

# Evaluation of Stock Market Prediction Techniques

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**Abstract**—This study evaluates the performance of traditional and deep learning models in predicting stock prices using a mix of financial and behavioral data. The Dow Jones Industrial Average (DJIA) was forecasted for one-day, three-day, and seven-day horizons using ARIMA, LSTM, and Temporal Convolutional Networks (TCN). The input consisted of 50+ feature engineered signals like technical indicators with sentiment and intent signals from news and Reddit data.

Results showed that ARIMA performed best for short-term forecasts, while the stacked LSTM gave the most reliable performance across all time frames. TCN performed best compared to other models across multiple time horizons. The findings highlight the importance of using multimodal data and selecting models based on forecast horizon.

**Keywords**— Stock prediction, ARIMA, LSTM, TCN, Sentiment analysis, Multimodal data, Time series forecasting.

## I. INTRODUCTION

The global stock market, valued at over \$100 trillion, plays a crucial role in shaping investment flows, corporate performance, and broader economic conditions [1]. Despite technological advancements, predicting future stock prices remains highly complex due to the dynamic, volatile, and nonlinear nature of financial time series data [2], [3]. Prices are influenced not only by historical patterns and technical indicators but also by external factors such as news sentiment, social media activity, and investor behavior [4]–[6].

Traditional methods such as Autoregressive Integrated Moving Average (ARIMA) have been used extensively for financial forecasting [7], offering reasonable short-term performance under stationary assumptions. However, their inability to model nonlinear dependencies limits their effectiveness in capturing market volatility [1]. To overcome these limitations, deep learning models such as Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs) have been proposed [8]–[10]. LSTM models are designed to retain long-range dependencies in time-series data, while TCNs leverage parallelized convolutions and causal padding to learn complex temporal features effectively [10], [11].

In recent studies, hybrid and multimodal approaches have been explored to enhance model robustness and accuracy. These include combining structured time series with unstructured data sources like news headlines and social sentiment [4], [5], [12]. Notably, multimodal systems have demonstrated

strong potential in capturing behavioral signals that precede market trends [13], [14].

This research aims to compare the performance of ARIMA, LSTM, and TCN models in forecasting the closing price of the Dow Jones Industrial Average (DJIA) index across multiple forecast horizons—one day, three days, and seven days ahead. A multimodal dataset was constructed using historical stock data with sentiment and intent signals extracted from financial news and Reddit discussions. Evaluation was carried out using standard regression metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ( $R^2$ ). The results show that TCN outperforms both ARIMA and LSTM across most timeframes, except for the longest horizon ( $t+7$ ), where ARIMA showed marginally better generalization under volatility [15], [16].

## II. RELATED WORK

The foundation for this study was laid by this work [17]. Transformer-based deep reinforcement learning model was combined with the Black-Litterman framework for portfolio optimization. Their method was applied on DJIA data and showed significant returns over traditional methods by effectively capturing dynamic asset correlations and investor views. The approach demonstrated that blending neural architectures with financial techniques like Black-Litterman could lead to better investment strategies. This paper directly inspired the direction of the current study: to explore deep learning methods applied to stock market prediction using multimodal signals.

Numerous studies have evaluated the performance of deep learning architectures in time-series forecasting. [18] provided a comparative review of MLP, CNN, and TCN models, highlighting that TCNs tend to outperform RNN-based models in trend prediction tasks. [10] demonstrated that TCNs outperform RNNs such as LSTM and GRU particularly in multi-output regression tasks. Similarly, [13] introduced a 3D-CNN-GRU model with optimization-driven feature selection, achieving high accuracy on NIFTY 50 stock index. These insights support the inclusion of Temporal Convolutional Networks and LSTM-based architectures in this experimental framework. Additional support for TCN's strength in forecasting non-stationary series comes from [15], who proposed a wavelet-

enhanced TCN hybrid that consistently outperformed LSTM and GRU.

