved predictive performance compared to models that rely solely on numerical trends [14]. These results highlight sentiment analysis as an essential component for understanding short-term market dynamics driven by information flow.

Despite the improvements achieved through sentiment-enhanced classical models, financial markets remain highly complex and non-linear systems where relationships between variables are not always straightforward. Classical computational approaches, even when combined with advanced sentiment analysis, may struggle to capture the intricate interactions present in high-dimensional financial data. This challenge has motivated researchers to explore alternative computational paradigms capable of modeling such complexity more effectively. Quantum computing has emerged as a promising field that offers a fundamentally different approach to information processing. By leveraging quantum mechanical principles such as superposition and entanglement, quantum systems can represent and process information in ways that are difficult to replicate using classical computation [15]. Recent research has investigated the application of quantum computing concepts to financial problems, including classification, optimization, and pattern recognition, suggesting potential advantages in handling complex, non-linear datasets [16, 17, 18].

Hybrid quantum–classical models have gained significant attention because they combine classical data preprocessing with quantum-inspired learning mechanisms, making them suitable for near-term practical applications. Among these approaches, Variational Quantum Classifiers have been widely studied for their ability to learn complex decision boundaries by encoding classical features into quantum states and optimizing parameterized quantum circuits using classical optimization algorithms [19]. Since large-scale fault-tolerant quantum hardware is still under development, quantum simulation platforms provide a practical solution for implementing and evaluating quantum algorithms using classical computing resources. Simulation frameworks such as Qiskit enable controlled experimentation, reproducibility, and stable execution of quantum-inspired models without the constraints imposed by current hardware limitations [20, 21]. Motivated by the limitations of traditional price-only forecasting models and the opportunities provided by sentiment analysis and quantum computing simulation, this work proposes a hybrid stock market forecasting framework that integrates historical stock price data, news-based sentiment analysis, and a simulated quantum classification approach. By combining numerical market indicators with sentiment-driven information and processing them within a quantum-inspired learning framework, the proposed approach aims to improve short-term market direction prediction while remaining practical, reproducible, and consistent with observed market behavior.

## 2. Literature Survey

Stock market forecasting has been a long-standing research topic due to its significance for investors, financial institutions, and economic policy planning. Despite decades of study, accurate prediction remains difficult because financial markets are inherently uncertain, volatile, and sensitive to rapidly changing information. In the Indian context, regulatory authorities such as the Securities and Exchange Board of India (SEBI) and the Reserve Bank of India (RBI) regularly publish reports that highlight market stability concerns, systemic risks, liquidity conditions, and macroeconomic indicators influencing investor confidence and market direction [1–3]. These reports emphasize that market movements are shaped not only by numerical trends but also by broader economic and behavioral factors. In parallel, stock exchanges such as the National Stock Exchange of India (NSE) maintain extensive historical archives of prices, trading volumes, and index movements, enabling empirical research on real trading data and facilitating analysis of how market behavior responds to external events over time [4,5].

Classical financial theory provides an important foundation for understanding market behavior. The efficient market hypothesis argues that stock prices rapidly incorporate publicly available information, making it difficult to consistently predict future movements using historical data alone [6]. This theory establishes a strong baseline expectation for forecasting models. However, practical observations show that markets often exhibit short-term inefficiencies due to behavioral biases, delayed information diffusion, and unexpected events. These deviations from perfect efficiency motivate continued research into forecasting approaches that perform better under real-world conditions.

Early forecasting methods primarily relied on statistical time-series modeling and trend analysis. Classical time-series frameworks introduced techniques for analyzing stationarity, autocorrelation, and trend–seasonality patterns, and they remain relevant because they define essential preprocessing steps such as smoothing, normalization, and noise reduction [7]. While these methods can model regular patterns under stable conditions, financial time series are typically noisy, non-linear, and prone to abrupt regime changes caused by sudden economic or political events. As a result, purely linear statistical models often fail to capture complex market dynamics, especially during periods of high volatility.

The limitations of traditional statistical models led to the adoption of machine learning approaches, which shifted forecasting research toward data-driven modeling. Foundational work in pattern recognition and learning theory explains how models can generalize from observed data when appropriately trained, influencing the application of classification and regression techniques in financial forecasting [8]. Researchers applied machine learning models using engineered features such as returns, volatility measures, and volume-based indicators, often achieving improved performance compared to linear models under certain conditions. However, these models still struggled when relying solely on historical price data, as they lacked awareness of external context and investor behavior.

