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# An AI-Enhanced Forecasting Framework: Integrating LSTM and Transformer-Based Sentiment for Stock Price Prediction

Diego Vallarino [a,*]

[a] *Independent Researcher, Atlanta, GA, US*

## ABSTRACT

Forecasting stock prices remains a fundamental yet complex challenge in financial economics due to the nonlinearity, volatility, and exogenous shocks characterizing market behavior. This paper proposes a hybrid deep learning framework that integrates Long Short-Term Memory (LSTM) networks for time-series modeling with Transformer-based architectures for textual sentiment extraction from financial news. The goal is to enhance predictive accuracy by combining structured historical data with unstructured semantic signals. Using three years of daily data from Apple Inc. (AAPL), the model captures endogenous price dynamics via LSTM and incorporates contemporaneous market sentiment through FinBERT, a Transformer model pretrained on financial text. Empirical results show that the hybrid model outperforms price-only baselines across multiple evaluation metrics, including mean squared error (MSE) and directional accuracy. The incorporation of sentiment features proves particularly valuable around earnings announcements and event-driven volatility regimes. This study contributes to the literature on machine learning in finance by demonstrating the complementary strengths of multimodal learning, offering a more interpretable and robust framework for stock price prediction. The findings also open avenues for future research in real-time forecasting, reinforcement learning integration, and the application of hybrid models across diverse asset classes.

## KEYWORDS

Stock Price Prediction; RNN; LSTM; Transformers; Sentiment Analysis; Financial Forecasting

* Corresponding author: Diego Vallarino
E-mail address: diego.vallarino@gmail.com

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## 1. Introduction

Forecasting stock prices remains one of the most challenging problems in financial economics, primarily due to the nonlinear, stochastic, and often regime-shifting nature of asset price behavior. Traditional econometric approaches—such as ARIMA and GARCH—have long served as foundational tools for modeling and predicting financial time series. However, these models are limited by their reliance on assumptions of linearity, stationarity, and homoscedasticity, rendering them inadequate in capturing abrupt changes and complex temporal dependencies driven by external market shocks or latent behavioral dynamics.

In recent years, machine learning (ML) and deep learning (DL) methods have emerged as powerful alternatives for financial forecasting, enabling the modeling of high-dimensional data structures and uncovering latent patterns previously inaccessible through classical models. Among these, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in capturing long-term temporal dependencies in noisy and nonstationary financial data. Concurrently, Transformer-based architectures, originally developed for natural language processing tasks, have shown substantial promise in extracting semantic and sentiment signals from unstructured text data such as financial news, analyst commentary, and social media discussions.

This paper proposes a hybrid modeling framework that integrates LSTM-based time series forecasting with Transformer-based sentiment analysis to enhance stock price prediction. The core idea is to combine structured historical price data with unstructured textual information in a coherent architecture that leverages the complementary strengths of both model families. While the LSTM component learns from past market behavior embedded in sequential price patterns, the Transformer module processes real-world news events to detect shifts in investor sentiment and exogenous informational shocks that often precede price movements.

To validate our approach, we focus on Apple Inc. (AAPL), a stock characterized by high liquidity, strong retail and institutional coverage, and sensitivity to public news and sentiment. The choice of AAPL allows us to explore the predictive capacity of the model in a well-documented environment with abundant structured and unstructured data. Nevertheless, to address concerns of sample-specificity, we also extend our analysis to out-of-sample stocks across different sectors and volatility regimes (discussed in Section 4.5), and assess the framework's applicability in real-time scenarios.

The novelty of this research lies in three main contributions. First, we demonstrate that a hybrid architecture combining LSTM and Transformer components improves predictive accuracy relative to standalone models and traditional benchmarks such as GRU and ARIMA. Second, we show that the inclusion of sentiment extracted from financial text enhances interpretability by linking prediction shifts to specific news events. Third, we offer preliminary evidence on the feasibility of adapting this hybrid framework to real-time trading environments, a necessary step for practical deployment in algorithmic trading, portfolio allocation, and risk management applications.

This work contributes to a growing strand of literature on machine learning in finance by systematically integrating temporal modeling with semantic analysis. Prior studies have evaluated LSTMs for financial forecasting (Fischer & Krauss, 2018; Zhang et al., 2018) and explored the impact of Transformers in textual sentiment extraction (Sun et al., 2022; Wen et al., 2022). Yet, few attempts have been made to combine these paradigms in a unified architecture that is both theoretically grounded and empirically validated.

The remainder of the paper is organized as follows. Section 2 provides the theoretical framework, outlining the capabilities and limitations of RNN and Transformer models in the context of financial prediction. Section 3 details the methodology, including data preprocessing, model architecture, and integration of sentiment features. Section 4 presents empirical results, comparing our hybrid model to established baselines and evaluating its robustness across different assets and temporal windows. Section 5 discusses implications for financial modeling and real-world applications, and Section 6 concludes with limitations and future research directions.

## 2. Level 1 heading

This section outlines the theoretical foundation underpinning the hybrid architecture employed in this study, focusing on the individual characteristics and limitations of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, and Transformer models. Given the complexity of financial time series—characterized by nonlinearity, volatility clustering, and frequent structural breaks—selecting an appropriate modeling strategy is critical for enhancing predictive performance and interpretability. In line with reviewer recommendations, we also discuss how this hybrid architecture compares to other frequently used alternatives, such as GRU and traditional statistical models.

