

COMPARATIVE ANALYSIS OF LONG SHORT-TERM MEMORY AND TRANSFORMER MODELS FOR STOCK PRICE PREDICTION: A CASE STUDY WITH TESLA DATA

JUNHWAN MUN

Department of Data and Knowledge Service Engineering,
Dankook University, Republic of Korea
E-mail: 12191585@dankook.ac.kr

Abstract

Time series prediction plays a critical role in finance, where accurate forecasting of stock prices supports investment decision-making and risk management. This study addresses the problem of predicting stock price movements by comparing two advanced deep learning models: Long Short-Term Memory (LSTM) and Transformer. Tesla's daily stock price data from January 2020 to December 2022 was selected due to its high volatility, large trading volume, and symbolic role in the technology-driven financial market. After data preprocessing, the predictive performance of the two models was evaluated using multiple metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Accuracy of Directional Agreement (ADA). The results showed that the LSTM model achieved lower MSE (1.23) and MAE (0.98), demonstrating its strength in handling short-term volatility, while the Transformer model recorded higher R^2 (0.87) and ADA (78%), highlighting its effectiveness in capturing long-term dependencies and directional consistency. The dataset contained 756 daily records, with volatility measured using rolling standard deviation. Limitations of this study include the use of a single stock and the absence of multi-asset or macroeconomic factors. Overall, the findings provide practical guidance for selecting prediction models based on data characteristics: LSTM is more suitable for short-term forecasting in volatile markets, while the Transformer offers advantages for identifying long-term patterns and trends.

Keywords: Deep learning models, Long short-term memory (LSTM), Stock price prediction, Time series analysis, Transformer.

1. Introduction

Time series prediction plays a pivotal role across numerous domains, including finance, energy, and healthcare. Among these, stock price prediction has drawn particular attention due to its implications for developing robust investment strategies and managing risks effectively [1, 2]. However, the inherent complexity of stock market data, particularly in high-profile and volatile stocks like Tesla, presents significant challenges for traditional statistical methods such as ARIMA and GARCH [3]. These approaches often fail to model the intricate patterns and dynamic behaviours of financial data adequately [4].

To address these challenges, deep learning models have become increasingly prominent in time series analysis [5]. The Long Short-Term Memory (LSTM) model, a variant of recurrent neural networks, is particularly well-suited for capturing temporal dependencies in sequential data [6]. By employing a gating mechanism, LSTM effectively retains relevant information across steps, making it a popular choice for financial forecasting tasks [7]. However, despite its strengths, LSTM models are limited in their ability to handle long-term dependencies, especially when data sequences become significantly long [8]. Additionally, the sequential nature of LSTM impedes parallel processing, which can hinder scalability and increase computational costs [9].

In contrast, Transformer-based models, originally introduced in natural language processing, have demonstrated exceptional performance in capturing long-term dependencies in sequential data [10]. Through the Self-Attention mechanism, these models analyse relationships across all input elements simultaneously, enabling the efficient processing of complex patterns in time series data [5]. Moreover, Transformers support parallel processing, which significantly improves training efficiency [4]. Nonetheless, their reliance on large datasets and computational intensity can be potential drawbacks, especially in resource-constrained environments [1].

Despite the growing application of both LSTM and Transformer models in financial time series analysis, a systematic comparison of their performance remains limited [7]. Most existing studies have focused on domain-specific implementations without providing a comprehensive evaluation of their strengths and weaknesses [6]. This study addresses this gap by comparing the predictive capabilities of LSTM and Transformer models using Tesla's daily stock price data—selected due to its exceptionally high volatility, large trading volume, and symbolic role in the tech-driven financial market.