Studies have also shown the integration of behavioral sentiment and technical indicators in prediction frameworks. [5] employed a Transductive LSTM with sentiment extracted from social media to improve model robustness in non-stationary regimes. [4] proposed a deep fusion architecture combining news headlines and time-series features, resulting in improved forecasting accuracy. Similarly, [19] combined BERT-based sentiment scores with LSTM models, while [20] used denoising techniques with deep LSTM networks for market index prediction. The consistent inclusion of sentiment signals across these studies shows that the stock market is heavily influenced by sentiment and intent of the trader and improves the accuracy of the models while predicting a stock movement.

The volatile and nonlinear nature of financial markets has been thoroughly explored in recent literature. [1] analyzed DJIA and S&P500 data during geopolitical crises, revealing that technical indicators retained predictive value under extreme uncertainty. [7] conducted a systematic review confirming that deep neural networks—particularly hybrid and ensemble models—are better suited to capture market volatility than traditional models. Further, [3] and [2] emphasized the importance of volatility-aware modeling frameworks, particularly in the presence of sudden financial shocks.

In addition to modeling strategies, several supporting techniques have emerged as key enablers for effective forecasting. [12] proposed a federated MLP-LSTM architecture for privacy-preserving stock prediction, while [21] introduced ResNLS with residual connections to enhance prediction. Preprocessing methods such as wavelet decomposition, as used in [15], and MinMax scaling, used throughout multiple studies including this study, have proven effective for stabilizing model training. Moreover, [11] highlighted that TCNs offer advantages in convergence speed and anomaly detection, especially in multivariate time series, further supporting their application in high-dimensional financial datasets.

Collectively, these works show that over the years from traditional models toward explainable, sentiment-aware, and volatility-resilient architectures are crucial in forecasting. The current study builds upon this foundation, aiming to benchmark classical and deep learning methods under a multimodal framework for DJIA (post geopolitical crisis) forecasting in such a volatile time frame.

### III. DATASET AND FEATURE ENGINEERING

This study uses a feature-engineered multimodal dataset focused on the Dow Jones Industrial Average (DJIA), spanning over 1900 trading days (~8 Years) was chosen from Kaggle [22]. There were three datasets - financial data, news articles, and Reddit discussions, captures both quantitative and behavioral signals that may influence market movements.

#### A. Technical Indicators

To represent core market movements, I included three key technical features: These features were engineered from historical price data<sup>1</sup>:

- **Log Returns:** Captures the daily log return of the closing price to measure relative change in price.

$$R_t = \log \left( \frac{P_t}{P_{t-1}} \right)$$

where  $R_t$  is the log return on day  $t$ , and  $P_t$  is the closing price on day  $t$ .

- **Volatility log10:** Represents the 10-day rolling standard deviation of log returns, scaled by the square root of 252 to annualize the volatility.

$$\sigma_t = \sqrt{252} \times \text{StdDev}(R_{t-9}, R_{t-8}, \dots, R_t)$$

where  $\sigma_t$  is the estimated annualized volatility at time  $t$ .

- **Percentage Change:** Computes the simple daily percentage change in price.

$$\Delta_t = \left( \frac{P_t - P_{t-1}}{P_{t-1}} \right) \times 100$$

where  $\Delta_t$  is the percent change at time  $t$ .

#### B. Sentiment and Intent Features

Behavioral features were computed using Natural Language Processing (NLP) techniques applied to both news headlines and Reddit posts. Three independent sentiment scoring techniques were used [4]:

- **VADER sentiment** for analyzing social media text.
- **FinBERT sentiment**—a transformer model fine-tuned on financial documents.
- **Smart sentiment**, a technique that corrected FinBERT outputs based on hand-written financial trigger words (e.g., down-weighting neutral sentiment if keywords like “crash” or “crisis” appeared).

To contextualize sentiment with behavioral intent, I implemented a custom keyword-matching dictionary to extract psychological signals from both Reddit and news text. The model computed nine intent types: *buying, selling, uncertainty, urgency, prediction, fear, greed, question, and action*.