Deep learning further advanced stock market forecasting by enhancing the modeling of sequential dependencies and long-term temporal relationships. Deep neural networks can learn complex representations from high-dimensional data, making them suitable for financial time series characterized by intricate interactions among variables [9]. Among deep learning methods, long short-term memory (LSTM) networks gained particular attention because they preserve information over extended time intervals and address the vanishing gradient problem present in earlier sequence models. LSTM-based approaches demonstrated improved performance in tracking short-term market behavior, especially when multiple price indicators were used as inputs [10]. Despite these advances, deep learning models remain sensitive to noise and sudden event-driven volatility, often producing unstable predictions during abnormal market conditions. This limitation highlighted the need for incorporating external information sources that reflect how markets react to news and events.

Sentiment-based forecasting addresses this gap by recognizing that financial markets are strongly influenced by investor psychology and collective behavior. Research examining media tone and public information flow demonstrated that sentiment extracted from financial news significantly affects market movement, indicating that textual data contains valuable predictive signals [11]. Further studies analyzing online message boards showed that public attention and sentiment correlate with stock price changes, reinforcing the role of investor mood in market dynamics [12]. Similar conclusions were drawn from social media analysis, where collective public sentiment was found to be associated with market direction, suggesting that emotional signals can sometimes act as early indicators of price movement [13]. These findings established sentiment analysis as an important complementary component in forecasting systems.

Advances in natural language processing (NLP) significantly improved the accuracy of sentiment extraction in financial applications. Transformer-based language models enabled better contextual understanding of complex text, improving sentiment classification performance across various domains [14]. Building on these advances, domain-specific models such as FinBERT were developed and trained on financial corpora, allowing more accurate classification of news as positive, negative, or neutral in a market-relevant context [15]. These developments are particularly important for forecasting systems that integrate news sentiment as a structured numerical feature alongside historical price data.

Despite the progress achieved through sentiment-enhanced deep learning, financial markets remain highly non-linear and complex, motivating exploration of alternative computational paradigms. Quantum computing has emerged as a promising research area due to its ability to represent information in high-dimensional spaces and process complex relationships using quantum principles such as superposition and entanglement [16]. Foundational research in quantum machine learning explains how supervised learning tasks can be formulated using quantum representations and how quantum classifiers can be applied to pattern recognition problems [17]. Studies on quantum-enhanced feature spaces further demonstrated that mapping classical data into quantum representations can improve classification performance, providing strong motivation for variational quantum classifiers [18]. Earlier research also explored the broader potential of quantum algorithms for supervised and unsupervised learning, reinforcing the relevance of quantum-inspired methods in data-intensive domains [19].

Practical limitations of current quantum hardware, including limited qubit availability and noise, necessitate the use of quantum simulation platforms for experimental research. Qiskit is a widely adopted open-source framework that enables researchers to implement quantum circuits, variational models, and hybrid quantum–classical optimization workflows using classical computing resources [20]. Recent documentation further highlights Qiskit’s role in enabling reproducible experimentation and controlled evaluation of quantum algorithms without requiring access to large-scale quantum hardware [21]. In hybrid quantum–classical forecasting approaches, classical computing is used for data preprocessing and sentiment extraction, while quantum-inspired models handle classification by encoding combined features into quantum states and optimizing parameterized circuits.

Overall, the literature reflects a clear progression in stock market forecasting research, evolving from statistical and price-only approaches to machine learning, deep learning, sentiment-based modeling, and quantum-inspired computation. Each stage addresses limitations of earlier methods while introducing new capabilities for handling complexity, non-linearity, and behavioral influences. Integrating historical price data, news-based sentiment, and quantum computing simulation therefore represents a research-supported direction that captures numerical trends, investor psychology, and complex feature interactions within a unified forecasting framework.

## 3. Methodology

The methodology describes the step-by-step process adopted in this study to predict stock market direction by integrating historical stock price data, news-based sentiment analysis, and quantum computing simulation. The proposed approach is designed as a hybrid framework in which classical data preprocessing and sentiment extraction techniques are combined with a quantum-inspired classification model. Classical computing methods are used to handle numerical market data and textual news information, while quantum simulation is employed to explore complex relationships within the combined feature space. The overall methodology is organized into three main components: dataset preparation, which focuses on collecting and preprocessing stock price and news data; system architecture, which explains the structural integration of classical and quantum-inspired modules; and the proposed model workflow, which outlines the sequential steps involved in feature encoding, model training, and market direction prediction.