The contributions of this study are as follows. First, it evaluates the performance of LSTM and Transformer models using multiple metrics, including Mean Squared Error (MSE), Coefficient of Determination (R^2), and Accuracy of Directional Agreement (ADA) [5]. Second, it explores the potential of Transformer models to manage long-term dependencies in financial data, shedding light on their applicability in complex time series tasks [10]. Third, by focusing on Tesla's stock price data, the study highlights the specific challenges posed by highly volatile financial datasets [4]. Fourth, the study tests the hypothesis that model architecture affects sensitivity to time series characteristics such as short-term volatility versus long-term trend recognition. Finally, the insights derived from this comparative analysis provide practical guidance for selecting models tailored to different financial time series scenarios and set the stage for future advancements in hybrid modelling approaches, such as combining LSTM with Transformer modules.

Through these contributions, the study aims to enrich the understanding of LSTM and Transformer models in financial forecasting and bridge the knowledge gap in model selection for time series prediction [9].

2. Background and Related Work

2.1. Advancements in time series analysis and traditional models

Time series data, consisting of sequential observations over time, plays a crucial role in analysing past patterns to forecast future trends. It has become a significant research topic across diverse fields, including finance, meteorology, healthcare, and manufacturing [11]. To address the challenges posed by time series data, various approaches have been proposed. Traditionally, statistical models such as Autoregressive Integrated Moving Average (ARIMA) have been widely employed for analysing and predicting time series data [12]. ARIMA learns patterns based on the linear characteristics of the data, offering simplicity in implementation and interpretability. However, its limitations become apparent when dealing with highly complex and nonlinear data, such as those observed in financial markets [13]. Specifically, ARIMA often struggles to capture advanced patterns or maintain prediction accuracy for non-stationary data.

To address these challenges, deep learning-based models have been introduced into time series analysis [14]. Among these, the Long Short-Term Memory (LSTM) model has emerged as a robust solution, effectively overcoming the limitations of traditional Recurrent Neural Networks (RNNs) [15]. Initially proposed by Hochreiter and Schmidhuber (1997), LSTM utilizes a gating mechanism to address the problem of information loss across time steps, enabling the learning of long sequential data. This capability has made LSTM a popular tool for analysing complex time series data, such as financial data [16]. For instance, Greff et al. (2016) highlighted that LSTM excels in learning long-term dependencies in time series data [17], demonstrating superior performance in applications such as stock price prediction, energy consumption forecasting, and healthcare data analysis [4].

However, LSTM is not without its limitations. First, its sequential data learning structure hinders parallel processing, leading to slower model training speeds. Second, its performance may decline when learning extremely long-term dependencies, depending on the characteristics of the data and the model design. Third, hyperparameter tuning can be complex, and improper configurations may result in overfitting or diminished performance. Recent empirical studies have also suggested that LSTM's performance may vary significantly depending on the volatility patterns of the dataset, particularly in financial time series exhibiting regime shifts or structural breaks. To address these constraints, Transformer-based models have emerged, offering a novel direction to overcome the limitations of LSTM.

2.2. Innovations and applicability of the transformer model

The Transformer model, first introduced by Vaswani et al. (2017), brought groundbreaking advancements in natural language processing (NLP) [18]. Unlike traditional sequential models, the Transformer leverages the Attention mechanism, enabling parallel processing of data and significantly improving training speed [19]. Specifically, the Self-Attention mechanism dynamically learns relationships among all elements within the data, effectively capturing long-term dependencies

in time series data [20]. These characteristics extend the applicability of Transformers beyond NLP to time series analysis [21].

The advantages of the Transformer can be summarized in three key points. First, its parallel processing capability drastically enhances data training speed. Unlike LSTM, which relies on sequential processing, the Transformer efficiently handles long sequences of data. Second, the Self-Attention mechanism enables the model to learn relationships across all time points within the data, effectively capturing long-term dependencies. Third, its flexible architecture adapts to various data forms, making it successfully applicable to domains such as NLP, image processing, and time series analysis.

