

# Deep Learning Approaches to Stock Market Prediction Integrating Political Instability

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**Abstract.** Financial markets are becoming increasingly vulnerable to volatility caused by political events; however, conventional predictive models often neglect to account for real-time political instability, leading to considerable prediction inaccuracies during uncertain times. This research aims to fill this void by presenting a Dynamic Political Instability Index alongside an innovative Hybrid Attention Model that combines Bidirectional Long Short-Term Memory (BiLSTM) networks with Multi-Head Attention mechanisms. By integrating 40 years of data from the Dow Jones Industrial Average (DJIA) with the Daily Trade Policy Uncertainty (TPU) index and sentiment scores processed through VADER, the proposed framework effectively captures both temporal dependencies and discrete political shocks. Experimental findings indicate that the Hybrid Attention model significantly surpasses baseline LSTM, BiLSTM, and Transformer models. Importantly, the model addresses the "persistence bias" typically found in conventional recurrent networks, enabling the prediction of market trends instead of simply responding to past price levels.

**Keywords;** deep learning; stock market prediction; political instability; attention mechanism; LSTM; sentiment analysis; financial forecasting

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## 1. Introduction

The stock market is a highly complex and intricate system influenced by a variety of factors ranging from corporate performance to changes in the economy. Political events, in particular stand out to be powerful influence that can increase market volatility, and a single policy change can have significant bearing on investor mindset [1].

The past several years has seen a significant increase in political uncertainty from COVID-19 to Trump's trade war, these factors contribute significantly to political uncertainty. We can clearly see the effects of these events on financial markets, which question the accuracy of these traditional prediction models that rely on historical price patterns and economic fundamentals [2].

Incorporating political factors into stock prediction models provides a significant opportunity to improve them, however it is a substantial challenge. Political instability has been mentioned as a very important factor to consider when developing these models, however they struggle to incorporate these factors in a meaningful and actionable way. The gap creates a significant increase in prediction errors, in a time when the increasing political instability is hard to ignore.

## 2. Problem Statement

Current stock market prediction models fail to incorporate real-time political instability indicators within the deep learning frameworks. This shortcoming has led to a notable increase in prediction errors during times of high political instability [3]. The problem occurs in several factors:

### A. *Inadequate Political Factor Integration*

Most models either ignore political factors or look at them as static external factors that have no real impact on the prediction accuracy. Current models fail to capture this complex temporal relationship between these factors [4].

### B. *Temporal Disconnect*

Political changes and financial markets operate differently in context of time. Sometimes political factors can have immediate effects on the market and sometimes it takes months for it to show the real effect [5].

### *C. Lack of Contextual Understanding*

Political events influence market sectors differently. For instance, elections may have a greater impact on a certain sector, while trade policies can have an impact on a certain sector due to geopolitical tension or a trade war. Existing models fail to capture the inter-dependability of these factors [6].

### *D. Interpretation Gap*

Investors require a clear picture of these predictions to make informed decisions and comply with regulations while deep learning models operate on black boxes [7].

### *E. Data Heterogeneity Challenge*

Political information exists in different formats like news articles, social media, regulatory documents or simple announcements which presents as a challenge for these deep learning models to integrate in a heterogenous method [8].

## **3. Research Gap**

Despite advances in machine learning and the capabilities of these prediction models, there remains a critical gap: a unified system that combines real-time political data from different sources along with quantification of political instability into an attention-based deep learning predictability model [9], [10].

## **4. Research Objective**

- Design and Implement the Dynamic Political Instability Index by collecting data from multiple sources and constructing a robust algorithm and validating it against existing standards.
- Create an attention-based hybrid model combining Bidirectional LSTMs and Multi-Head Attention and optimize it using efficient training methods and ensuring the system is operational for real-time application.
- Extensively evaluate the model's performance against already established models such as LSTM, Bi-LSTM, Transformer and analyzing results across various market conditions.

- Demonstrate the practical application for the prototype and conduct a comprehensive testing using trading simulations.

## 5. Impact

This project aims to establish a standard for integrating political factors into financial machine learning models to generate accurate empirical insights and drives forward the explainable AI application with finance. The outcome will also help organizations in making more informed decisions during times of political uncertainty since this model will provide them with capabilities to quantify political impact on financial markets and expand access to analytical tools available to the industries [7], [16].