Each intent feature was calculated as<sup>2</sup>:

$$I_i = I_i^{\text{news}} + I_i^{\text{reddit}}, i \in \{\text{buying, selling, fear, uncertainty, } \dots\}$$

However, the raw intent scores ranged from  $-2$  to  $+1.8$ , while sentiment scores (e.g., VADER, FinBERT) lie within  $[-1, +1]$ . To align these distributions and avoid introducing scale bias during model training, all intent values were **min-max normalized** to the  $[-1, 1]$  range.

Finally, sentiment and intent features were fused to create hybrid behavioral indicators:

$$\begin{aligned} \text{sentiment\_minus\_fear} &= \text{finbert\_final\_sentiment} \\ &\quad - \text{normalized\_fear\_intent} \\ \text{sentiment\_minus\_uncertainty} &= \text{finbert\_final\_sentiment} \\ &\quad - \text{normalized\_uncertainty\_intent} \end{aligned}$$

These feature-engineered intents aimed to identify emotional nature of the stock market, such as positive sentiment

<sup>2</sup>LaTeX formatting for formulas were assisted by ChatGPT [23].

overshadowed by fear or uncertainty—critical signals. All features were scaled and merged into ‘multimodal\_dataset’ for time series modeling.

### C. Target Variables

The forecasting task is framed as a **multi-output regression problem**, where the models predict three future target variables:

- **t+1** — Closing price of the next trading day,
- **t+3** — Closing price three days ahead,
- **t+7** — Closing price seven days ahead.

This enables the models to learn both short-term and mid-term temporal dependencies in the architecture. All target variables were normalized using `MinMaxScaler`, and the input features were segmented into sliding window of **60 time steps** (for LSTM) and window of **30 time steps** for TCN, which leverages dilated convolutions and does not require long historical sequences.

## IV. METHODOLOGY

This study compares three models—ARIMA, LSTM, and Temporal Convolutional Network (TCN)—for forecasting DJIA closing prices at three horizons: t+1, t+3, and t+7. A multimodal dataset of technical, sentiment, and intent features was used. Supervised learning sequences were constructed using a sliding window approach over the time series.

### A. Modeling Pipeline

The pipeline followed five key steps:

- 1) **Data Preprocessing:** Missing values were dropped because during feature engineering percentage change and volatility log 10 introduced NaN values which only could be dropped. All sentiment and intent features were scaled to the range  $[-1, 1]$  using `MinMaxScaler`.
- 2) **Sequence Generation:** For LSTM, 60-step sequences (3 months) were used. For TCN, a 30-step window was found optimal after experimentation.
- 3) **Train-Test Split:** A manual 80:20 chronological split was applied to maintain temporal order and prevent lookahead bias. The model was trained only on train dataset in a separate notebook and same for the test.
- 4) **Model Training:** Each model was reinitialized for every forecast horizon to avoid memory leakage. TensorFlow memory was explicitly cleared between runs to ensure accurate and isolated training.
- 5) **Evaluation:** Performance was measured using RMSE, MAE, and  $R^2$  on training and unseen data. Additionally, residual and forecast plots were generated for visual analysis.

### B. Baseline: ARIMA

ARIMA was implemented as a univariate baseline model. For each forecast horizon, the model was retrained at each time step using past values up to  $t$ . The auto arima function was used to automatically determine the best parameters  $(p, d, q) = (1, 1, 1)$ , and predictions were made in a rolling

window fashion. Model performance was evaluated on a true future holdout series, not just in-sample forecasts. After each training cycle, and models were serialized with `joblib` for testing on the unseen data.

### C. LSTM Architectures

Two variants of LSTM were trained for each forecast horizon using a supervised learning setup:

- **Single-layer LSTM:** This model used 64 hidden units followed by a dropout layer and a dense output unit. It served as a fast and lightweight benchmark.
- **Stacked LSTM:** A deeper model with two LSTM layers (64 units + 32 units), both regularized using  $L_2$  constraints. Dropout was used after each layer to improve generalization. This version was found to generalize better across short-term and mid-term horizons.