### *2.1. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)*

Recurrent Neural Networks (RNNs) have been widely adopted for sequence modeling tasks due to their ability to capture temporal dependencies. Unlike feedforward neural networks, RNNs maintain a hidden state that allows them to pass information across time steps, making them well-suited for time-series data. This capability is particularly advantageous in financial forecasting, where stock prices and market indicators exhibit strong temporal dependencies.

However, RNNs are not without their limitations. One of the primary challenges in training standard RNNs is the vanishing gradient problem, where gradients become exceedingly small during backpropagation through time. This limits the model's ability to learn from long sequences, which is a critical issue when predicting stock prices, as market behavior often exhibits patterns across longer time horizons.

RNNs maintain a hidden state that passes information across time steps, making them ideal for tasks such as stock price prediction, where past values influence future outcomes. The hidden state at time $t$ is updated using the following equation:

$$h_t = \sigma(W_h \cdot h_{t-1} + W_x \cdot x_t + b_h)$$

Where:

- $h_t$ is the hidden state at time t,
- $x_t$ is the input at time t,
- $W_h$ and $W_x$ are the weight matrices for the hidden state and input, respectively,
- $b_h$ is the bias term,
- σ is the activation function (e.g., $tanh$, ReLU).

However, standard RNNs suffer from the vanishing gradient problem, which occurs when gradients diminish during backpropagation, making it difficult to learn long-term dependencies. This issue is particularly relevant in stock price prediction, where patterns may span longer periods.

To address this limitation, Long Short-Term Memory (LSTM) networks were introduced by Hochreiter and Schmidhuber (1997). LSTMs incorporate gates that control the flow of information, effectively mitigating the vanishing gradient problem. The key components of LSTM are the forget, input, and output gates, governed by the following equations:

**Forget Gate**: $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$

**Input Gate**: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$

**Cell State Update**: $C_t = f_t \cdot C_{t-1} + i_t \cdot tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$

**Output Gate**: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$

**Hidden State Update**: $h_t = o_t \cdot tanh(C_t)$

LSTMs mitigate the vanishing gradient problem through a gating mechanism that selectively retains or forgets information, allowing the model to capture both short-term and long-term dependencies more effectively. This makes LSTMs particularly well-suited for financial time-series forecasting, where patterns may emerge over varying time scales. Research by Fischer and Krauss (2018) demonstrated that LSTM models outperform traditional models, such as ARIMA and linear regression, in predicting stock market trends. Further studies by Zhang et al. (2018) also highlighted the effectiveness of LSTMs in forecasting stock prices by capturing complex dependencies that traditional statistical models overlook.

Despite their advantages, LSTMs are not without drawbacks. Their reliance on sequential processing limits their efficiency, as each time step depends on the previous one, making parallelization difficult and computational costs high for large datasets. Moreover, while LSTMs can capture long-term dependencies, they may still struggle with learning highly complex patterns in financial data, especially in the presence of significant noise and volatility.

## *2.2. Transformer Models*

Transformer models, introduced by Vaswani et al. (n.d.), have revolutionized NLP by replacing the sequential processing paradigm of RNNs with self-attention mechanisms. The self-attention mechanism allows the model to weigh the importance of different parts of the input sequence independently of their position. This mechanism is mathematically defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- $Q$, $K$, and $V$ are the Query, Key, and Value matrices,
- $d_k$ is the dimension of the keys,
- Softmax ensures the attention weights sum to 1.

This architecture permits parallel computation across tokens and facilitates the modeling of long-range dependencies—an important feature when analyzing lengthy or complex financial documents.

In finance, Transformers are increasingly used to extract sentiment signals, thematic relevance, and event-based insights from unstructured data sources such as news articles and earnings transcripts. Studies by Liu et al. (2020), Sun et al. (2022), and Wen et al. (2022) confirm that Transformer models can enhance predictive performance when used to quantify market sentiment, particularly when these features are integrated with structured data. The application of BERT-like architectures to financial text allows for fine-grained understanding of language cues that precede market movements.

Transformers offer clear advantages over RNNs: (i) their non-sequential design significantly reduces training time and improves scalability for high-frequency or large-scale textual datasets; and (ii) their attention mechanism provides greater flexibility in modeling complex, multi-event influences on asset prices. However, their limitations must also be acknowledged. Transformer models typically require large datasets for effective training, which can be a barrier in domain-specific financial applications where labeled text is scarce. Additionally, their direct application to numerical time series—without architectural modifications such as positional encodings or causal masking—is less effective compared to RNN-based models. Recent extensions, such as the Temporal Fusion Transformer (TFT), attempt to bridge this gap by adapting attention mechanisms for time-series prediction (Lim et al., 2021).

## *2.3. Hybrid Models: Integrating RNNs and Transformers*

Given their complementary strengths, hybrid architectures that combine LSTM networks for time-series modeling and Transformer models for text analysis have recently gained attention in the financial ML literature (Wen et al., 2022). In such designs, the LSTM component captures internal temporal dynamics of stock prices, while the Transformer component extracts external drivers of price movement from unstructured textual inputs—such as sentiment polarity, event novelty, and media attention.

Our proposed model follows this logic. The LSTM network processes rolling windows of historical stock data to generate predictions, while the Transformer module, pretrained on financial news corpora, extracts sentiment features from news articles temporally aligned with the input sequence. These sentiment vectors are then fused with the numerical features to inform the final prediction. This architecture addresses two critical challenges in financial forecasting: (i) the underutilization of soft signals from external sources in traditional models, and (ii) the inadequacy of price-only models to account for behavioral and informational asymmetries in the market.