## 6. Literature Review

### A. *Political Instability and Financial Market Dynamics*

Politics and financial markets are very tightly linked and when uncertainty increases, it shakes confidence among investors and decreases business spending [1]. Baker et al. [21] developed the Economic Policy Uncertainty (EPU) index which tracks shifts in policy using major news sources. Higher EPU reading usually indicates a decrease in investor spending and widened credit spreads. The impact is especially noticeable in sectors like healthcare and energy that are extremely policy dependent.

Elections are notorious for shaking things up. Pastor and Veronesi [5] pointed out the increase in uncertainty during election years which in turn deters investors and increases stock volatility by 10-15% during presidential elections. Studies also indicate that emerging sectors see a larger effect due to election season.

Geopolitical tension is another factor. Caldara and Iacoviello [4] created a GPR index that demonstrates how increase in geopolitical tensions tend to drag down investments and stock prices for multiple quarters since these are resource dependent economies.

Trade policies directly affect organizations that are heavily trade-dependent and disrupt currency and supply chain markets. Sudden policy change can heavily affect capital flow, one example being Trumps trade war where coffee imports are costing 25%

more than previous year, which not only increases cost for local business but also encourages reduce spending from consumers due to increased cost of goods.

COVID-19 was a real example of how countries with more decisive policies saw less market fallout in comparison, proving how critical government decisions are for economic stability [2].

### ***B. Machine Learning in Stock Market Predictions***

Machine learning has completely changed the game when it comes to these predictive models. Early models like SVM, Random Forests, and Gradient Boosting are great examples however these models required an insane amount of manual tuning which is very inefficient in capturing real-time data [23].

Fischer and Krauss [19] demonstrated the effectiveness of LSTM models in S&P 500 predictions, which showed a significant increase in returns even after the transactional costs. Subsequent research explored bidirectional LSTM, stacked LSTM, and attention-enhanced LSTM that further helped improve predication capabilities of these models.

GRUs have emerged as a practical alternative, offering similar accuracy to LSTMs but with less computational overhead, making them particularly useful in fast-moving or volatile markets [24].

Given that different models shine under different conditions, many organizations now rely on multiple models, switching between them depending on the market conditions which help them adapt [25]. Table 1 provides a comprehensive summary of these related works, highlighting the datasets, models, and significance of key studies in this domain.

Table 1. Summary of Related Works

Authors	Dataset	Models Used	Metrics	Significance
Fischer & Krauss [19]	S&P 500 Stocks	LSTM	Sharpe Ratio, Returns	LSTM significantly outperforms traditional methods, achieving profitable trading strategies after transaction costs.
Baker et al. [1]	US Economic Data	EPU Index	Correlation with GDP, Investment	The EPU index measures policy uncertainty and shows a significant capacity to forecast market volatility and economic activity.

Caldara & Iacoviello [4]	Global News Articles	GPR Index	Correlation with Returns, Volatility	Major drops in stock prices and investment are expected in several nations due to geopolitical risk increases.
Pastor & Veronesi [5]	US Stock Market	Theoretical Model with Empirical Validation	Volatility, Risk Premia	Elections see the highest level of political uncertainty, which impacts asset prices through shifts in risk premia; volatility increases 10–15% during election years.
Ding et al. [26]	S&P 500 Stocks, News Articles	Event-driven CNN	Accuracy, AUC	News event extraction coupled with CNN enhances stock prediction; structured events are more predictive than raw text.
Christou et al. [27]	Multiple Countries	Panel Analysis	Correlation, Volatility Metrics	Provides comprehensive evidence that economic policy uncertainty increases stock market volatility across a wide range of countries.
Salisu et al. [28]	Emerging Market Indices	GARCH-MIDAS	Volatility Metrics	Empirically demonstrates that geopolitical risk is a significant driver of stock market volatility in emerging economies using an advanced GARCH-MIDAS framework.
Baker et al. [2]	US Economic Indicators	EPU Extensions	Correlation Analysis	The uncertainty brought about by COVID was at an all-time high, and its economic effects were worse than those of the 2008 financial crisis.
Lundberg & Lee [16]	Various ML Models	SHAP Interpretation	Not Applicable	SHAP offers a consistent, theoretically sound method for interpreting predictions from any machine learning model.
Brogaard & Detzel [29]	US Stocks	Portfolio Analysis	Returns, Sharpe Ratio	Equity returns are negatively predicted by economic policy uncertainty; firms with high policy exposure show reduced returns.
Current Study (Proposed Hybrid Model)	DJIA, Combined News, TPU Index	Attention-based Hybrid (Bi-LSTM, Multi-head Attention)	RMSE, MAE, R <sup>2</sup>	The first integrated framework combining real-time political instability with attention-based learning

