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Prediction of AAPL Closing Price based on ARIMA-LSTM Hybrid Model

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Abstract:

In the context of highly volatile financial markets, accurately predicting stock prices remains an important and difficult task, particularly for major technology firms such as Apple Inc. (AAPL). Forecasting methods that are more traditional, like the Autoregressive Integrated Moving Average (ARIMA) model, perform well in linear analysis but have trouble handling the non-linear patterns that are common in financial information. In order to handle both linear and non-linear dynamics, this study presents a novel hybrid model that combines ARIMA with Long Short-Term Memory (LSTM) networks. This model efficiently leverages the advantages of both approaches. Utilizing historical closing price data for AAPL obtained from Yahoo Finance, the study demonstrates that the ARIMA-LSTM model significantly enhances predictive accuracy and adapts proficiently to the complexities inherent in stock market fluctuations. As seen by the data, the model's predictive ability has significantly improved, accounting for 91.1% of the fluctuation in stock prices. In addition to providing a more trustworthy prediction framework, this hybrid approach offers analysts and investors helpful information to assist them negotiate the turbulent nature of financial markets.

Keywords: Stock price prediction; ARIMA-LSTM hybrid models; time series analysis.

1. Introduction

In the global financial markets, forecasting stock prices has always been a challenging and popular topic, especially for tech giants like Apple Inc. (AAPL), whose stock price fluctuations are not only influenced by the company's operations and technological innovations but are also closely related to global economic conditions and market psychology [1]. Sher indicated that accurate prediction of stock prices is crucial for investors as it helps them make wiser investment decisions, reduces unnecessary financial risks, and contributes to the stability of the financial markets [2].

Singh noted that forecasting the stock market is one of the most challenging issues in time series analysis due to its chaotic and complex nature. However, the application of deep learning and machine learning has shown promising improvements in prediction accuracy. Lu uniquely combined convolutional neural networks (CNN), bi-directional long short-term memory (BiLSTM), and an attention mechanism (AM) to predict the next day's stock closing values with impressive accuracy [3]. Chen reported that a deep learning approach utilizing convolutional neural networks has proven somewhat reliable in predicting the movements of stock prices in the Chinese market, using input data such as opening, high, low, closing prices, and trading volume [4]. Gangwani suggested that the Logistic Regression method outperformed previous machine learning models for intraday stock predictions based on technical indicators, particularly regarding accuracy, mean squared error (MSE), and root mean squared error (RMSE) for forecasting the next day's closing price [5]. Researchers have widely employed time series models and machine learning to predict future stock trends. Despite notable advancements, these methods still encounter challenges, such as handling nonlinear relationships, complex market fluctuations, and difficulties in generalizing across different market conditions [6, 7]. This study aims to develop a more accurate hybrid model that integrates the strengths of Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) models to enhance stock price prediction accuracy. This approach is particularly effective in addressing the stock market's high volatility and complexity, with expectations that the hybrid model will reduce prediction errors and improve the reliability of investment decisions.

Sharma used the ARIMA model to predict Apple's stock, a model widely used for its efficiency in handling linear time series data. However, Sharma believed that the standalone ARIMA model underperforms in handling nonlinear patterns, which limits its predictive accuracy in the complex financial market environment [8]. Numerous academics have suggested hybrid models that combine ARIMA with LSTM networks in order to overcome this problem. Time series data with long-term dependencies and nonlinear patterns are more easily handled and predicted by LSTM, an effective recurrent neural network, according to Sherstinsky [9]. The ARIMA-LSTM model combines the nonlinear relationship-capturing power of LSTM with the flexibility of ARIMA to handle linear trends. ARIMA excels at extracting long-term dependencies in data, while LSTM addresses complex time dependencies and nonlinear patterns. Through this, it provides a more comprehensive analysis and prediction of time series data, particularly in highly volatile environments like financial markets, improving prediction accuracy and reducing errors [10]. Dave's research also demonstrated that this hybrid model has shown superior predictive capabilities in various fields, but it still faces numerous challenges when applied to specific stock predictions, such as model parameter selection, the complexity of data preprocessing, and the risk of overfitting [11].