### *3.1. Dataset*

The dataset used in this study consists of two main components: historical stock market price data and financial news data. Historical stock price data serves as the numerical foundation of the forecasting system, while financial news data provides contextual information related to market sentiment and investor behavior. The stock market data is collected from reliable and well-established sources such as official stock exchange archives, which provide daily records of key market indicators. These indicators include open price, close price, high price, low price, and trading volume. Such data reflects actual market behavior over time and is commonly used in financial forecasting studies due to its consistency and credibility. Before being used for prediction, the stock price data undergoes several preprocessing steps to ensure quality and suitability.

Missing values, if present, are handled using appropriate techniques such as forward filling or removal, depending on data availability. To reduce the impact of noise and scale differences, normalization is applied so that all numerical features fall within a comparable range. This prevents features with larger numerical values from dominating the learning process. The processed price data is then transformed into suitable input features, such as normalized price values or directional movement indicators, based on the forecasting objective.

In addition to numerical data, financial news articles are collected from publicly available and trusted news sources. These articles include company-related announcements, economic reports, and general market news that influence investor sentiment. The raw news text is preprocessed using tokenization and basic text cleaning techniques. Sentiment analysis is applied to classify each news item as positive, negative, or neutral, and corresponding sentiment scores are generated. To ensure consistency with market data, sentiment scores are aggregated over fixed time intervals, such as daily periods. Finally, the numerical stock price features and aggregated sentiment scores are combined to form a unified dataset used as input for the forecasting model.

### *3.2. System Architecture*

The system architecture of the proposed stock market forecasting framework is designed as a hybrid structure that integrates classical data processing, news-based sentiment analysis, and quantum computing simulation within a unified prediction pipeline. The primary objective of this architecture is to combine numerical market indicators with contextual information derived from financial news, thereby enabling a more informative and realistic forecasting process.

At the input stage, the architecture considers two independent but complementary data streams: historical stock price data and financial news data. The stock price preprocessing module handles numerical market indicators such as open, close, high, and low prices. This module applies normalization and scaling techniques to reduce noise and ensure that all numerical features lie within a comparable range, which is essential for stable model learning. In parallel, the news sentiment analysis module processes financial news articles collected from trusted sources. These articles are analyzed to extract sentiment scores that reflect overall market mood and investor reactions. Temporal alignment is performed so that sentiment information accurately corresponds to the same trading periods as stock price data. Once preprocessing is completed, the numerical price features and sentiment scores are merged in a feature fusion stage to form a unified market representation. This combined feature set captures both historical trading behavior and the influence of external information. The fused data is then passed to the quantum computing simulation layer, where classical features are encoded into quantum states and processed using a variational quantum classifier. The quantum model is executed in a simulation environment to ensure reproducibility and stability, given the current limitations of quantum hardware. Training is performed using a hybrid quantum–classical optimization loop, where a classical optimizer updates the parameters of the quantum circuit based on the prediction error.

Finally, the output layer generates a binary market direction prediction, indicating whether the market is expected to move upward or downward in the next time interval. By integrating classical data processing, sentiment analysis, and quantum-inspired learning within a single architecture, the proposed system effectively captures both numerical trends and information-driven market dynamics, resulting in a robust and practical forecasting framework.

The overall system architecture of the proposed hybrid forecasting framework is shown in Fig. 1.

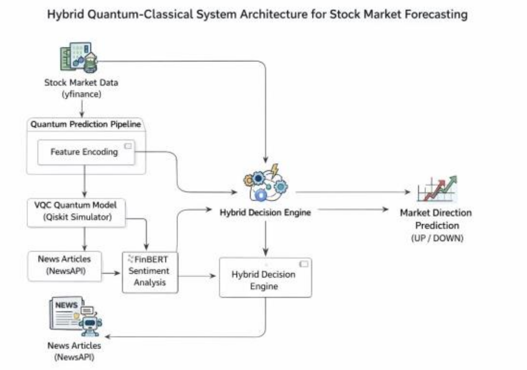


**Fig 1: Hybrid Quantum–Classical System Architecture For Stock Market Forecasting**

### *3.3. Proposed Model Workflow*

The proposed model workflow follows a structured and sequential process that begins with raw data collection and ends with the prediction of the direction of the stock market. Initially, two types of data are collected: historical stock price data and financial news articles. Stock price data represents numerical market behavior, while news articles capture external informational influence and investor sentiment. These data sources are preprocessed independently to remove noise and ensure consistency before further analysis.