Input sequences of shape (50, features) were used. The model predicted one output value for each sample, corresponding to the price at  $t + h$ . Targets were normalized independently, and inverse scaling was performed post-prediction.

All training runs used the Adam optimizer with a learning rate of  $1 \times 10^{-4}$ , mean squared error (MSE) loss, batch size 32, and early stopping on validation loss with a patience of 5 epochs. The models and scalers were saved for reuse during testing.

### D. Temporal Convolutional Network (TCN)

The TCN model was trained to predict the **log return** of DJIA prices at future horizons. The predicted log return was then used to reconstruct the actual price using:

$$\hat{P}_{t+h} = P_t \cdot e^{\hat{r}_{t+h}}$$

where  $\hat{r}_{t+h}$  is the predicted log return and  $P_t$  is the closing price at the end of the input window.

TCN architecture:

- **Input:** Sequences of 30 time steps and all available features.
- **Architecture:** 1D dilated causal convolutions with 32 filters and kernel size 2, followed by `GroupNormalization`, dropout (0.2), and a dense output layer.
- **Training:** Adam optimizer, Huber loss, batch size 32, early stopping with patience 5.
- **Clipping:** Predicted log returns were clipped between  $[-0.15, 0.15]$  to avoid exponential blow-ups during price reconstruction.

As with LSTM, the TensorFlow graph was cleared between runs. Models were saved along with their respective scalers and feature metadata.

### E. SHAP Analysis for TCN

To interpret the contribution of individual features across different forecast horizons, SHAP (SHapley Additive exPlanations) analysis was performed on trained TCN models using the `KernelExplainer`.

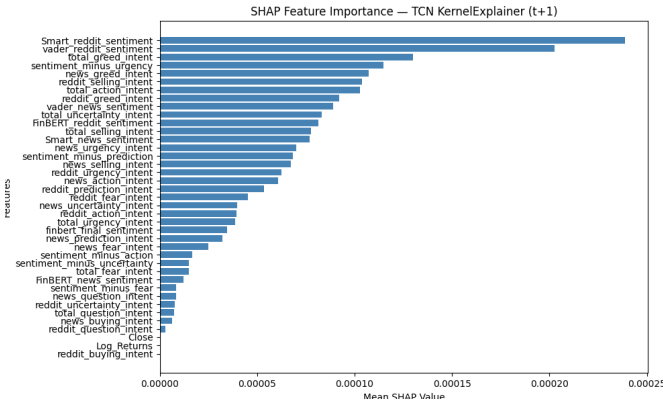


Fig. 1. SHAP feature importance — TCN prediction at t+1 horizon

#### Key observations:

- For **t+1**, the most important signals were Smart reddit sentiment, vader reddit sentiment, and total greed intent.
- For **t+3**, features like reddit prediction intent, news urgency intent, and news greed intent dominated.
- For **t+7**, higher-level sentiment aggregates such as Smart reddit sentiment and Smart news sentiment had the most influence.

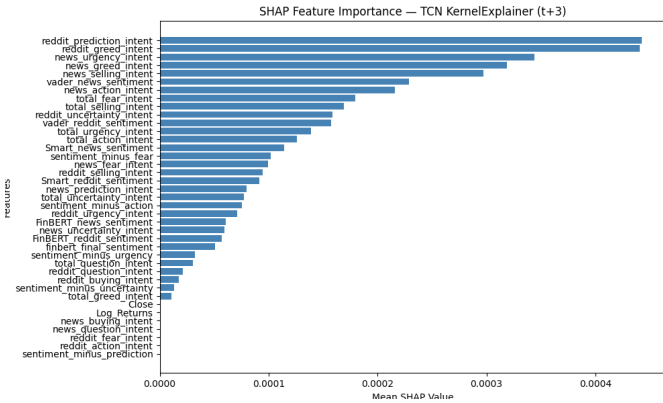


Fig. 2. SHAP feature importance — TCN prediction at t+3 horizon

Interestingly, traditional technical indicators such as `Close` and `Log Returns` ranked among the least influential. This validated the hypothesis that multimodal behavioral signals are more informative for modern financial forecasting than legacy technical metrics.