The purpose of this study is to investigate how well the ARIMA-LSTM model predicts the closing prices of AAPL shares. By examining how well LSTM captures nonlinear dependencies and how well ARIMA handles linear interactions, a more accurate prediction model is built, with improved structure and parameters to improve accuracy and stability. The method involves using ARIMA to predict linear trends and then using LSTM to predict nonlinear dynamics. The goal is to validate the model's effectiveness in predicting highly volatile stock prices, providing a more stable and accurate prediction method to reduce investment risks and increase returns.

2. Methods

2.1 Data Source

The data used in this paper is sourced from the Yahoo Finance website, consisting of the historical closing prices of Apple Inc. (AAPL) stock from February 1, 2021, to August 21, 2024, covering a total of 895 trading days.

2.2 Variable Selection

Apple's stock closing prices are influenced by various internal factors, such as company performance, and external global economic conditions, making the price trends dynamic and subject to fluctuations over time. The market behavior is often unpredictable, with price changes happening frequently, as demonstrated in Figure 1:

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Fig. 1 AAPL Closing Prices

From early 2021 to early 2022, the price generally increased, climbing from around $120 to nearly $180. In early 2022, the stock experienced a pullback, reaching a low of approximately $130 in mid-2022, followed by a partial rebound. Throughout the second half of 2022 and 2023, the price fluctuated significantly, with multiple highs and lows, indicating increased market uncertainty. Toward the end of 2023 and into 2024, AAPL's price resumed an upward trend, reaching its highest point near $200 in early 2024. Overall, AAPL's stock price showed notable growth during this period, but also experienced several significant corrections.

2.3 Method Introduction

This paper proposes an ARIMA-LSTM hybrid model, which offers more comprehensive sequence modeling capabilities. It is suitable for time series data, such as stock opening prices, which have both linear trends and complex nonlinear relationships. The methodology is as follows:

After extracting the trend of AAPL closing prices, ARIMA is used for fitting, including the selection of orders (p, d, q), model parameter estimation, and residual analysis. Stationarity tests are conducted to determine whether differencing is needed and how many differences are required. After the white noise assumption, autocorrelation and partial autocorrelation plots are used to identify tailing or truncation, roughly determining the ARIMA model. The specific ARIMA model type is further refined using AIC and BIC criteria. ARIMA is then used for prediction, residuals are extracted and tested for normality, and the LSTM model is trained on these residuals. Finally, the predictions from the ARIMA and LSTM models are combined to form the final hybrid model predictions. The performance of the hybrid model is evaluated through computed metrics.

3. Results and Discussion

3.1 ARIMA Model Fitting

Here are the results of the ADF test on the data:

Table 1. Augmented Dickey-Fuller Test Results

Statistic	Result
ADF Statistic	-0.879
p-value	0.795
Critical Values (1%)	-3.438
Critical Values (5%)	-2.865
Critical Values (10%)	-2.568

Table 1's Augmented Dickey-Fuller (ADF) test findings indicate that the time series may not be stationary. The value is higher than the crucial values at the 1%, 5%, and 10% significance levels, according to the ADF statistic of -0.879. As so, this paper is unable to rule out the null hypothesis. Additionally, the p-value of 0.795 considerably above the standard significance level of 0.05, further supporting the conclusion of non-stationarity. Therefore, to achieve stationarity and ensure the reliability of subsequent modeling and forecasting, differencing the data is necessary. After differencing, the trend of the data changes to:

