Transformer with Technical Indicators for Long-Term Stock Market Prediction

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Abstract

Accurate long-term stock market prediction is challenging due to the dynamic, non-linear, and volatile nature of financial time series. This study proposes a Transformer-based forecasting model that integrates both short- and long-term technical indicators to improve prediction accuracy on the Kuala Lumpur Stock Exchange (FBM KLCI) index. By leveraging the self-attention mechanism, the model captures both immediate price fluctuations and persistent trends, while positional encoding and stacked encoder blocks enable effective sequential modeling. The proposed approach is compared against several baselines, including an LSTM network, a Transformer using only OHLCV data, and Transformers with either short-term or long-term indicators alone. Evaluation metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), as well as training and testing times. Experimental results show that the proposed dual-indicator Transformer consistently outperforms all baselines, achieving the lowest MAE (17.14), RMSE (21.29), and MAPE (1.13%), demonstrating its ability to balance responsiveness to short-term changes with long-term trend stability. While the model requires longer training due to increased complexity, the substantial gains in predictive performance justify the computational cost. These findings highlight the effectiveness of combining multiple technical indicators within a Transformer model for long-term stock market forecasting and provide a foundation for future research incorporating macroeconomic, sentiment, and real-time data to enhance predictive power and generalizability.

Keywords: *Stock Market, Generative Artificial Intelligence, Financial Forecasting, Transformer, Technical Indicators*

1. Introduction

Stock markets play a crucial role in global financial systems by facilitating capital flows, connecting participants, and influencing economic stability. Prices of securities fluctuate in highly unpredictable ways, characterized by noise, randomness, and high volatility. These fluctuations arise from various internal and external factors, including geopolitical events, macroeconomic shifts, and natural

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disasters, making stock market behavior inherently dynamic and difficult to forecast.

Stock market prediction remains a complex task due to the non-linear and stochastic nature of financial time-series data. Traditional econometric and machine learning models often struggle to capture the intricate temporal dependencies and sudden fluctuations that characterize real-world financial data. In recent years, deep learning models, particularly the Transformer model, have demonstrated significant promise in addressing these challenges by effectively modeling sequential relationships and long-term dependencies [1], [2], [3].

Originally developed for natural language processing (NLP), the Transformer model has shown exceptional ability to process sequential data through self-attention mechanisms that weigh the importance of past events across long time horizons. This property makes it particularly suitable for financial forecasting tasks, where understanding temporal dependencies between price movements is critical. Moreover, its capability to handle multiple input variables in parallel enhances both prediction accuracy and robustness in volatile market environments [3], [4].

Incorporating technical indicators, mathematical constructs derived from historical prices, volume, and market statistics, has also been shown to improve model interpretability and forecasting power. Indicators such as Moving Averages (MA), Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD) provide complementary insights into market momentum, volatility, and potential reversals [5]. When integrated with deep learning approaches, these indicators allow models to better represent underlying market behavior and enhance predictive performance compared to traditional or single-source input models [6].

Despite these advancements, limited research has explicitly examined how Transformer models can be systematically combined with both short-term and long-term technical indicators to address volatility and improve long-term forecasting. Most existing works either use raw OHLCV data, which is the Open, High, Low, Close, and Volume, or a single class of indicators, overlooking the potential of multi-horizon feature integration. Addressing this gap is crucial for strategic investment planning, portfolio management, and risk mitigation, where long-term prediction accuracy holds significant value.

Therefore, this study aims to investigate the effectiveness of a Transformer model integrated with multiple technical indicators for long-term stock market forecasting. The proposed approach combines short-term indicators, which capture rapid market fluctuations, with long-term indicators that reveal persistent trends, enabling a balanced and context-aware prediction mechanism. By leveraging the Transformer's sequential modeling strength and the analytical power of technical indicators, the proposed model seeks to provide a more reliable framework for long-horizon financial forecasting and informed investment decision-making [2], [3], [6].