TCN was robust in learning the patterns between feature engineered behavioural intent and the actual price of the stock.

After analyzing SHAP output, there is a pattern which TCN did learn- Stock market is heavily influenced primarily on traders behavior compared to other technical indicators and

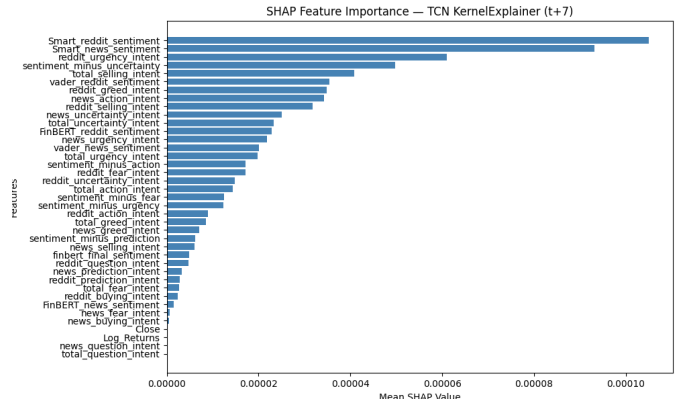


Fig. 3. SHAP feature importance — TCN prediction at t+7 horizon

metrics. This setting simulates real-life decisions that traders make while purchasing a stock.

Implementing SHAP really helped fine-tune TCN and reducing the feature set as during training, TCN was only able to learn noise which was indicating that the model was overfitting.

## V. RESULTS AND EVALUATION

This section presents the performance of all models—ARIMA, LSTM (Simple and Stacked), and TCN—on forecasting the DJIA closing price at future horizons of t+1, t+3, and t+7. Evaluation metrics include Coefficient of Determination ( $R^2$ ), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). All models were trained on 80% of the data and evaluated on the remaining 20%, with TensorFlow memory cleared between each model run to ensure isolated performance measurement.

### A. ARIMA Performance

TABLE I  
ARIMA TRAIN AND TEST PERFORMANCE

Horizon	Train			Test		
	$R^2$	RMSE	MAE	$R^2$	RMSE	MAE
t+1	0.9921	238.87	136.61	<b>0.8655</b>	<b>228.79</b>	<b>170.45</b>
t+3	0.9877	297.54	190.21	0.7433	316.38	236.20
t+7	0.9800	380.06	260.24	0.5662	413.11	317.17

The ARIMA model showed excellent performance for short-term forecasting (t+1), with the highest test  $R^2$  among all models in that category. This aligns with its strength in capturing autoregressive and trend components in stationary series. However, the model's performance dropped off rapidly for longer horizons due to its inability to incorporate external or nonlinear signals like sentiment or volatility.

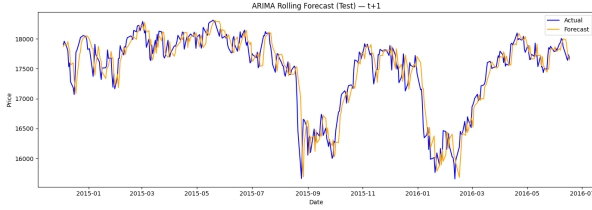


Fig. 4. ARIMA Forecast — t+1 Horizon

The t+1 prediction plot reveals that ARIMA closely follows the actual DJIA prices, particularly during low-volatility phases. Minor lags appear during sharp directional changes, suggesting the model's lag in adapting to market shocks.