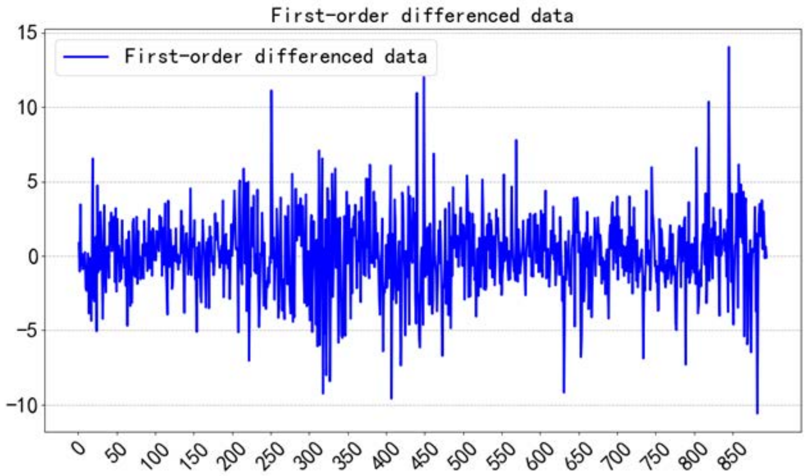

Fig. 2 First-ordered Differenced Data

After taking the first-order difference, the changing of data trend shown in Figure 2, and the ADF statistic is -29.403, with a p-value close to 0.01. This paper rejects the null hypothesis that a unit root exists based on the findings of the ADF test at a significance level of 0.05 (the p-value is considerably less than the significance threshold), indicating stationarity after the first-order difference. And it passed the white noise test.

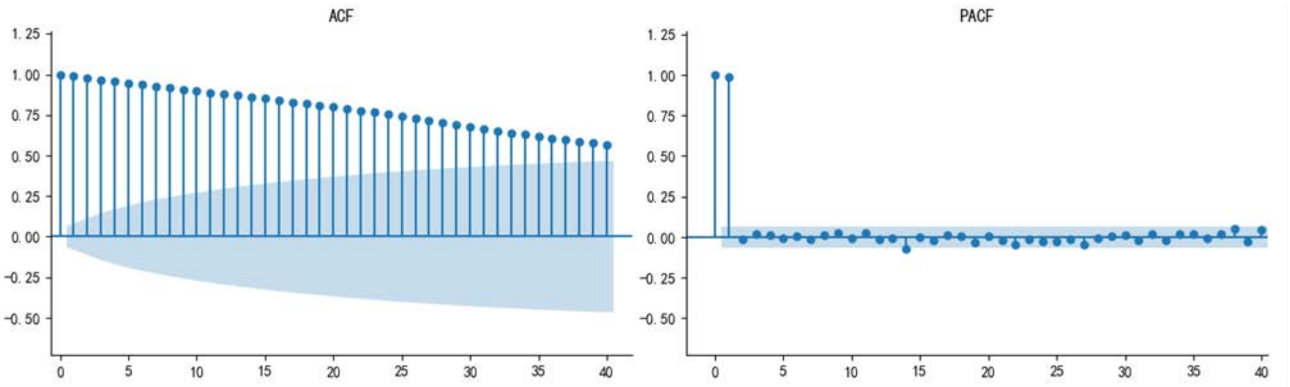

Fig. 3 ACF and PACF plot

The first graph shows a gradual decline in autocorrelation, suggesting an AR component, with insignificance after 10–20 lags, hinting at ARMA or ARIMA. The second graph (PACF) has a peak at lag 1, typical of AR(1). Together, the time series likely follows an AR(1) model. Finally, the model was identified as an AR(1) model (ARIMA(0,1,0)) using AIC and BIC methods (Figure 3). The Figure 4 is a graph of ARIMA model predictions and expected values

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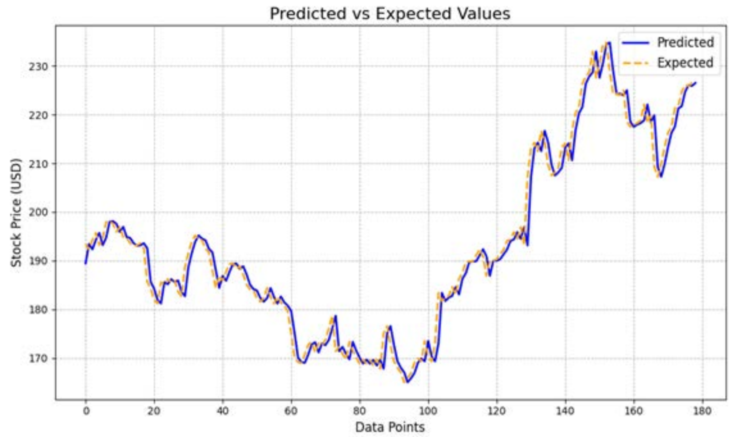

Fig. 4 Predicted vs Expected Values

3.2 Residual Acquisition

Testing if residuals follow a normal distribution is crucial for validating model assumptions, as many statistical methods assume normally distributed, independent residuals. Deviations from this can impact parameter estimates, confidence intervals, and hypothesis testing, and may indicate model shortcomings. Normally distributed residuals improve prediction reliability, making confidence intervals and errors easier to interpret. Thus, checking residual normality helps in diagnosing and refining the model if needed (Figure 5, 6).