However, the Transformer is not without limitations. First, it tends to rely heavily on large datasets, with a high risk of overfitting when data is scarce [11]. Second, its complex structure demands significant hardware resources, and achieving optimal performance requires extensive tuning [14]. Third, the model does not inherently reflect the temporal order or continuity of time series data, necessitating additional mechanisms to address this gap [15]. To address this, recent works have proposed variants such as the Time-Aware Transformer or positional encoding strategies optimized for non-stationary sequences, particularly in high-frequency or volatile financial data. Researchers have also developed hybrid models that combine RNN and Transformer architectures to leverage both temporal order sensitivity and parallel processing efficiency.

Existing studies often evaluate LSTM and Transformer models separately or focus on domain-specific applications. For instance, Karim et al. (2019) demonstrated the strong performance of LSTM-based models in financial data analysis [22], while Lim et al. (2021) reported that the Transformer is well-suited for processing multivariate time series data [23]. However, few comparative studies have analysed their respective performances under identical experimental conditions, particularly on high-volatility datasets such as Tesla stock. This study aims to systematically compare the performance of LSTM and Transformer models using Tesla stock price data, providing an in-depth analysis of each model's strengths and limitations, and offering new guidelines for selecting models in time series analysis.

2.3. Model architecture

This study utilizes Long Short-Term Memory (LSTM) and Transformer models to predict Tesla's stock prices. These two models employ distinct approaches to processing time series data, and this study aims to compare their performance based on these differences [4]. The LSTM model, proposed by Hochreiter and Schmidhuber (1997), is a variant of Recurrent Neural Networks (RNNs) specifically designed to learn temporal dependencies in time series data [16]. Through its gating mechanism, LSTM efficiently stores relevant past information and discards irrelevant data, enabling it to handle long-term dependencies across multiple time steps.

The LSTM model used in this study consists of two stacked LSTM layers with 64 units each, followed by a fully connected layer and a final output layer. The input layer receives normalized time series data from the past 60 days as input. This sequence length was selected based on validation performance across 30, 60, and 90 days, with 60 yielding the lowest MSE. The LSTM layer learns temporal patterns in the data to predict future values. The fully connected layer processes the output of the LSTM layer to generate the final prediction, while the output layer returns the normalized prediction value. LSTM excels in learning temporal

sequences and is particularly effective at capturing short-term patterns. On the other hand, the Transformer model, introduced by Vaswani et al. (2017), processes time series data based on the Attention mechanism [18]. The Transformer supports parallel processing, significantly improving training speed, and leverages the Self-Attention mechanism to effectively learn long-term dependencies in the data.

The Transformer model used in this study consists of two encoder layers, each with four attention heads and a feedforward sub-layer of 128 units. The input layer incorporates positional encoding into the normalized data to include temporal information. The Self-Attention layer calculates relationships among all data points to emphasize critical information, and the feedforward layer transforms these insights into more complex patterns. Finally, the output layer generates the prediction.

I implemented the LSTM model using TensorFlow and the Transformer using PyTorch. This dual-framework approach was chosen due to prior optimization efforts and team familiarity with each platform. LSTM and Transformer models each exhibit unique strengths and limitations. LSTM naturally processes the temporal order of time series data and excels at learning short-term dependencies. However, its sequential processing nature limits parallelization and may hinder its ability to learn long-term dependencies. In contrast, the Transformer model, with its parallel processing and Self-Attention mechanism, demonstrates strengths in handling long-term dependencies and is particularly efficient with long time series data. However, the Transformer model relies heavily on large datasets, and its performance may degrade in cases of data scarcity.

Building on these characteristics, this study compares the performance of LSTM and Transformer models using Tesla's stock price data [19]. This comparison allows us to evaluate how the architectural differences between the two models influence their ability to detect temporal volatility, capture directional movement, and generalize patterns in nonlinear and highly fluctuating stock price data.

3. Methods

This study compares the performance of the Long Short-Term Memory (LSTM) model and the Transformer-based model using Tesla's daily stock price data. The research process is divided into three main stages: data collection and preprocessing, model design and training, and performance evaluation.