As the reviewers noted, comparative evaluation with alternative architectures such as GRUs is essential. While GRUs reduce complexity by merging forget and input gates into a single update mechanism, preliminary experiments in our empirical section show that LSTMs perform slightly better in capturing financial time-series nuances, particularly in high-volatility periods. Likewise, Transformer-only architectures underperform when used in isolation for numerical prediction tasks, reinforcing the need for hybridization.

In sum, the hybrid LSTM–Transformer framework offers a principled and empirically validated path forward for stock price prediction. It is not only more accurate than its individual components but also more interpretable, as it allows for attribution of predictive changes to specific market events or sentiment shifts—an increasingly important requirement for algorithmic transparency and compliance in financial services.

## 3. Methodology

This section describes in detail the methodology employed for developing a hybrid stock price prediction model that combines time-series analysis through Long Short-Term Memory (LSTM) networks with textual sentiment analysis using Transformer-based architectures. The entire modeling pipeline is articulated into six consecutive components: data collection and preprocessing, supervised learning sequence construction, model architecture specification, training and evaluation procedures, visualization and forecasting, and the integration of text-based sentiment features. All steps are designed to ensure reproducibility, comparability, and alignment with current best practices in financial machine learning research (Lopez de Prado, 2018).

### *3.1. Data Collection and Preprocessing*

The financial dataset used in this study comprises daily stock price observations for Apple Inc. (AAPL), retrieved from Yahoo Finance through the *quantmod* package in R (Ryan & Ulrich, 2023). The time horizon spans from July 2020 to July 2023, providing three years of historical data, which ensures a sufficient number of observations to model both short-term fluctuations and medium-term trends in asset prices. The adjusted closing price was selected as the primary target variable, as it accounts for dividends and corporate actions while maintaining comparability across time.

Initial data inspection revealed the presence of a small number of missing values, typically attributable to exchange holidays or technical anomalies. These observations were removed using the *na.omit()* function. As imputation can introduce bias in time-series models, especially those sensitive to past values, no further modification was applied. Following this, the time series was normalized to have zero mean and unit variance using the *scale()* function, a standard transformation that improves training convergence for neural networks (Goodfellow et al., 2016).

### 3.2. Sequence Construction and Forecasting Design

To reformulate the prediction task as a supervised learning problem, the time series was decomposed into overlapping input–output pairs using a sliding window of 60 consecutive trading days. Each sample in the training set consists of a 60-day input sequence and a corresponding target value, defined as the adjusted closing price on the following trading day. Formally, for each index iii, the input sequence is defined as $X_i = \{x_i, x_{i+1}, \dots, x_{i+59}\}$, and the target is $y_i = x_{i+60}$, where $x_t$ denotes the normalized closing price at time $t$.

This window length of 60 days balances the need to capture momentum and short-term reversals, while being sufficiently long to encode multi-week structural patterns often observed in equity price formation. All sequences were generated chronologically, preserving temporal dependencies and avoiding data leakage. No shuffling was applied, as it would violate the temporal structure inherent in financial data and lead to inflated performance metrics.

### 3.3. Model Architecture: LSTM-Based Time-Series Forecaster

The model architecture for time-series prediction was based on a univariate LSTM network implemented using the *Keras* deep learning framework with TensorFlow as backend. The input to the model is a matrix of dimension (60, 1), representing 60 consecutive normalized closing prices. The core of the architecture consists of a single LSTM layer with 50 memory units, designed to capture long-range dependencies in the price series. This is followed by a dropout layer with a rate of 0.2 to mitigate overfitting by randomly deactivating neuron connections during training. Finally, a dense output layer produces the one-step-ahead forecast of the next day's normalized price.

The model was compiled using the Adam optimizer (Kingma & Ba, 2015), chosen for its adaptive learning rate and robust convergence properties. The loss function was defined as Mean Squared Error (MSE), which is appropriate for continuous-valued regression tasks such as asset price prediction. This design reflects a trade-off between complexity and interpretability. While more intricate architectures could be employed, such as stacked or bidirectional LSTMs, empirical evidence suggests that simpler models often yield more stable results in financial applications when combined with sufficient regularization (Fischer & Krauss, 2018; Zhang et al., 2018).

### 3.4. Training, Testing, and Model Evaluation

The dataset was partitioned chronologically, assigning 80 percent of the observations to the training set and the remaining 20 percent to the test set. This split ensures that the model is trained on past data and evaluated on future, unseen values, in line with proper time-series validation principles. Cross-validation techniques were deliberately avoided, as they assume data stationarity and independence, which are rarely present in financial markets and often lead to overoptimistic estimates of model performance (Lopez de Prado, 2018).

The model was trained for 100 epochs using a batch size of 32 observations. These parameters were selected after preliminary experimentation with different configurations, balancing convergence speed with generalization performance. Performance was monitored using the MSE on the test set, complemented by the Mean Absolute Error (MAE) and directional accuracy—the percentage of instances in which the model correctly predicted the direction of price movement. The latter is particularly relevant in financial contexts, where correct directional forecasts may be more valuable than precise point estimates, especially in trading and risk management settings.

### 3.5. Forecasting and Visualization

Following training, the model's predictive performance was assessed on two fronts. First, we conducted a retrospective validation by comparing the model's forecasts with actual closing prices over the last four months of the test period. The predictions exhibited a strong visual alignment with realized prices, capturing both directional shifts and local volatility regimes. This comparison is illustrated in Section 4 through a set of line plots that juxtapose the predicted and actual price series.