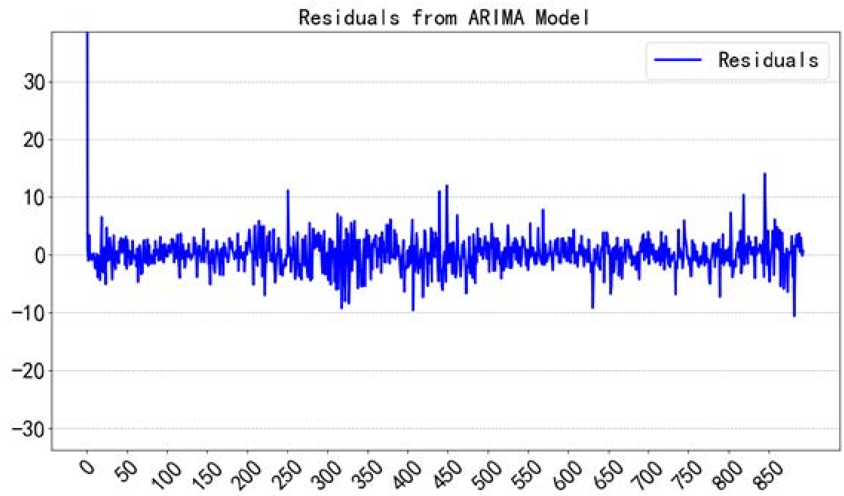

Fig. 5 Residuals of ARIMA

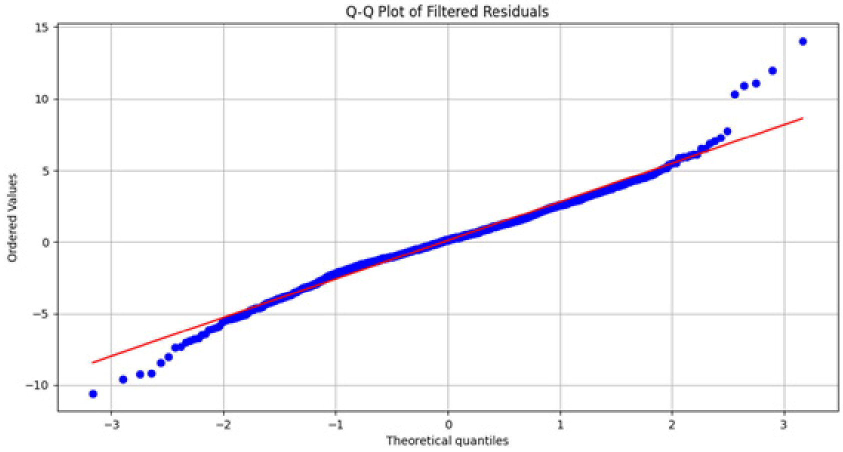

Fig. 6 Q-Q Plot

When training an LSTM model, normalization or standardization is essential to ensure input data is within a reasonable range. This common preprocessing step in deep learning, especially for RNNs like LSTM, accelerates convergence, stabilizes gradients, and improves generalization by aligning input data to a consistent scale and distribution, preventing issues like gradient vanishing or exploding. According to Figure 6 Q-Q chart and the residual bar chart Figure 7, it can be obviously found that it roughly conforms to the normal distribution.