### B. LSTM (Simple)

TABLE II  
SIMPLE LSTM TRAIN AND TEST PERFORMANCE

Horizon	Train			Test		
	R <sup>2</sup>	RMSE	MAE	R <sup>2</sup>	RMSE	MAE
t+1	0.9881	294.14	225.36	<b>0.7606</b>	<b>319.58</b>	<b>263.98</b>
t+3	0.9863	315.44	241.68	0.2669	559.01	459.02
t+7	0.9855	323.81	246.69	0.4156	501.07	384.07

The simple LSTM architecture generalizes really well on the t+1 horizon, with a test R<sup>2</sup> of 0.76. However, generalization quickly deteriorates for longer-term targets, reflecting underfitting and the limited expressiveness of a shallow network when handling multimodal volatility-prone financial data.

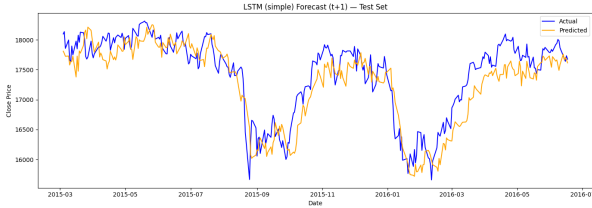


Fig. 5. Simple LSTM Forecast — t+1 Horizon

The t+1 plot demonstrates that while the model captures the directional movement of the price trend, it shows delay around peaks and valleys, suggesting insufficient sensitivity to sudden changes despite using sentiment-enhanced features.

### C. LSTM (Stacked)

TABLE III  
STACKED LSTM TRAIN AND TEST PERFORMANCE

Horizon	Train			Test		
	R <sup>2</sup>	RMSE	MAE	R <sup>2</sup>	RMSE	MAE
t+1	0.9826	355.83	272.09	0.3267	535.94	454.12
t+3	0.9858	320.75	251.53	0.3985	506.37	409.86
t+7	0.9700	466.63	365.38	<b>0.4252</b>	<b>496.95</b>	<b>376.23</b>

The stacked LSTM model overfit slightly on the training set, especially at t+1 where test R<sup>2</sup> dropped significantly. However,

its deeper structure helped stabilize predictions at t+7, where it beats the simple LSTM model by a small margin. This highlights its utility in longer sequences, but at the cost of variance on shorter ones.

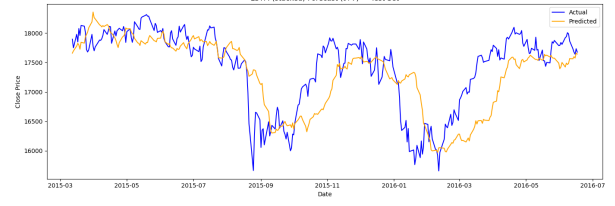


Fig. 6. Stacked LSTM Forecast — t+7 Horizon

The t+7 forecast illustrates that while the model roughly tracks price levels, deviations during large jumps show an inability to anticipate unexpected shocks—likely due to its deterministic nature despite behavioral inputs.

### D. Temporal Convolutional Network (TCN)

TABLE IV  
TCN TRAIN AND TEST PERFORMANCE

Horizon	Train			Test		
	R <sup>2</sup>	RMSE	MAE	R <sup>2</sup>	RMSE	MAE
t+1	0.9953	186.12	136.56	<b>0.8767</b>	<b>225.27</b>	<b>169.23</b>
t+3	0.9910	257.10	189.87	0.7584	316.20	231.83
t+7	0.9831	351.86	257.75	0.5483	434.50	331.63

The TCN model clearly outperformed all others at t+1 and t+3 horizons. Its dilated convolutions captured short and medium-term dependencies better than recurrent models. SHAP analysis further confirmed that intent and sentiment signals had stronger influence in these short-term scenarios.