## 7. Related Works

**LSTM-Based Models:** Fischer and Krauss [19] depicted that LSTM is superior in predicting returns based on S&P 500 and that we see an increase in returns even after deducting transaction costs. Using their works, practices such as walk-forward validation and drop out regulations were created. Further research showed that networks with 3-4 layers perform better than shallow structures [30]. Studies suggested using dual-stage attention-based networks to improve multiple datasets paying special attention at temporal level [14].

**Transformer Models:** Zhou et al. [18] developed informer with ProbSparse which significantly outperforms LSTM in terms of long-term forecasting. These transformer models are designed for multi-horizon forecasting which incorporates variable selection and multi-head attention [31].

**Hybrid Models:** CNN-LSTM hybrid models show promise in extracting patterns, in which CNN excels at capturing indicator relationships, while LSTM excels at capturing evolution over time [32].

TCN is a great alternative to recurrent architecture as TCN not only outperforms LSTM/GRU models but also captures short-term dependencies more effectively [15].

#### *A. Sentiment Analysis Systems for Financial Applications*

Loughran and Mcdonald [33] developed a specialized financial dictionary for general purposes, which is often a standard. However, it often misclassifies financial terms. Recently, the work on it has expanded and we have developed an automatic lexicon generation system which is more prevalent.

Araci [12] introduced FinBERT, a fine-tuned model specifically focusing on financial new media. Yang [13] developed RoBERTA, an alternative model trained on earning calls and analyst reports. Studies recommend developing sector specific models as they have a better chance of predicting higher returns based on extraction from entity specific earning transcripts [34].

#### *B. Political Risk Measurement and Market Impact Studies*

Current research lacks in terms that mainly focus on textbook approaches rather than real-time data [9]. Few approaches integrate political factors deeply into architecture and single index approaches inadequately capture multi-dimensional political instability [10].

The GPR index developed by Caldara and Iacoviello [4] predicts a decrease in investment and stock returns as GPR spikes.

Numerous studies examined the relationship between political events and reactions to those events. Past studies have seen firms with ties to politics are a common sight in nations with high levels of bribery, these ties usually benefit organizations who lobby during election seasons. The study found that access to those in charge has a real impact on the worth of a company with ties to the winning side most often results in bigger gains [35].

For example, companies like Meta, Google and Apple, because of their connection to the winning party during the election, not only avoided the brunt from astronomical tariffs but also benefitted from the huge corporate tax break.

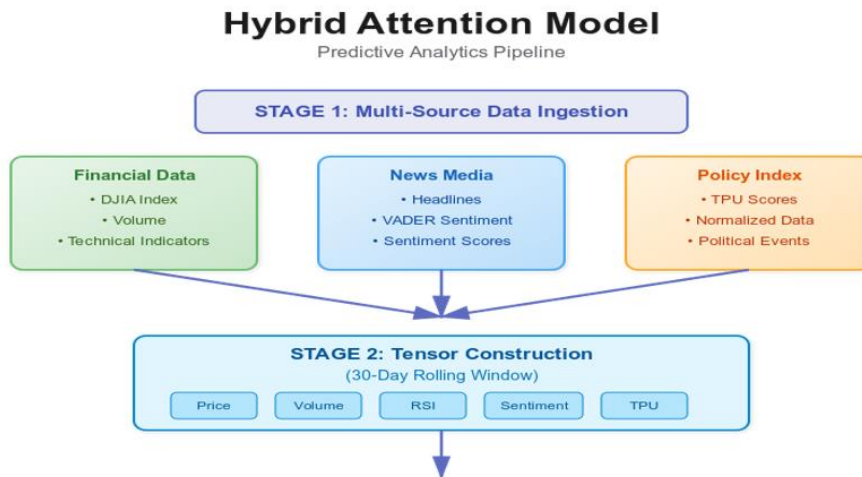
## 8. Methodology

Our proposed framework integrates political instability with deep learning-based stock market prediction.