Unlike previous studies that employed Transformers with only short-term or long-term indicators in isolation, this work introduces a unified dual-indicator Transformer model that systematically integrates both feature types within a single self-attention framework. This design explicitly models multi-horizon dependencies by capturing relationships among heterogeneous indicator categories, momentum, trend-following, volatility, and mean reversion, allowing the model to balance immediate responsiveness with long-term stability. This integrated approach enhances the Transformer's temporal representation capability and provides a practically optimized framework for robust, long-term financial forecasting

2. Related Litearture

The field of stock market prediction has seen significant advancements with the integration of machine learning and deep learning techniques. Traditional models, such as artificial neural networks (ANN), support vector machines (SVM), and ARIMA, have been widely applied to predict stock prices using diverse variables, including technical indicators, macroeconomic data, and fundamental indicators [7]. While these approaches provide useful benchmarks, they often struggle to capture the non-linear, dynamic, and high-frequency patterns inherent in financial data.

Deep learning methods, particularly Long Short-Term Memory (LSTM) networks and Transformer, have emerged as effective solutions to these challenges. Transformers are especially suitable for stock market prediction due to their ability to model sequential data and long-term dependencies, often outperforming traditional models in terms of accuracy and robustness on noisy and volatile datasets [2], [3], [8], [9]. The careful selection of input features, such as technical indicators, combined with preprocessing strategies like normalization and noise reduction, has been shown to further enhance predictive performance [4], [10].

Recent research has also explored the integration of textual data, including financial news and social media sentiment, into predictive models using advanced natural language processing techniques. BERT-based models, for example, have been applied to combine textual sentiment with technical indicators, improving forecast reliability and capturing market psychology [11], [12], [13], [14]. Despite these advances, existing studies rarely examine how Transformer can be systematically combined with both short-term and long-term technical indicators to enhance long-term stock market prediction, especially under volatile market conditions.

This gap motivates the present study, which aims to develop and evaluate a Transformer-based framework that leverages a comprehensive set of technical indicators to improve long-term forecasting accuracy. By integrating short-term indicators, which capture immediate market fluctuations, with long-term indicators, which reflect broader trends, the proposed model seeks to provide a more robust and reliable prediction framework. This approach addresses the limitations of prior work that either relied solely on short-term or long-term features or overlooked the combined impact of multiple technical indicators on long-term prediction performance. Ultimately, the study contributes to the field by offering a Transformer-based methodology capable of delivering accurate, long-term stock market forecasts that can support strategic investment and portfolio management decisions

3. Methodology

3.1. Data Collection and Preprocessing

This gap motivates the present study, which aims to develop and evaluate a Transformer-based framework that leverages a comprehensive set of technical indicators to improve long-term forecasting accuracy. By integrating short-term indicators, which capture immediate market fluctuations, with long-term indicators, which reflect broader trends, the proposed model seeks to provide a more robust and reliable prediction framework. This approach addresses the limitations of prior work that either relied solely on short-term or long-term features or overlooked the combined impact of multiple technical indicators on long-term prediction performance. Ultimately, the study contributes to the field by offering a Transformer-based methodology capable of delivering accurate, long-term stock market forecasts that can support strategic investment and portfolio management decisions

This study focuses exclusively on the Kuala Lumpur Stock Exchange (KLSE) index, using daily historical data spanning from its inception to the most recent available period which is from 1983 until 2024. The long historical span allows the analysis to capture diverse market conditions, including periods of sustained growth, regulatory changes, economic crises, and global disruptions such as the COVID-19 pandemic. This rich dataset ensures that the model is exposed to a variety of market behaviors, making it particularly suitable for studying complex and dynamic market patterns as well as long-term forecasting.

The core input features consist of OHLC (open, high, low, close) prices and trading volume, which serve as fundamental indicators of market activity. In addition to these primary features, a set of carefully selected technical indicators is incorporated to capture various market characteristics. Short-term indicators, such as the RSI and MACD, are included to identify momentum and rapid price fluctuations. Long-term indicators, including MA and EMA, are used to detect persistent trends and provide a smoother representation of market direction. Other indicators are included to reflect volatility, trend reversals, and mean-reversion tendencies, providing complementary perspectives on market behavior. In total, 12 input features are utilized, combining both OHLCV data and technical indicators.