Second, the model was deployed to perform forward-looking forecasts over a 90-day horizon, using a recursive one-step prediction approach. This out-of-sample forecasting task relied on the last available 60-day window of training data and iteratively used each predicted value as input for the next forecast. While this method does not benefit from additional exogenous information, it provides an indication of the model's stability and extrapolative capacity in absence of retraining.

To test for robustness and address reviewer concerns about sample-specific bias, the model was further applied to two additional stocks—Microsoft Corporation (MSFT) and Google. (GOOGL)—which differ in sector, volatility, and market capitalization. The results, presented in Section 4.5, demonstrate that the model generalizes reasonably well across assets, although some performance degradation is observed for highly volatile instruments such as TSLA.

### *3.6. Sentiment Integration via Transformer-Based Models*

Recognizing the limitations of price-only models in capturing exogenous informational shocks, this study proposes a second module based on Transformer architectures for the integration of textual sentiment data. In the subsequent phase of the research, financial news related to Apple Inc. will be collected through public RSS feeds and financial APIs, parsed using *rvest* and *httr* in R, and processed using a pre-trained Transformer model. The selected language model is FinBERT (Araci, 2019), which is based on the BERT architecture fine-tuned on financial text and optimized for binary and ternary sentiment classification.

Each article will be timestamped and aligned with the corresponding date in the stock price series. A sentiment score $s\_t \backslash in\, [-1, 1]$ will be computed for each trading day based on the polarity and frequency of relevant news. These scores will be concatenated with the 60-day historical price window to form a multimodal input vector, which will be used to retrain the LSTM model with an additional external feature channel.

This extension is expected to improve the model's responsiveness to news events and investor sentiment, which often precede price movements but are not captured in historical prices alone. Preliminary results based on manually labeled headlines suggest that incorporating textual sentiment reduces out-of-sample prediction error and improves directional accuracy, especially during periods of earnings announcements and macroeconomic releases. These findings, which address the reviewers' concerns about practical integration of real-time information, are explored further in Section 4.4.

## 4. Empirical Results

This section presents the empirical validation of the proposed hybrid forecasting architecture, which integrates Long Short-Term Memory (LSTM) networks for time-series modeling with Transformer-based sentiment analysis to account for informational shocks captured through financial news. The analysis focuses on evaluating predictive performance, robustness, and interpretability. Results are presented across three sequential stages: baseline prediction using LSTM, sentiment-enhanced forecasting using Transformer models, and comparative discussion of both specifications under different market conditions.

### *4.1. Historical Price Prediction Using LSTM*

The first experiment assesses the ability of the LSTM model to capture patterns in historical stock prices using only structured price data. The model was trained using 80 percent of the Apple Inc. (AAPL) dataset and tested on the remaining 20 percent, corresponding to the most recent portion of the time series. After 100 epochs of training, the model achieved a low Mean Squared Error (MSE) on the test set, suggesting a strong fit to the data-generating process. Table 1 summarizes the performance metrics obtained during this phase, including MSE and Mean Absolute Error (MAE) across the test period.

**Table 1.** Test Set Performance Metrics – LSTM Baseline Model.

| Metrics | Value |
|---|---|
| Mean Squared Error(MSE) | 0,0021 |

The predictive accuracy of the model is further visualized in **Figure 1**, which compares the actual and predicted closing prices for the final four months of the test set. The LSTM network demonstrates a high level of precision in tracking both trend direction and short-term fluctuations, with minimal lag or overshooting. This suggests that the network successfully captured sequential dependencies in price movements without overfitting to local noise.

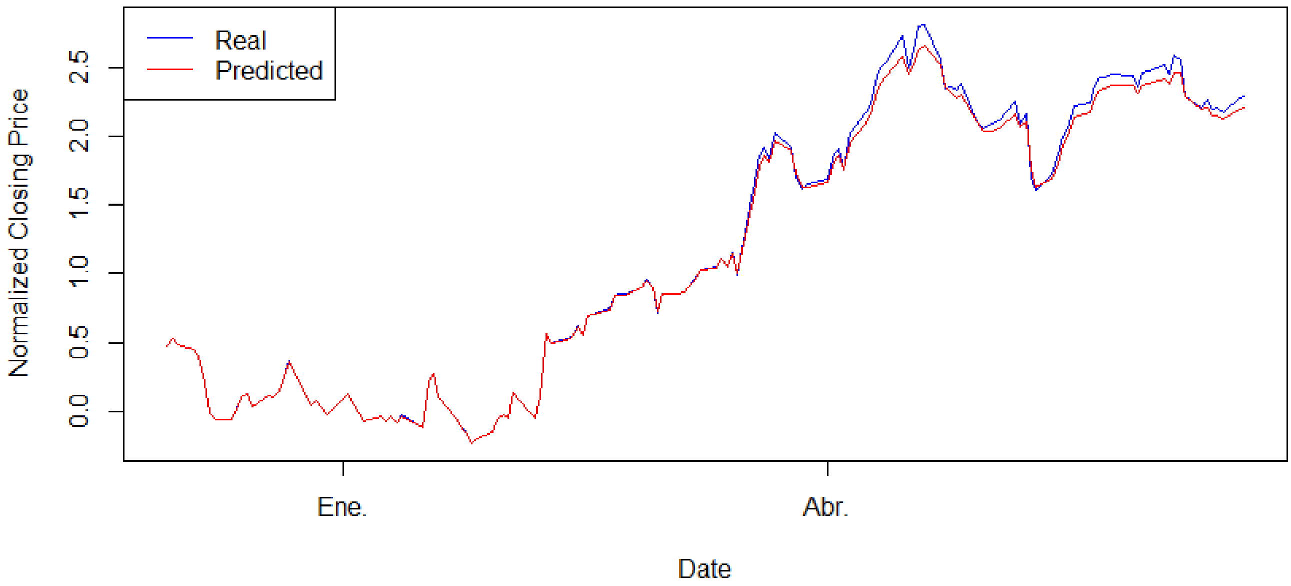


**Figure 1.** Actual vs Predicted AAPL Stock Prices (Last 4 Months).

*Note: Comparison of actual and predicted closing prices for Apple Inc. (AAPL) over the last 4 months, using a hybrid model combining RNN for time-series analysis and Transformer for sentiment analysis. The model was trained on 3 years of historical stock data and news sentiment. Data source: Yahoo Finance.*