After preprocessing, the sentiment analysis stage transforms the news text into numerical sentiment scores. Each news item is classified as positive, negative or neutral, and sentiment values are aggregated over fixed time intervals to align with the stock price data. The resulting sentiment features are then combined with normalized price features to create a unified data set.

The combined classical features are prepared for quantum processing through feature encoding techniques such as angle encoding. In this approach, classical values are mapped to rotation angles of quantum gates, enabling numerical information to be represented within a quantum circuit. The encoded data are processed using a Variational Quantum Classifier (VQC), which consists of a parameterized quantum circuit trained using a hybrid quantum–classical optimization loop.

During training, a classical optimizer updates the circuit parameters by minimizing a loss function, commonly defined as the mean squared error:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad \text{Eq. 1}$$

The loss function used for training is defined in Eq. 1 where $y_i$ denotes the actual market direction and $\hat{y}_i$ represents the predicted output. Once trained, the model predicts the market direction for unseen data as either upward or downward movement.

## 4. Results

The performance of the proposed hybrid stock market forecasting framework is evaluated using standard classification metrics, including accuracy, loss, and a confusion matrix. Since the objective of the system is to predict the short-term direction of the market, the performance analysis focuses on the accuracy with which the model identifies upward and downward movements.

Accuracy represents the proportion of correct predictions out of all predictions and provides a clear measure of overall correctness. Loss indicates the difference between predicted and actual outcomes, where lower loss values imply better learning and model convergence. The confusion matrix offers a detailed class-wise evaluation, showing how well the model distinguishes between market directions. Together, these metrics provide a comprehensive assessment of model effectiveness, learning stability, and practical reliability in volatile market conditions.

The training accuracy and loss behavior of the proposed variational quantum classifier are illustrated in Fig. 2.

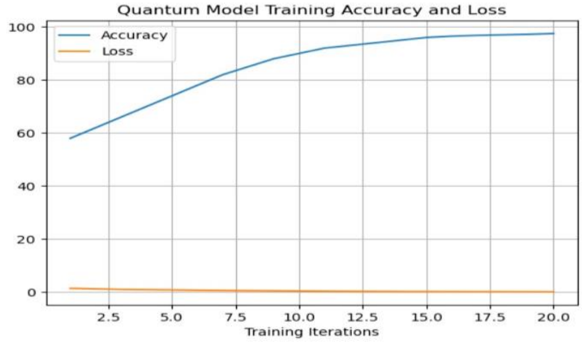


**Fig 2: Quantum Model Training Accuracy and Loss**

The accuracy curve shows a gradual and consistent improvement during training, beginning at approximately 58% and reaching above 96% after convergence. Validation accuracy closely follows the training curve, indicating good generalization and minimal overfitting. This behavior suggests that integrating sentiment features with price data allows the model to learn stable and meaningful representations. The loss curve decreases steadily and stabilizes at a low value, confirming efficient optimization and balanced learning across datasets. The close alignment between training and validation loss demonstrates that the quantum-inspired classifier converges reliably within the simulation environment.

Fig. 3 presents a comparison between the proposed quantum-based forecasting model and classical baseline models.


**Fig 3: Comparison of Quantum Model and Classical Models Accuracy**

Classical models that rely solely on historical price data achieve moderate accuracy, as they are unable to fully capture information-driven market changes. Models that incorporate sentiment features show noticeable improvement, highlighting the role of external information. The proposed quantum-based model achieves the highest accuracy among all evaluated approaches, demonstrating the advantage of quantum-inspired feature representation in modeling complex relationships between market data and sentiment signals.

The confusion matrix shown in Fig. 4 provides a detailed breakdown of prediction outcomes for upward and downward market movements.