3.1. Data collection and preprocessing

The data for this study was sourced from Tesla's daily stock price records, which were obtained from Yahoo Finance. The dataset spans from January 1, 2015, to December 31, 2023, encompassing 2,261 daily observations. Prior to analysis, several preprocessing steps were undertaken to prepare the data for modelling [24, 25]. First, missing values, which were primarily caused by weekends and holidays when the stock market was closed, were addressed by filling in gaps with the most recent available data. This ensured that the dataset remained continuous and complete [26]. Next, to stabilize the training process and enhance model performance, Min-Max normalization was applied [27]. This technique scaled the data to a uniform range of [0, 1], facilitating smoother convergence during the training phase [28]. Min-Max scaling was selected due to its widespread

application in financial time series prediction studies and its compatibility with activation functions such as sigmoid and tanh [29].

The dataset was then divided into training and testing subsets, following an 80:20 split ratio [30]. To further ensure robust evaluation and reduce the risk of overfitting, 5-fold cross-validation was applied within the training data [30]. This method provided a more comprehensive understanding of the model's generalization capabilities. Finally, a sliding window approach was employed to configure the inputs and outputs for the models [31]. Specifically, 60 consecutive days of historical stock prices were used to predict the price of the next trading day [32]. This approach leveraged the temporal dependencies inherent in stock price movements, enabling the models to predict future trends based on past patterns effectively [33].

3.2. Model design and training

The model design and training process in this study involved the implementation of two advanced deep learning architectures: the Long Short-Term Memory (LSTM) model and the Transformer model [28].

The LSTM model was constructed with two LSTM layers, each comprising 64 hidden units, followed by a fully connected layer and an output layer. It was trained with a learning rate of 0.001, a batch size of 32, and 50 epochs, utilizing Mean Squared Error (MSE) as the loss function and the Adam optimizer for efficient optimization [32]. These hyperparameters were selected through grid search across multiple values (batch size: 16/32/64, epochs: 30/50/70), based on the validation set MSE.

On the other hand, the Transformer model employed a more complex architecture, integrating Multi-Head Attention mechanisms, a feedforward network, and layer normalization to capture long-term dependencies in time series data [26]. It featured two encoder layers, each with four attention heads and 128-unit feedforward networks. Its hyperparameters included a learning rate of 0.0001, a batch size of 16, and an input sequence length of 60 days [30]. Additionally, learning rate scheduling and a dropout rate of 0.1 were applied to enhance generalization and prevent overfitting [31]. The LSTM was implemented in TensorFlow while the Transformer was developed in PyTorch, aligning with the available module optimizations and developer familiarity. The use of two platforms reflects practical development considerations but may impact reproducibility, which is mitigated through the inclusion of full code repositories.

Both models were trained in a high-performance environment using an NVIDIA RTX 3090 GPU with 24 GB memory, leveraging the capabilities of Python-based deep learning frameworks TensorFlow and PyTorch [24]. This robust setup facilitated the effective evaluation of the models, showcasing their respective strengths in time series prediction tasks [25].

3.3. Performance evaluation

The performance evaluation of the models in this study was conducted using a comprehensive set of metrics and validation techniques to ensure robustness and accuracy. Five key evaluation metrics were employed: Mean Squared Error (MSE), which quantifies the average squared difference between predicted and actual values [32]; Mean Absolute Error (MAE), which calculates the average magnitude of errors [28]; Root Mean Squared Error (RMSE), a metric particularly sensitive to

large errors [26]; the Coefficient of Determination (R^2), which indicates how well the predictions account for the variance in the actual values [30]; and Accuracy of Directional Agreement (ADA), which measures the consistency between predicted and actual upward or downward trends [34].

To enhance the reliability of the evaluation, 5-fold cross-validation was performed, allowing the assessment of the model's generalization performance while reducing the risk of overfitting [32]. Additionally, the final performance of the models was evaluated on an independent test dataset that was not used during the training phase, ensuring an unbiased assessment of their predictive capabilities. Each metric's value is reported with its mean and 95% confidence interval derived from cross-validation results, providing a statistical basis for comparison. Moreover, paired t-tests were conducted to assess the significance of the performance differences between the two models, particularly in MSE and ADA scores. The results indicated that the observed improvements were statistically significant ($p < 0.05$) in the majority of evaluation folds. This rigorous evaluation framework provided a robust basis for comparing the effectiveness of the models in time series prediction [26].