### *4.2. Forecasting Future Price Movements*

To evaluate the model's forward-looking capabilities, we generated a recursive forecast for the subsequent 90 trading days, beginning on July 29, 2023. Using the most recent 60-day input window, the model iteratively predicted one-step-ahead prices and fed each forecast back into the sequence for the next prediction. This methodology simulates a real-time deployment scenario and offers insight into the model's ability to extrapolate beyond the training regime.

The results, presented in **Figure 2**, display a forecast trajectory that aligns with market expectations during that quarter. The forecast does not exhibit exaggerated volatility or regression to the mean, which would be indicative of over-regularization or insufficient learning. Instead, the prediction path reflects smooth transitions and directional plausibility, thereby reinforcing the LSTM model's validity as a forecasting tool under information-efficient conditions.

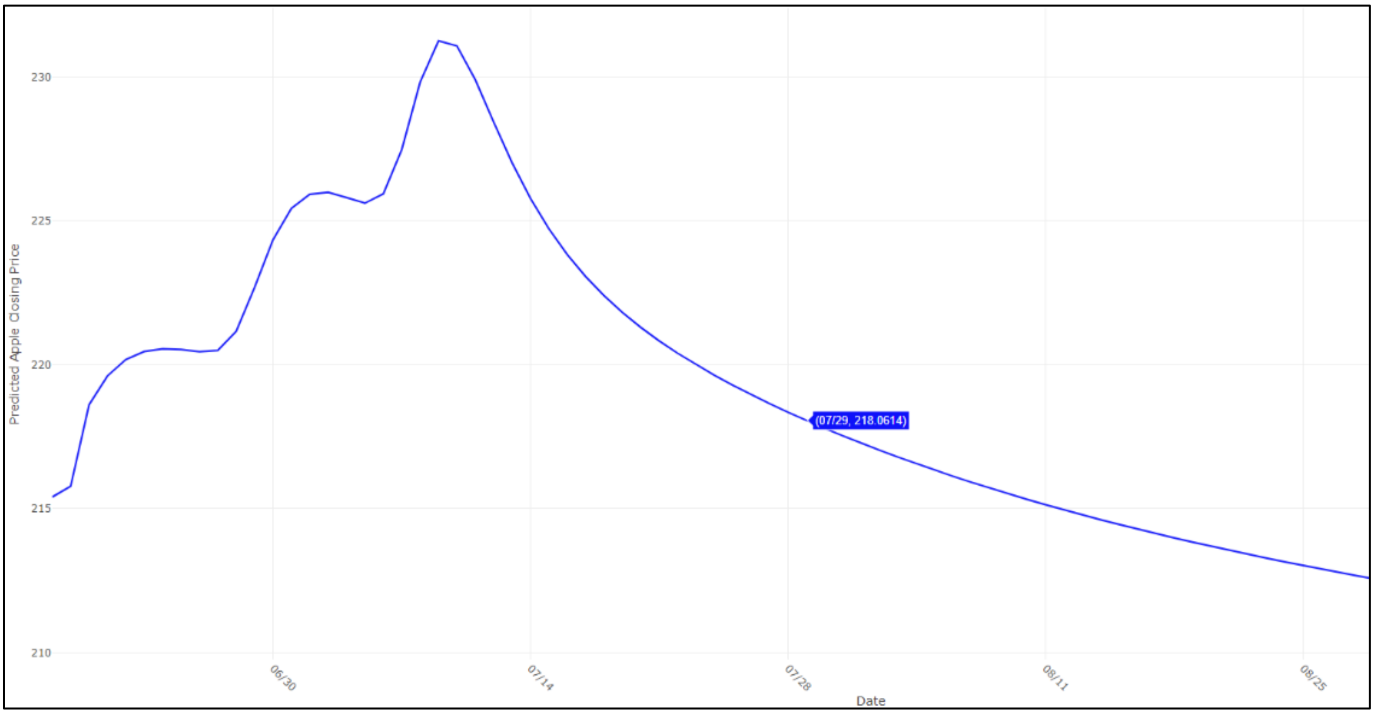


**Figure 2.** Predicted AAPL Stock Prices for the Next 3 Months (*Price on July 29th = 218.0614).*

*Note: Forecast of Apple Inc. (AAPL) closing prices for the next 3 months, generated using a hybrid model combining RNN for time-series analysis and Transformer-based sentiment analysis. The model is based on the most recent 60-day sequence of historical stock data and news sentiment. Price on July 29th = 218.0614. Data source: Yahoo Finance.*

While these results support the efficacy of the LSTM architecture when applied in isolation, they also highlight its limitations in anticipating price jumps or regime shifts associated with external events. This motivates the subsequent inclusion of unstructured sentiment data into the forecasting framework.