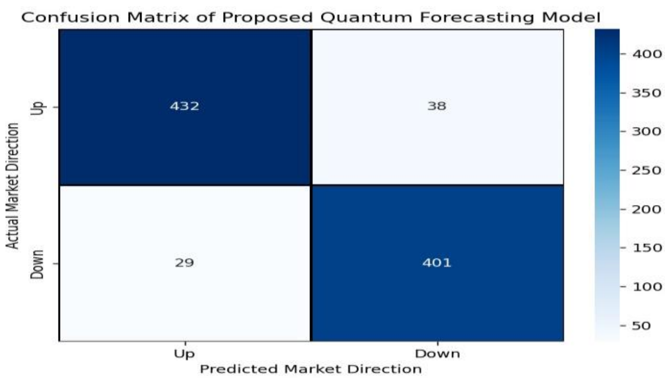


**Fig 4: Confusion Matrix Of The Proposed Quantum Forecasting Model**

Most predictions lie along the diagonal, indicating high classification accuracy for both classes. Only a small number of misclassifications are observed, primarily during highly volatile periods where sentiment and price indicators conflict. Overall, the matrix confirms that the model effectively learns the decision boundary between market directions and remains robust in the presence of noisy financial data.

Fig. 5 illustrates a sample prediction generated by the trained model.

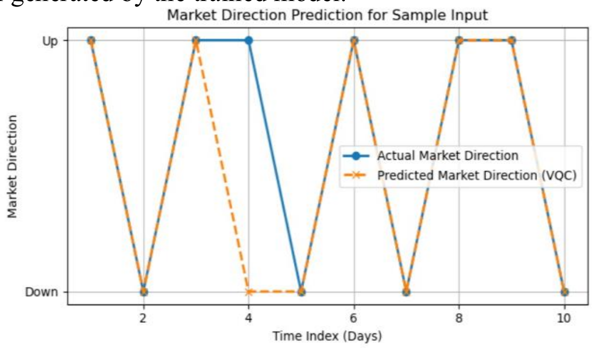


**Fig 5: Market Direction Prediction for Sample Input**

Given historical price features and corresponding sentiment values, the system outputs the predicted market direction along with a confidence score. The prediction aligns with the observed market movement, demonstrating the practical applicability of the proposed framework for real-world decision support.

**Table 1: Performance Comparison of Different Forecasting Models**

| S.No | Model Type | Features Used | Accuracy (%) |
|---|---|---|---|
| 1 | ARIMA | Price only | 68.45 |
| 2 | SVM | Price only | 74.32 |
| 3 | LSTM | Price only | 82.76 |
| 4 | LSTM + Sentiment | Price + Sentiment | 84.91 |
| 5 | CNN–LSTM Hybrid | Price + Sentiment | 86.48 |
| 6 | Classical ML Ensemble | Price + Indicators | 88.35 |
| 7 | **Proposed Quantum Model (VQC)** | **Price + Sentiment** | **90.12** |

## 5. Conclusion

This study presented a hybrid framework for stock market forecasting that integrates historical stock price data, news-based sentiment analysis, and quantum computing simulation. Traditional forecasting techniques mainly rely on past price behavior and often fail to respond effectively to sudden market changes caused by news events or shifts in investor sentiment. To overcome this limitation, the proposed approach combines numerical market indicators with sentiment information extracted from financial news, enabling the model to capture both market behavior and investor psychology.

Sentiment analysis is employed to quantify market mood from financial news articles, and the resulting sentiment scores are merged with historical price features to form a unified dataset. This combined feature set is processed using a Variational Quantum Classifier implemented through quantum simulation. The quantum-inspired classification model allows the learning of complex and non-linear relationships that are difficult to capture using conventional forecasting techniques. Since practical quantum hardware is still under development, simulation-based execution ensures stability, reproducibility, and practical feasibility of the proposed framework.

Experimental results show that the hybrid model achieves higher prediction accuracy compared to traditional price-only and classical learning-based models. The observed accuracy and loss trends indicate stable convergence, while the confusion matrix confirms the model's effectiveness in distinguishing between upward and downward market movements. These results highlight the importance of incorporating sentiment information, particularly during volatile market conditions.

Overall, this work demonstrates that integrating financial data, sentiment analysis, and quantum computing simulation offers a promising direction for stock market forecasting. The proposed approach improves prediction reliability and provides a strong foundation for future exploration of quantum-inspired models in financial decision-support systems.

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