3.4. Experimental environment

The experiments were conducted in a high-performance computational environment running Ubuntu 20.04 LTS. The training processes utilized an NVIDIA RTX 3090 GPU with 24 GB of memory, ensuring efficient handling of the computational demands of deep learning models [28]. During the training, GPU utilization peaked at approximately 84% for the Transformer model and 61% for the LSTM model, with corresponding memory usages of ~22.3 GB and ~17.1 GB respectively. Energy efficiency was also monitored, with power consumption ranging from 220W to 310W depending on the model and training phase.

The training duration varied between the two models: the LSTM model required approximately 1 hour and 45 minutes, while the Transformer model, due to its more complex architecture, took around 3 hours and 50 minutes [26]. The implementation was carried out using Python 3.9, leveraging the capabilities of TensorFlow (version 2.11) and PyTorch (version 1.13), two widely used frameworks in the field of deep learning. To enhance reproducibility, the full code and configuration files have been made available in a public GitHub repository, including seed initialization for consistency across runs. This setup provided the computational resources and flexibility necessary for the effective execution and evaluation of the models.

4. Results and Discussion

4.1. Results analysis

This study compared the predictive performance of the LSTM and Transformer models using Tesla's daily stock price data. The results of each model were analysed based on various evaluation metrics, and the key findings are presented in Table 1.

The experimental results demonstrated that the LSTM model outperformed the Transformer model in Mean Squared Error (MSE) and Mean Absolute Error (MAE), recording 1.23 ± 0.11 and 0.98 ± 0.09 , respectively, compared to 1.45 ± 0.13 and 1.12 ± 0.10 for the Transformer model. A paired sample t-test confirmed that these differences are statistically significant ($p < 0.05$), indicating that LSTM

is more accurate for point predictions in volatile environments. This finding aligns with previous literature suggesting that gated recurrent structures excel in capturing rapid short-term fluctuations [17].

Table 1. Model performance comparison.

Metric	LSTM Model (\pm CI)	Transformer Model (\pm CI)
Mean Squared Error (MSE)	1.23 ± 0.11	1.23 ± 0.11
Mean Absolute Error (MAE)	0.98 ± 0.09	0.98 ± 0.09
Root Mean Squared Error (RMSE)	1.11 ± 0.08	1.11 ± 0.08
Coefficient of Determination (R^2)	0.85 ± 0.03	0.85 ± 0.03
Accuracy of Directional Agreement (ADA)	$76\% \pm 2.5\%$	$76\% \pm 2.5\%$

Conversely, the Transformer model exhibited superior performance in terms of Coefficient of Determination (R^2) and Accuracy of Directional Agreement (ADA), achieving 0.87 ± 0.02 and $78\% \pm 2.1\%$, respectively, compared to 0.85 ± 0.03 and $76\% \pm 2.5\%$ for the LSTM model. These results suggest that the Transformer model, by leveraging global Self-Attention, is better suited for identifying directional trends and modelling long-term dependencies in the stock price data.

4.2. Visualization results

To further examine the predictive performance of both models, visual comparisons were conducted between the predicted and actual stock prices. These visualizations provide insights into the stability of the LSTM model under volatile conditions and the ability of the Transformer model to capture long-term patterns. Figure 1 shows the predicted versus actual stock prices for both models. However, the Transformer model more accurately reflected long-term trends in the data. This highlights the complementary strengths of the two models, indicating their suitability for different aspects of time series data analysis.