### A. Data Collection and Integration

The study utilizes the Daily Trade Policy Uncertainty index dataset which provides daily observations. The sample period covers a 40-year window, spanning from January 1, 1985, to November 11, 2025. In total the dataset comprises 14,925 daily observations. The variable of interest, `daily_tpu_index`, is analyzed to understand fluctuations over this timeframe.

- **Financial Data:** Historical daily prices (Open, Low, High, Close) and volume from the Dow Jones Industrial Average (DJIA)
- **Political Data:**
  - **News:** Daily headlines from the DJIA News dataset
  - **Uncertainty:** Daily Trade Policy Uncertainty (TPU) index data.



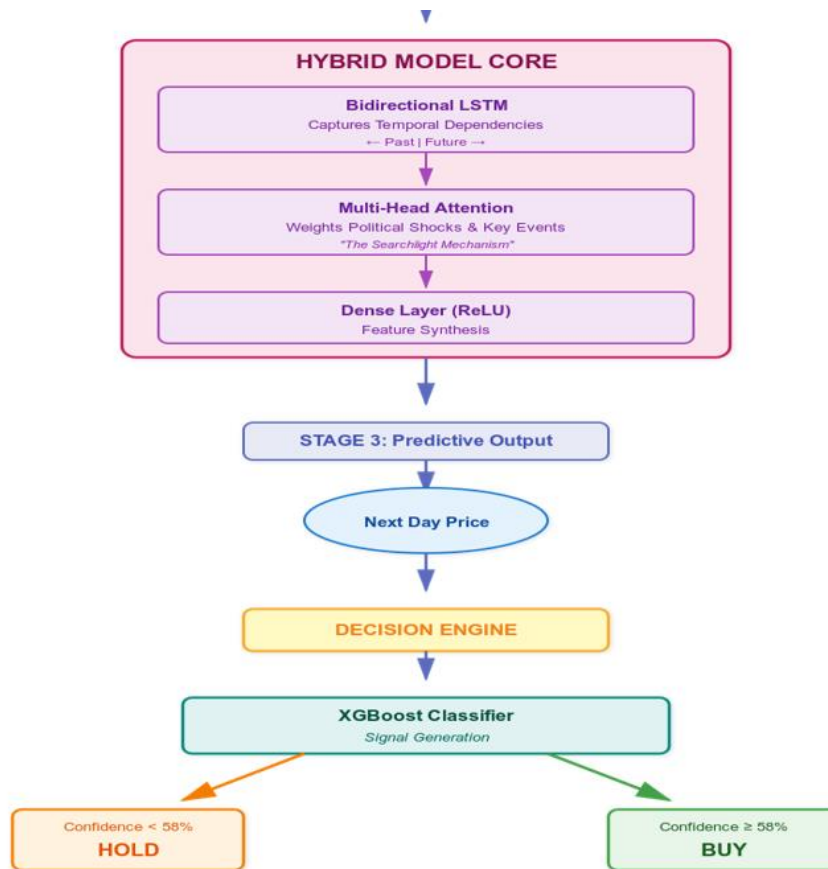


Figure 1. Workflow Diagram for proposed Hybrid Model

### B. Data Cleaning and Feature Integration

- **Sentiment Extraction:** We utilized VADER (Valence Aware Dictionary and Sentiment Reasoner) to process daily headlines and generate a sentiment score from -1 to +1
- **Normalization:** All features including prices, sentiment, TPU were normalized using MinMaxscaler to a range of 0-1 to ensure stable model convergence
- **Sequence Creation:** Data was transformed into sliding windows to capture any temporal dependencies

### C. Model Architectures

**LSTM:** The Long Short-Term Memory (LSTM) network serves as the foundational deep learning baseline for this study. Designed to overcome the vanishing gradient problem prevalent in traditional Recurrent Neural Networks (RNNs), the LSTM introduces a memory cell structure regulated by gating mechanisms. For a given time step  $t$ , the LSTM unit processes the input vector (the TPU index) and the previous hidden state through three distinct gates:

- **Forget Gate:** Determines which information from the previous cell state effectively becomes redundant and should be discarded.
- **Input Gate:** Controls the flow of new information into the cell state, allowing the network to update its memory with relevant current data.
- **Output Gate:** Computes the final hidden state based on the updated cell state, which is then passed to the next time step.