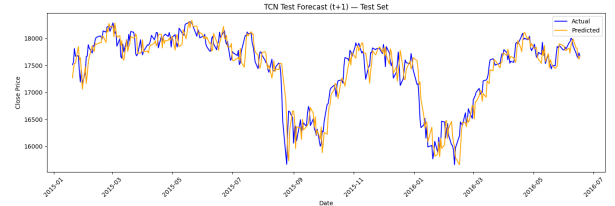


Fig. 7. TCN Forecast — t+1 Horizon

The t+1 TCN plot shows a tight fit between predictions and actual values, particularly around both local peaks and troughs. Better than ARIMA and LSTM, it adapted rapidly to directional shifts, validating the role of parallel temporal processing in financial forecasting.

## VI. LIMITATIONS

Despite the promising results achieved through the application of ARIMA, LSTM, and TCN models on a multimodal dataset, several limitations should be acknowledged to address the scope and generalizability of the findings.

First, the dataset used in this study was limited to approximately eight years of DJIA data, with only 1,989 trading days. While this time span includes periods of high volatility and geopolitical stress, it may not fully capture structural market regime shifts or rare macroeconomic events that could influence long-term generalization. Additionally, the reliance on a single market index (DJIA) may constrain the use of insights to other markets with different liquidity structures, asset compositions, or investor behavior.

Second, although sentiment and intent signals were extracted from both news and Reddit, the construction of these behavioral features depended on a keyword-matching approach. While effective in identifying broad emotional categories, this method may overlook linguistic cues or sarcasm that can significantly alter sentiment interpretation, particularly in user-generated content. Furthermore, intent classification was conducted using hand-crafted rule sets rather than learned models, which may have introduced bias or omitted context-specific meanings.

Third, the normalization strategy, while necessary for model convergence, may have unknowingly smoothed out extreme values that hold predictive significance during financial shocks or black swan events. Moreover, all models were trained and evaluated on a fixed time window using chronologically split data. This setup, while guarding against leakage, does not account for real-time deployment challenges such as concept drift or shifting sentiment baselines over time.

Finally, the deep learning models (LSTM and TCN) were optimized using standard architectures and hyperparameters. While adequate for benchmarking, further exploration of architecture search or ensembling techniques may yield improved results, particularly for long-horizon predictions. Model explainability, although feature engineering and SHAP analysis was used, remains limited in its granularity and interpretability for traders or users in financial contexts.

These limitations highlight areas for future refinement and emphasize the need for careful interpretation of results in practical forecasting situations.

## VII. CONCLUSION

This study compared the effectiveness of ARIMA, LSTM (Simple and Stacked), and Temporal Convolutional Network (TCN) models for forecasting the DJIA closing price across three horizons:  $t+1$ ,  $t+3$ , and  $t+7$ . Each model was trained using a multimodal dataset combining technical indicators with sentiment and intent signals derived from news and Reddit discussions.

Among all models, the TCN architecture demonstrated the strongest overall performance—especially at short-term horizons ( $t+1$ ,  $t+3$ ). Its ability to process sequential data using dilated causal convolutions allowed it to capture both rapid sentiment-driven fluctuations and broader temporal trends. ARIMA, while effective in  $t+1$  forecasting due to its low-variance nature, failed to generalize beyond short horizons. LSTM models showed moderate improvement with added

depth, but struggled with overfitting and volatility during long-term forecasts.

SHAP analysis further validated that behavioral features—particularly Reddit sentiment and urgency-related intents—were highly influential predictors, often outperforming traditional price-derived indicators in short-term contexts. This underlines the growing role of alternative data in financial time series modeling.

While TCN emerged as the most robust model in this study, its performance at  $t+7$  still trailed behind ARIMA's simplicity in some cases. This reflects a broader trade-off between model complexity and horizon length: deep models learn more patterns, but may generalize poorly in low-signal regimes without careful tuning.

**Future work** may explore ensemble techniques that combine the stability of ARIMA, the sequence-learning strength of LSTM, and the parallelism of TCN. Integrating more granular features like intraday sentiment, volume spikes, or macroeconomic news could further improve forecasting accuracy. Additionally, interpretability tools like SHAP should remain central to understanding these black-box models in high-stakes financial environments.

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