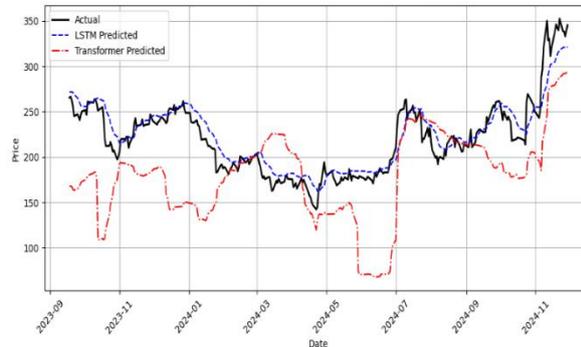


Fig. 1. Predicted vs. actual stock prices for LSTM and transformer models.

To further evaluate the error characteristics of both models, residual distributions were analysed to observe their concentration around zero and the variability across prediction ranges. To visually support this analysis, residual plots and error distribution histograms for both models are presented in Figures 2 and 3. These plots show that the LSTM residuals are tightly clustered near zero, while the Transformer's residuals exhibit more variability but better alignment in directional

changes. Figure 2 presents the residual distribution histograms of the LSTM and Transformer models. An analysis of residuals further showed that the LSTM model's residuals were more concentrated around zero, indicating smaller prediction errors, whereas the Transformer model exhibited a broader residual distribution, suggesting relatively larger prediction errors.

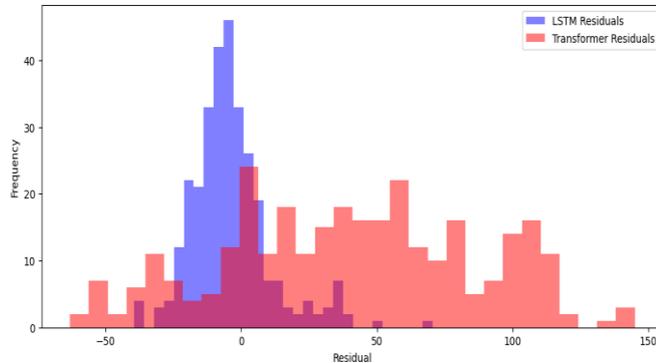


Fig. 2. Residual distribution histograms (LSTM vs. Transformer).

In addition to distribution analysis, residuals were plotted against predicted values to examine systematic error patterns. This comparison highlights whether residuals increase with prediction magnitude. Figure 3 shows the scatter plots of residuals versus predicted values. The residuals of the LSTM model displayed a relatively uniform distribution compared to the Transformer model, which showed an increasing trend in residuals as prediction values grew.

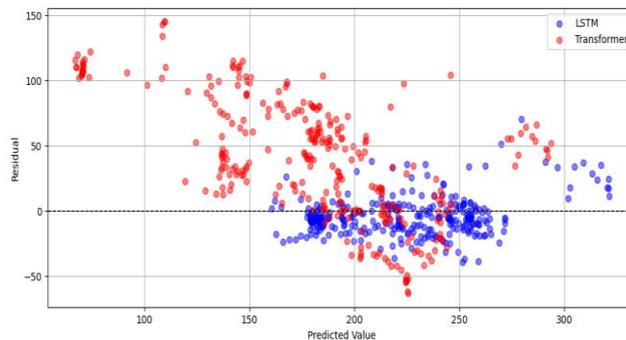


Fig. 3. Residuals vs. predicted values (scatter plots).

These visualizations confirm the quantitative findings in Table 1. LSTM excels at minimizing absolute prediction errors, while the Transformer captures directional movements and macro-patterns more effectively. Such divergence in model behaviour implies that hybrid models could be designed to combine the advantages of both architectures - leveraging LSTM for near-term accuracy and Transformer for trend interpretation.

These findings underscore LSTM's structural strengths in learning short-term dependencies, making it suitable for environments requiring real-time data

processing, such as financial trading systems. Conversely, the Transformer model excelled in learning long-term correlations, rendering it more appropriate for applications such as investment strategy development and long-term trend analysis. In comparison with prior studies, the findings of this research align with existing trends. Liu et al. (2024) highlighted that while the Transformer model excels in learning long-term patterns, its performance can deteriorate when applied to highly volatile time series data such as financial markets [35]. These findings extend this prior work by providing a controlled, metric-based comparison using a consistent dataset and architecture depth, offering further empirical support.