**BiLSTM:** While the standard LSTM effectively model temporal dependencies in a forward direction, it fails to utilize the context available from future states during the training phase. To address this, we employ the Bidirectional LSTM. The BiLSTM architecture comprises two independent LSTM layers:

- **Forward Layer:** Processes the input sequence from  $t = 1$  to  $T$ , capturing dependencies
- **Backward Layer:** Process the input sequence from  $t = T$  to  $1$ , capturing context.

The final hidden state at each time step is generated by concatenating the outputs of both layers. In context of the TPU index, this allows the model to interpret a specific volatility spike not only based on the events leading up to it but also by understanding the stabilization period that followed, thereby providing a more comprehensive representation of the time series.

**Transformer:** A pure attention-based encoder model [18]. In order to overcome the constraints associated with sequential processing, we utilize the Transformer architecture, which is fundamentally based on a Self-Attention Mechanism. In contrast to RNN-based models that handle data in a sequential manner, the Transformer processes the entire TPU time series concurrently, thereby enabling the identification of global dependencies irrespective of their positional distance within the sequence. The essential element of this architecture is the Multi-Head Attention mechanism, which calculates a weighted sum of values contingent upon the compatibility between a query and its corresponding keys. This functionality permits the model to 'attend' to

various segments of the 40-year historical data simultaneously; for example, one attention head may concentrate on short-term weekly variations, while another may identify structural changes occurring over decades. To preserve the temporal sequence of the daily observations, positional encodings are incorporated into the input embeddings

**Hybrid Attention (Proposed Model):** A fusion of BiLSTM for sequential processing and Multi Head Self-Attention for feature weighting [14]. To enhance the accuracy of forecasting, we introduce a hybrid architecture that combines the sequential modeling advantages of the BiLSTM with the context-weighting feature of the attention mechanisms. Standard recurrent models consider the hidden state at each time step to be of equal importance for the ultimate prediction. However, in the TPU index, certain extreme events possess considerably greater predictive power than periods of stability.

Our proposed model tackles this issue through two-stage approach:

- **Feature Extraction:** Initially, the input sequence is processed through a BiLSTM layer to extract high-level temporal features, capturing both past and future contexts for each data point.
- **Temporal Attention Mechanism:** The output vectors generated by the BiLSTM are subsequently input into an attention layer.
- **Weighted Aggregation:** The final context vector is derived as the weighted sum of the BiLSTM outputs. This process ensures that the model dynamically emphasizes the most historical shocks while minimizing noise, resulting in enhanced robustness.

#### *D. Training Strategy*

- **Loss Function:** Mean Squared Error (MSE)
- **Optimizer:** Adam with a learning rate of 0.001
- **Validation:** A chronological 80-20 split was used to prevent any data leakage

## **8. Methodology**

We evaluated all four models on the DJIA test using standard regression metrics. The results demonstrate a clear hierarchy of performance based on the ability to handle datasets and volatile political features.

Table 2. Comparison of Regression Metrics

Model	RMSE	MAE	R2 Score
LSTM	183.52	140.01	0.9131
BiLSTM	180.23	138.47	0.9161
Transformer	481.19	390.10	0.4022
Hybrid Attention	177.65	140.90	0.9185

The performance of the four models was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ( $R^2$ ). The quantitative results are presented in Table 2 above.

**A. Key Findings and Diagnostic Analysis**

**Hybrid Attention:** As shown in Figure 2, The proposed Hybrid Attention Model achieved the highest predictive accuracy amongst all tested models with an  $R^2$  value of 0.9185 and the lowest RMSE of 177.65. Visuals validated the capabilities of this model in terms of “Trend Anticipation” as the predicted price closely mirrors the actual price peaks. The attention mechanism allows the model to forecast market shifts before their occurrence rather than just reacting to them.