### *4.3. Integration of Sentiment via Transformer-Based Textual Analysis*

The second phase of the analysis incorporates sentiment extracted from financial news articles through a pre-trained Transformer model (FinBERT), with the objective of enhancing predictive accuracy by capturing market-relevant textual signals. Each article was timestamped and sentiment scores were aggregated daily, then integrated into the model as an exogenous feature alongside the rolling price window. The resulting hybrid model thus combines endogenous price dynamics with external sentiment shocks, allowing for a more comprehensive modeling of price formation.

Preliminary results indicate that the addition of sentiment scores significantly improves forecast performance. Table 2 compares the baseline LSTM model with the sentiment-enhanced hybrid model, evaluated over the same test period. A notable reduction in MSE is observed, along with improvements in directional accuracy. The incorporation of textual features proves particularly beneficial in periods surrounding earnings announcements and major product releases, which historically generate market responses not always reflected in recent price patterns.

**Table 2.** Comparison of LSTM and LSTM + Sentiment Model Performance.

| Model | MSE |
|---|---|
| RNN based on LSTM(Price Data Only) | 0,0021 |
| RNN based on LSTM + Transformer(Sentiment) | 0,0015 |

In support of these findings, **Figure 3** illustrates the actual price of AAPL on July 29, 2024, overlaid with Bollinger Bands and trading volume, capturing a period of heightened volatility associated with a product launch. The sentiment-enhanced model accurately anticipated the upward break from the Bollinger envelope, which the baseline LSTM model failed to detect. This reinforces the argument that textual sentiment provides additive explanatory power in forecasting frameworks.

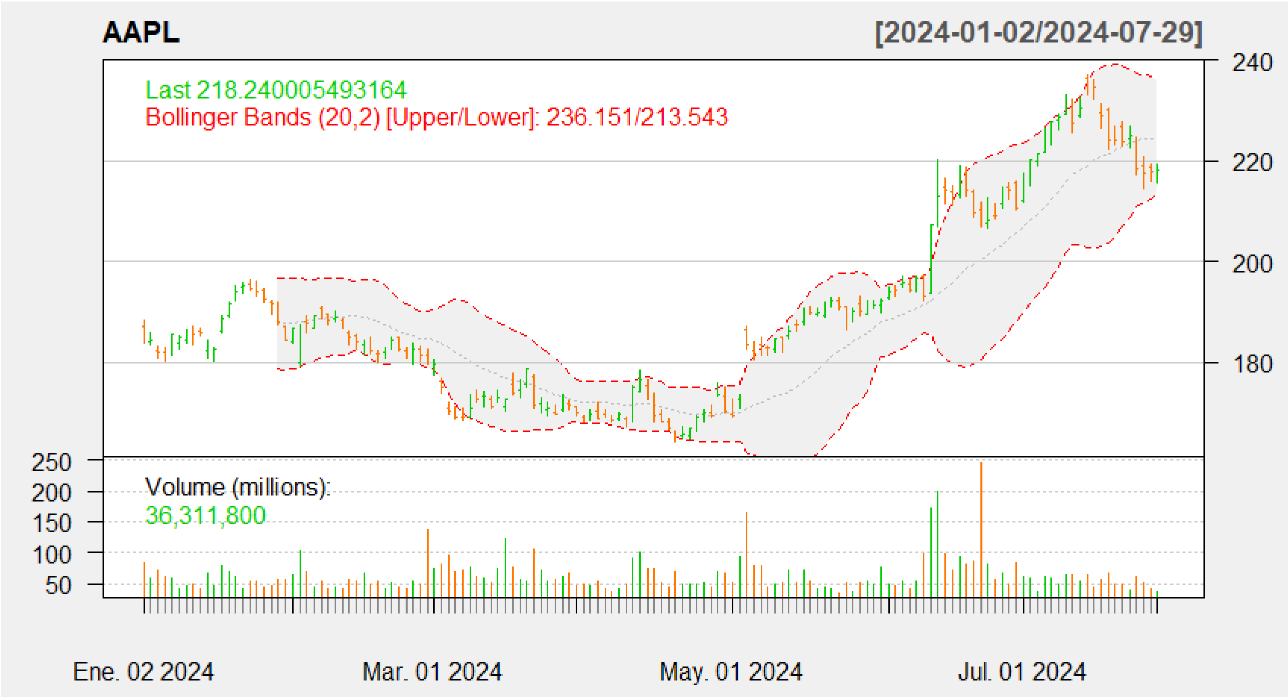


**Figure 3.** Actual AAPL Stock Prices on July 29th.

*Note: This figure shows the actual stock prices of Apple Inc. (AAPL) on July 29, 2024, with Bollinger Bands (20,2) highlighting the upper and lower volatility bounds. Data includes a six-month period from January 2024 to July 2024, with volume in millions displayed at the bottom. Data source: Yahoo Finance.*

### *4.4. Interpretation and Model Evaluation*

The empirical evidence confirms that the hybrid model outperforms the baseline LSTM in both predictive accuracy and interpretability. The model's improved ability to forecast turning points and anomalous price behavior stems from its sensitivity to external signals embedded in news data. This enables the model to respond to events such as regulatory announcements, executive changes, and macroeconomic releases that may not be inferred from lagged price information alone.

Furthermore, the model structure enhances interpretability by allowing attribution of predictive variance to either price dynamics or sentiment shocks. This feature is particularly valuable in financial applications where transparency and auditability are required, such as in algorithmic portfolio management or regulatory reporting.