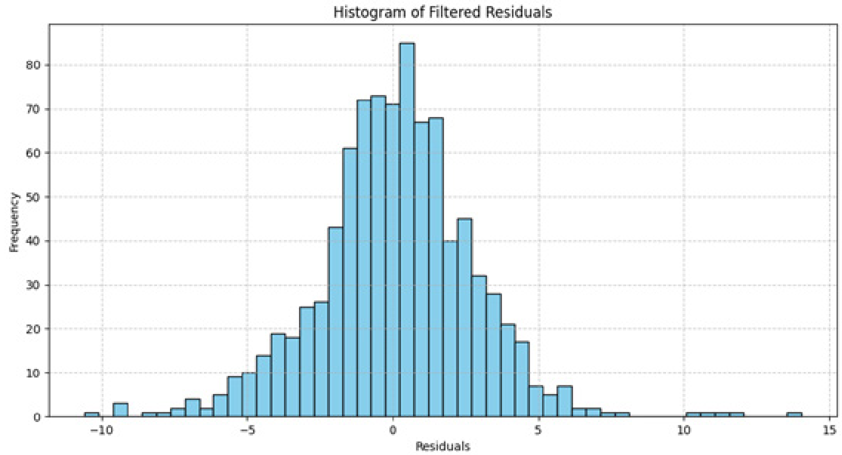

Fig. 7 Histogram of Residuals

3.3 LSTM Model Training

Next, LSTM model is used to train the residual of ARIMA model. Here the residuals are taken as input sequences, and the LSTM model learns the nonlinear pattern of residuals (Figure 8).

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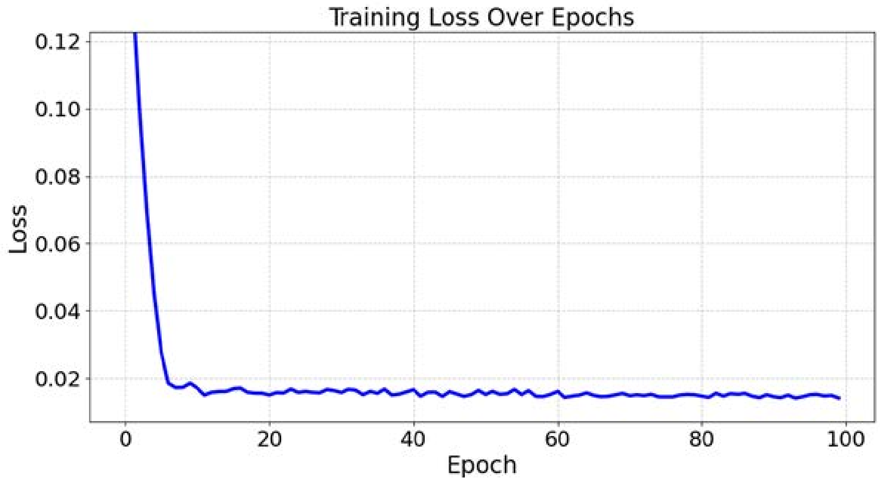

Fig. 8 Loss Value

At the beginning of LSTM training, the loss value was high, indicating the model struggled to identify patterns in the data. However, as training continued, the loss gradually decreased, demonstrating that the model was learning and adjusting its parameters to enhance accuracy. Eventually, the loss leveled off, suggesting the model had reached an optimal state where additional learning did not lead to significant performance gains. The final low loss value indicates that the model fitted the training data well, successfully capturing both short-term and long-term dependencies without overfitting (Figure 9).