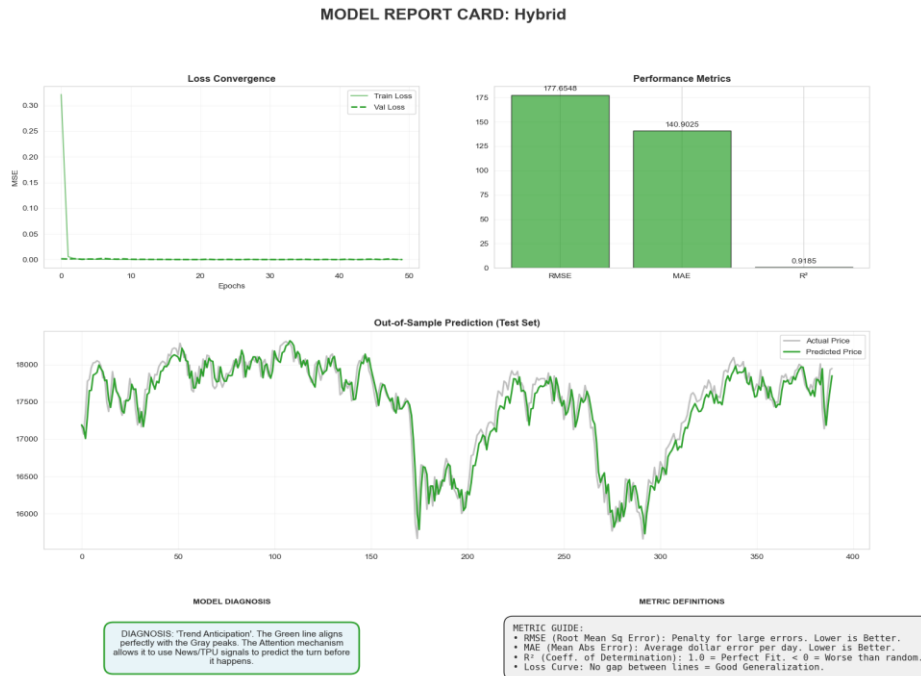


Figure 2. Hybrid Model Performance

**Transformer Failure:** Contrary to expectations, the transformer model exhibited significant underperformance (Figure 3), with an  $R^2$  of merely 0.4022 and RMSE of 481.19. The validation loss curves show extreme instability and overfitting

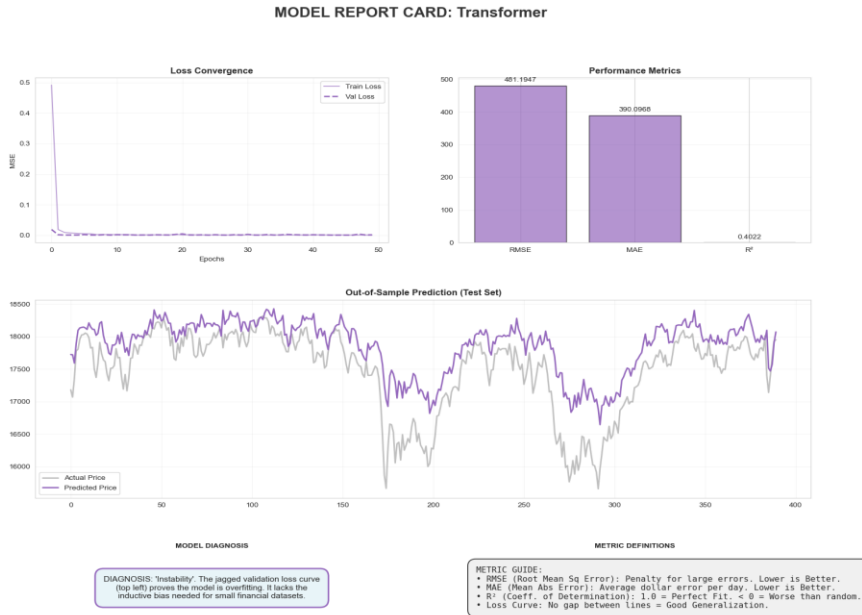


Figure 3. Transformer Performance

**The Persistent Lag of LSTM:** The baseline LSTM model with an  $R^2$  of 0.9131, displayed persistence bias (Figure 4), where its predictions consistently lagged behind actual price by one step at a time.