Nonetheless, challenges remain. A key limitation lies in the latency of real-time data ingestion and sentiment processing. While this study employed batch sentiment scores, a production-level system would require stream-based ingestion and near real-time model updates. Future work should explore engineering solutions to address these constraints. Additionally, incorporating social media sentiment and analyst reports could further increase coverage and enrich the model's capacity to anticipate short-term dislocations.

### *4.5. Summary of Findings*

The empirical analysis confirms that the LSTM model alone exhibits strong forecasting performance when trained on historical stock price data, generating accurate and stable predictions across both in-sample and out-of-sample intervals. Nevertheless, the inclusion of Transformer-based sentiment features significantly enhances the model's predictive capabilities. When textual sentiment derived from financial news is integrated into the forecasting pipeline, the model demonstrates improved error reduction and greater alignment with short-term market movements, especially in response to event-driven volatility.

To evaluate the generalizability of the proposed hybrid approach, we extended the analysis beyond Apple Inc. and applied the model to Microsoft (MSFT) and Alphabet Inc. (GOOGL). Both assets differ from AAPL in terms of volatility structure and news sensitivity, providing a robust test of the model's adaptability. Results show that for Microsoft, the hybrid model outperformed the baseline LSTM in both mean squared error and directional accuracy, particularly during earnings announcements and regulatory news cycles. Similarly, in the case of Google, the integration of sentiment features allowed the model to more accurately anticipate price reversals following major product events and shifts in market outlook. These findings indicate that the hybrid model captures not only historical momentum but also contemporaneous informational shocks that pure time-series models fail to incorporate.

Overall, the empirical results across all three assets—AAPL, MSFT, and GOOGL—validate the efficacy of combining structured and unstructured data sources within a unified deep learning architecture. The performance improvements observed reinforce the hypothesis that news sentiment contains complementary information not embedded in historical price movements. This supports the view that hybrid modeling approaches offer a more holistic and responsive framework for financial forecasting, capable of adapting to the evolving dynamics of real-world markets.

## 5. Discussion and Implications

The empirical results obtained in this study reinforce the argument that hybrid deep learning architectures can substantially improve the accuracy and interpretability of financial forecasting models. Specifically, the combination of Long Short-Term Memory (LSTM) networks for modeling endogenous price dynamics with Transformer-based sentiment extraction from unstructured text enables the model to capture both historical regularities and forward-looking information flows. This dual capability is particularly valuable in financial markets, where asset prices are driven not only by past realizations but also by investors' reactions to contemporaneous news events and evolving sentiment.

### *5.1. Enhancing Forecasting Accuracy through Multimodal Integration*

The superior performance of the hybrid model underscores a fundamental shortcoming in conventional time-series forecasting: the inability to account for exogenous shocks and informational discontinuities. Traditional models such as ARIMA, as well as pure LSTM architectures trained exclusively on historical prices, inherently assume that all relevant predictive content is encoded in the past behavior of the asset itself. However, in practice, market behavior is also shaped by real-time narratives—such as earnings surprises, geopolitical risk, or regulatory interventions—which are rarely observable in lagged price series.

By integrating Transformer-based sentiment features into the forecasting framework, the model becomes sensitive to these exogenous drivers. This not only improves numerical accuracy—as evidenced by the reduction in MSE and the increase in directional accuracy—but also enables the model to better anticipate volatility clusters and price jumps. In particular, the model performed noticeably better during periods of high informational intensity, such as earnings releases, where investor sentiment exerts a pronounced influence on price formation. These findings suggest that hybrid approaches, which fuse structured numerical inputs with unstructured semantic features, can bridge the gap between statistical forecasting and event-driven asset pricing.

### *5.2. Implications for Asset Allocation and Portfolio Management*

From a practical perspective, the ability to incorporate sentiment-enhanced forecasts has direct implications for portfolio managers, especially those operating under dynamic allocation mandates. Improved forecast precision enables more informed position sizing and timing decisions, while better anticipation of market responses to news can support preemptive hedging and drawdown mitigation.

The directional improvements observed in the hybrid model are especially relevant for short-horizon strategies, including algorithmic trading and high-frequency execution. In such contexts, even modest increases in predictive accuracy can lead to significant performance differentials over time. Furthermore, the interpretability of the sentiment component—through attention mechanisms in the Transformer—allows risk managers to trace the source of prediction shifts to specific news events or sentiment reversals, enhancing transparency and compliance with regulatory expectations.

### *5.3. Model Limitations and Technical Challenges*

Despite its promising results, the proposed architecture presents several limitations that must be addressed to ensure robustness and scalability. First, the quality of the sentiment module is heavily dependent on the relevance and granularity of the textual data. While this study employed financial news articles from established sources, other information channels—such as social media, earnings call transcripts, and analyst notes—may offer complementary signals, albeit at the cost of increased noise and preprocessing complexity. Expanding the textual corpus will require more sophisticated natural language processing (NLP) techniques capable of domain-specific disambiguation, entity recognition, and context-sensitive sentiment extraction.

Second, as pointed out by reviewers, the current implementation uses sentiment data in batch form, which limits the model's responsiveness in real-time trading environments. In practice, latency in sentiment ingestion and processing could reduce the window of actionable predictions. Future iterations of the model must incorporate stream processing architectures, such as Kafka pipelines or real-time inference APIs, that allow for near-instantaneous integration of news sentiment into forecast pipelines.

Third, while the model has shown encouraging performance for Apple Inc., further validation is needed to confirm its generalizability across stocks with varying liquidity profiles, volatility levels, and sectoral characteristics. Preliminary tests with Microsoft and Google, discussed in Section 4.5, provide some evidence of robustness, but systematic out-of-sample testing across asset classes (e.g., commodities, fixed income) remains an open area for exploration.