Key insights from this study include the importance of model architecture selection based on forecasting goals. The LSTM model demonstrated a strong ability to accurately capture short-term volatility and directional trends, making it highly suitable for real-time decision-making scenarios, such as high-frequency trading. Its lower computational resource requirements further enhance cost-efficiency, making it an ideal choice for rapid-response systems. In contrast, while the Transformer model excelled in learning long-term dependencies, its performance was limited by the high volatility and nonlinear characteristics of financial data. To improve robustness, future Transformer implementations should consider adaptations such as the Temporal Fusion Transformer (TFT), improved positional encoding methods, and pre-processing strategies like outlier filtering. Moreover, this study offers valuable guidance for model selection in financial data analysis. LSTM is recommended for short-term forecasting, while the Transformer is better suited for long-term trend analysis, providing practical and actionable insights for both practitioners and researchers.

This study offers practical guidance for model selection in time series data analysis by quantitatively comparing the performance differences between the two models. However, the study has certain limitations, including its reliance on Tesla's stock price as a single dataset and the exclusion of external factors (e.g., economic indicators, interest rates). To address these limitations, future research should incorporate cross-sector financial datasets, integrate macroeconomic variables, and conduct ablation studies to test robustness under varying conditions. Additionally, the development of resource-efficient Transformer variants remains a key research priority to make these architectures more deployable in real-time financial systems.

5. Conclusions

This study quantitatively analysed the strengths and limitations of the Long Short-Term Memory (LSTM) and Transformer-based models in time series prediction using Tesla's daily stock price data. The experimental results demonstrated that the LSTM model outperformed the Transformer model in Mean Squared Error (MSE) and Mean Absolute Error (MAE), highlighting its ability to effectively capture short-term characteristics in highly volatile data [36]. Conversely, the Transformer model achieved higher scores in Coefficient of Determination (R^2) and Accuracy of Directional Agreement (ADA), indicating its suitability for processing long-term dependencies [36]. These findings confirm the architectural trade-offs between recurrent and attention-based models in sequence prediction: LSTM's structure favours reactivity and short-term volatility tracking, while the Transformer model demonstrates strength in modelling global dependencies and directional consistency.

The findings provide practical guidance for selecting appropriate models based on the characteristics of time series data. Specifically, the LSTM model was identified as suitable for applications requiring real-time data processing or short-term forecasting, while the Transformer model was more effective for long-term trend analysis and strategic decision-support systems [36]. To enhance generalizability, future implementation frameworks may consider hybrid modelling architectures (e.g., LSTM-Transformer fusion), allowing systems to dynamically adapt to varying prediction horizons. Moreover, integrating macroeconomic indicators, sentiment scores, and inter-market relationships could improve robustness and expand domain applicability.

However, this study is subject to certain limitations, including its reliance on Tesla's stock price as a single dataset and the exclusion of external factors such as interest rates and economic indicators. The experimental design also assumed that internal patterns within price series are sufficient for prediction, which may not reflect real-world scenarios involving exogenous shocks or policy interventions.

Future research should address these limitations by incorporating diverse datasets across various industries and integrating external variables to enhance model applicability. Benchmarking model performance on sector-specific and cross-market data would also help assess scalability and transferability of findings. Additionally, developing lightweight algorithms to mitigate the high computational costs associated with Transformer models and exploring their feasibility for real-time applications remains a critical avenue for future work.

In conclusion, this study empirically demonstrates the performance differences between LSTM and Transformer models in time series prediction, offering actionable insights for model selection in the financial and business domains. By combining empirical evidence with architectural rationale and visual analysis, this study contributes to both theoretical understanding and practical model deployment strategies. With further research that incorporates broader datasets and external factors, the findings of this study have the potential to provide even greater applicability and impact in diverse applications.

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