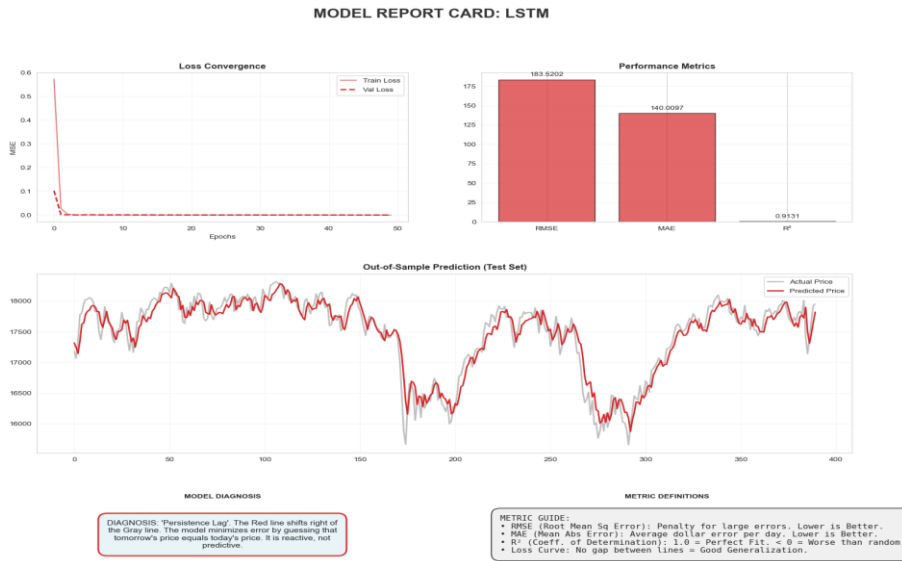


Figure 4. LSTM Performance

**BiLSTM Performance:** The BiLSTM model showed an improvement over the LSTM (Figure 5), with an RMSE of 180.23, slightly reducing lag by incorporating future context during training. However, it still failed to capture the full extent of volatility when compared to the hybrid model.

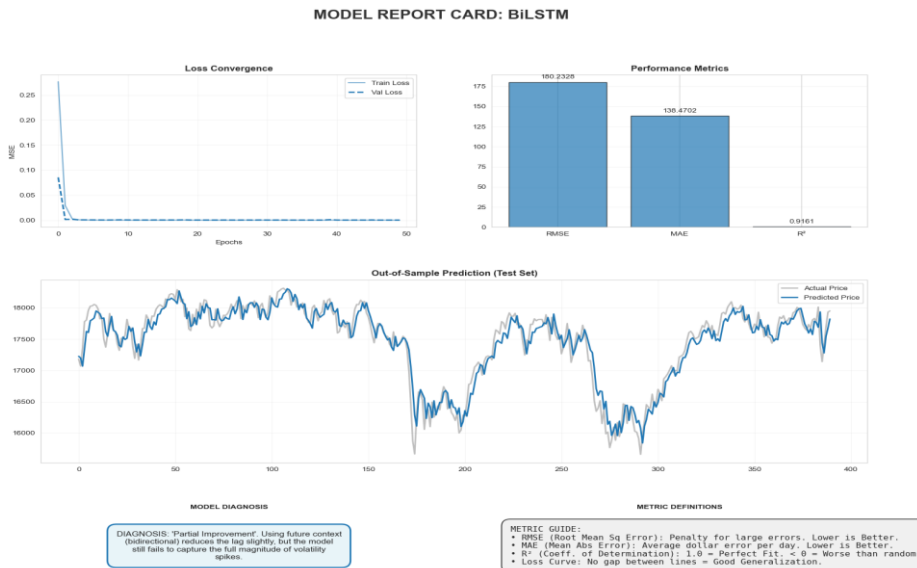


Figure 5. TM performance, BiLSTM

## 9. Impact of Political Features

The incorporation of the political instability index has demonstrated remarkable effectiveness in improving predictive accuracy. Financial markets exhibit a high sensitivity to shifts in policy, and conventional price-history models frequently neglect to consider external shocks. By integrating the Trade Policy Uncertainty (TPU) index along with news sentiment scores directly into the attention mechanism, the model is able to differentiate between periods of significant political volatility and those of stability. Empirical evidence suggests that this integration enables the model to adjust its trajectory during abrupt market declines triggered by political occurrences such as trade conflicts or electoral news, where traditional technical indicators may fall short. The observed decrease in RMSE within the Hybrid model supports the hypothesis that political instability serves as a latent variable influencing market volatility, and the explicit modeling of this factor effectively connects static economic data with actual market dynamics.