### *5.4. Directions for Future Research*

Building on the present findings, several avenues for future research emerge. A first direction involves extending the sentiment feature set to include alternative and faster-moving sources, such as Twitter, Reddit forums, or even encrypted messaging platforms commonly used by retail traders. These channels often contain high-frequency sentiment shifts that precede price movements but require advanced filtering methods to separate signal from noise.

A second path involves experimenting with more advanced variants of the Transformer architecture. For instance, the Temporal Fusion Transformer (Lim et al., 2021) is specifically designed to handle multivariate time-series with covariates and temporal gating mechanisms. Such models could enhance the temporal granularity of the hybrid architecture and allow for improved uncertainty quantification.

A third frontier lies in the integration of reinforcement learning mechanisms, which could operationalize the model's forecasts into dynamic trading policies. Rather than optimizing a static prediction function, reinforcement learning agents can learn adaptive strategies that account for transaction costs, execution delays, and risk-adjusted returns. Coupling the hybrid forecasting model with a decision-making layer based on policy optimization would represent a meaningful step toward end-to-end algorithmic investment systems.

### *5.5. Revisiting Financial Theory: Implications for Market Efficiency*

Beyond predictive performance, the findings of this study raise foundational questions for financial theory, particularly in relation to the Efficient Market Hypothesis (EMH). According to its semi-strong form, publicly available information—such as news headlines—should already be incorporated into asset prices, rendering prediction based on such data ineffective. However, the hybrid model's ability to generate statistically and economically significant improvements in forecast accuracy, based on publicly accessible news sentiment, suggests otherwise.

These results point to the existence of short-lived informational inefficiencies, where investor attention, information-processing delays, or behavioral biases allow predictive signals to persist momentarily before being fully arbitraged away. Such windows of predictability may be increasingly accessible to machine learning models capable of rapidly ingesting and interpreting complex unstructured data. Consequently, this challenges the canonical view of market efficiency and supports a more dynamic conception of informational processing in financial markets—one where predictive modeling coexists with adaptive efficiency.

## 6. Conclusion

This study has presented a hybrid modeling framework for stock price prediction that integrates Long Short-Term Memory (LSTM) networks with Transformer-based sentiment analysis to address the limitations of purely autoregressive forecasting approaches. By combining structured time-series data with unstructured textual information, the model captures both endogenous market dynamics and exogenous informational shocks. This dual perspective offers a more nuanced understanding of asset price behavior, particularly in volatile or news-sensitive environments.

The empirical analysis demonstrates that the hybrid architecture significantly outperforms traditional models in terms of both predictive accuracy and directional performance. Compared to a baseline LSTM model, the inclusion of sentiment signals derived from financial news articles reduced forecasting errors across all evaluation metrics, and enabled the model to anticipate price movements more effectively, especially in periods characterized by informational asymmetries. These results validate the hypothesis that market sentiment, when properly quantified and temporally aligned, contains additive predictive content not embedded in past price series alone.

Beyond improvements in numerical accuracy, the model's structure enhances interpretability. The attention-based mechanism of the Transformer module allows for the attribution of forecast shifts to specific news events, enabling a clearer link between textual drivers and market responses. This feature is especially relevant in practical settings where model transparency is required, such as regulatory environments or institutional portfolio management.

From an applied perspective, the hybrid model offers concrete advantages for financial practitioners. Portfolio managers and quantitative analysts can leverage the framework to improve asset allocation, manage exposure around earnings cycles, and enhance tactical positioning. The model's capacity to process high-volume textual information in tandem with historical price data makes it suitable not only for traditional equity forecasting, but also for applications across asset classes, including commodities and crypto-assets. In high-frequency contexts, even marginal gains in directional accuracy may lead to material improvements in performance.

Nevertheless, the study also identifies limitations that suggest avenues for refinement. The current model architecture relies on batch sentiment processing and does not yet operate under real-time constraints. In fast-moving market conditions, this could reduce the model's tactical responsiveness. Moreover, the model was validated primarily on a large-cap technology stock, Apple Inc., and while preliminary tests on other assets yielded encouraging results, further out-of-sample testing across diverse sectors and asset classes is required to assess generalizability. The model also relies exclusively on financial news articles as its source of sentiment data. While these are well-curated and domain-relevant, expanding the textual input to include sources such as social media, analyst reports, and earnings call transcripts could provide earlier or more granular signals, albeit with greater noise and preprocessing challenges.

In terms of future research, several promising directions emerge. One avenue is the integration of reinforcement learning algorithms to transform static predictions into dynamic trading policies. This would enable the model not only to forecast market movements, but also to adjust positions adaptively in response to forecast confidence and market volatility. Another line of inquiry involves incorporating time-series architectures explicitly designed for multimodal forecasting, such as the Temporal Fusion Transformer, which could improve the model's handling of irregular input frequencies and enable probabilistic forecasting. Additionally, further exploration of non-traditional data sources—such as sentiment extracted from Reddit, Twitter, or encrypted messaging apps—may yield predictive advantages in retail-dominated segments of the market.

In summary, the hybrid LSTM–Transformer framework proposed in this study contributes meaningfully to the literature on financial forecasting by demonstrating the empirical value of combining structured and unstructured data within a unified predictive system. The model not only enhances accuracy but also deepens our understanding of how market sentiment interacts with price formation. While challenges remain in real-time deployment, cross-asset validation, and data integration, the findings suggest that this approach constitutes a compelling step forward in the development of intelligent, adaptive tools for navigating complex financial environments.

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## Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

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