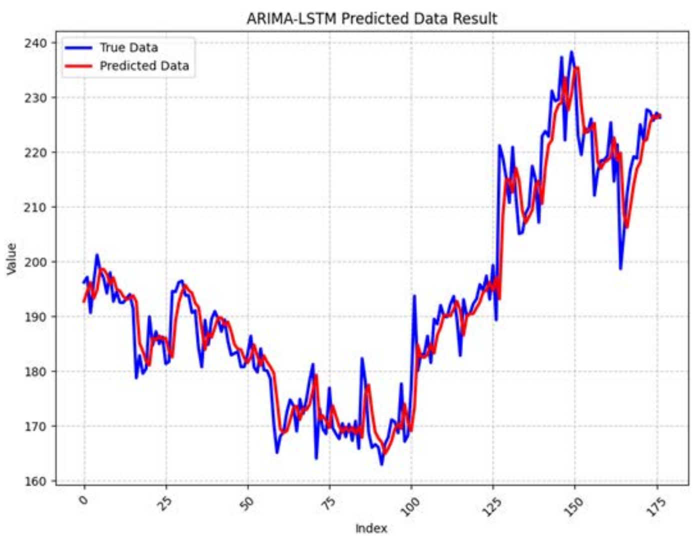

Fig. 9 ARIMA-LSTM Prediction

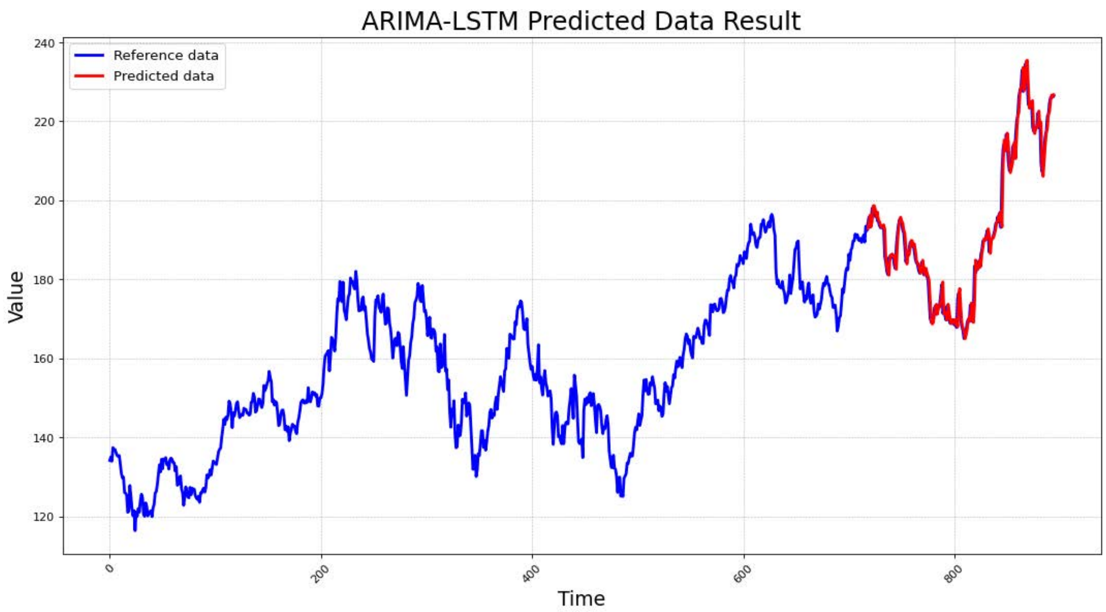

Fig. 10 Prediction Result

The findings shown in Figure 10 demonstrate how successfully the ARMI-LSTM fusion model, which combines LSTM's capacity to identify nonlinear patterns with ARIMA's capacity to capture linear trends, predicts stock closing prices. It is evident that the model's projected stock price, with low mean square error (MSE: 33.659), mean absolute error (MAE: 4.115), and root mean square error (RMSE: RMSE), is quite consistent with the actual value. Simultaneously, the model has a 0.911 coefficient of determination (R2), suggesting that it accounts for around 91.1% of variations in stock prices. However, critically speaking, the mean square error still needs to be reduced, and more models can be integrated to reduce the error in the future. Overall, the model performs well in forecasting accuracy and generalization ability, and can be used as an important tool for financial forecasting and decision-making

4. Conclusion

This study's main contribution is the creation of a hybrid model that combines Long Short-Term Memory (LSTM) networks with Autoregressive Integrated Moving Average (ARIMA), which is a major development in the field of stock price forecasting. By accurately capturing the intricate interplay between linear and non-linear dynamics included in financial data, this model improves forecast accuracy and robustness to fluctuations in the market. Quantitative finance has a significant gap as traditional forecasting techniques frequently struggle to handle these complexity. This study not only solves current shortcomings but also lays the groundwork for further research into hybrid modeling techniques by providing investors with a more dependable tool to reduce risk and maximize rewards

Looking forward, several critical avenues for further research are identified. Although the current model demonstrates potential, its existing configuration is unable to process real-time data, which restricts its adaptability to abrupt market fluctuations. Future studies should aim to enhance the model's architecture by incorporating additional ML techniques, such as ensemble methods, to improve generalization and minimize prediction errors. Furthermore, the integration of real-time data processing capabilities will render the model more dynamic and responsive, providing investors with timely and actionable insights. Given that the current model's mean squared error (MSE) is not yet optimal, addressing this concern through methodological enhancements will be essential. Continuous refinement in these areas will ensure that the hybrid model remains a valuable asset for strategic investment and decision-making in increasingly volatile financial markets.

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