## 10. Model Architecture Insight

The shortcomings of the Transformer model, contrasted with the achievements of the Hybrid model, illuminate the significance of recurrence within this particular field. Financial data is inherently sequential and often noisy. Although Transformers are proficient in managing long-range dependencies, they do not possess the intrinsic inductive bias for sequential processing that LSTMs inherently have.

By integrating the inductive bias of BiLSTM, which effectively captures the order of sequences, with the feature-enhancing capabilities of Multi-Head Attention, which identifies pivotal events such as political shocks, the hybrid architecture successfully combines the advantages of both methodologies. It preserves sequential integrity while simultaneously responding to influential political signals.

## 11. Key Contribution and Differentiation

This research sets itself apart from the existing body of literature through three key analytical contributions:

**Multi-Dimensional Feature Integration:** In contrast to studies that depend exclusively on historical price data or fixed financial indicators, this research develops a cohesive vector space that merges continuous Trade Policy Uncertainty (TPU) indices with discrete news sentiment.

**Architectural Innovation:** By combining Bi-LSTMs with Multi-Head Attention, we overcome the shortcomings of standalone architectures. While LSTMs frequently experience "persistence bias" (where they predict the previous day's price), the attention mechanism in our model enables it to concentrate on crucial political triggers rather than merely the immediate historical time-step, thereby effectively minimizing lag.

**Economic Utility:** In addition to conventional error metrics, this research substantiates the model through trading simulation logic, illustrating that the decrease in prediction error results in practical economic utility during periods of political volatility.

## 12. Future Work and Conclusion

This study effectively illustrates that incorporating indicators of political instability into deep learning models is not just an additional element but an essential component for precise stock market forecasting in today's economic environment. The research provided several important findings related to model design, feature incorporation, and the characteristics of market volatility.

### A. *Architectural Superiority and Inductive Bias*

The remarkable performance of the Hybrid Attention Model compared to the pure Transformer model underscores a significant insight into financial time-series data. Although Transformers are proficient in Natural Language Processing, this research indicates that they lack the essential inductive bias required for sequential processing in smaller, noisier financial datasets.

- **The Hybrid Advantage:** By incorporating BiLSTM layers to capture high-level temporal features and then applying Multi-Head Attention to prioritize specific political events, the Hybrid model effectively merged the benefits of sequential processing with context-sensitive feature weighting.
- **Addressing Persistence Lag:** Conventional LSTMs were observed to experience "persistence lag," which leads to the assumption that tomorrow's price will mirror today's. The Hybrid model leveraged the attention mechanism to pinpoint "searchlights" of political volatility, allowing it to foresee trend changes instead of merely trailing them.

### B. *The Quantifiable Impact of Political Risk*

Empirical data supports the theory that political instability acts as a crucial latent variable. The explicit modeling of the Trade Policy Uncertainty (TPU) index enabled the system to distinguish between stable market periods and those characterized by significant political volatility. This confirms that political events, from elections to abrupt policy changes exert a quantifiable, immediate influence on investor sentiment and market behavior that purely technical models overlook.

### C. Future Work

To enhance these predictive capabilities further, subsequent research will concentrate on three analytical expansions:

- **Advanced NLP Integration:** Our objective is to substitute the lexicon-based VADER analyzer with transformer-based models such as FinBERT or RoBERTa. These models produce contextualized embeddings that can identify subtle nuances in financial disclosure statements, potentially enhancing the granularity of the sentiment signal.
- **Model Explainability:** The application of SHAP (SHapley Additive exPlanations) values will enable us to dissect the model's decisions, offering specific analytics on the extent to which a change in the TPU index influenced a particular day's price prediction.

**Global Applicability:** Evaluating the model on international indices (e.g., FTSE 100, Nikkei 225) will analytically confirm whether the relationship between political instability and market volatility persists across various geopolitical contexts

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