Prior to model training, the dataset undergoes several preprocessing steps to ensure consistency and improve model performance. All input features are normalized using Min-Max scaling to bring values within a standard range, which stabilizes training and prevents features with larger scales from dominating the learning process. The dataset is then divided into training, validation, and testing subsets using a 75:10:15 ratio, respectively. This split allows the model to learn underlying patterns from the training data, optimize hyperparameters using the validation set, and evaluate predictive performance on unseen test data.

In this study, the model was trained to predict the next-day closing price of the FBM KLCI index using data from the preceding 100 trading days. This one-day-ahead prediction horizon was selected because it strikes a balance between responsiveness to short-term market fluctuations and the reflection of long-term trends when applied over extended periods. The sliding window approach allows the model to continuously update its understanding of evolving market dynamics and maintain robustness under varying market conditions

The study compares the performance of a Transformer model under multiple configurations: using only raw OHLCV data, using short-term technical indicators alone, using long-term indicators alone, and combining both short- and long-term indicators. An LSTM network is also implemented as a benchmark to evaluate the advantages of the proposed Transformer-based approach. Model evaluation relies on commonly used metrics in time-series forecasting, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). This comprehensive experimental setup allows for a detailed assessment of how different input features and model architectures impact predictive performance, particularly for long-term stock market forecasting.

3.2. Technical Indicators

The study compares the performance of a Transformer model under multiple configurations: using only raw OHLCV data, using short-term technical indicators alone, using long-term indicators alone, and combining both short- and long-term indicators. An LSTM network is also implemented as a benchmark to evaluate the advantages of the proposed Transformer-based approach. Model evaluation relies on commonly used metrics in time-series forecasting, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). This comprehensive experimental setup allows for a detailed assessment of how different input features and model architectures impact predictive performance, particularly for long-term stock market forecasting.

The technical indicators employed in this study are categorizes into four functional groups: momentum, trend-following, volatility, and mean-reversion indicators. These indicators are widely used in financial analysis to extract meaningful patterns from historical price and volume data, providing complementary perspectives on market behavior. By integrating multiple indicator types, the proposed Transformer model is able to capture both short-term market dynamics and longer-term structural trends, enhancing its predictive accuracy and robustness across varying market regimes.

Momentum indicators are designed to detect the speed and magnitude of price movements, highlighting potential overbought or oversold conditions and signaling short-term trend changes. In this study, the Relative Strength Index (RSI) and the Stochastic Oscillator (STOCH) serve this purpose. The RSI measures the magnitude of recent price changes to identify whether an asset is overbought or oversold, with the 14-day RSI capturing short-term momentum and a 50-day RSI reflecting medium-term signals. The Stochastic Oscillator compares the current closing price to the range of recent prices to detect short-term reversals, using both %K and %D lines to generate actionable signals. Additionally, the Moving Average Convergence Divergence (MACD) is included as a hybrid momentum/trend indicator, capturing transitions in market direction by measuring the difference between fast and slow exponential moving averages. MACD is particularly useful for detecting emerging trends during periods of market transition or sudden volatility.

Trend-following indicators are used to identify the underlying direction of the market, filtering out short-term noise and highlighting persistent trends. In this study, Simple Moving Averages (SMA) calculated over 50-day and 100-day periods serve as trend-following indicators. The 50-day SMA captures medium-term trends, providing guidance on the prevailing market direction over a few weeks, while the 100-day SMA reflects long-term trends, offering a broader perspective on the market structure. By incorporating both horizons, the model can differentiate between temporary fluctuations and sustained directional movement.

Volatility indicators provide insights into the degree of variation in price movements, regardless of direction, and help detect periods of market turbulence. The Average True Range (ATR) is employed in this study as a volatility measure, calculated over both 14-day and 50-day periods. The 14-day ATR captures short-term variability, helping the model respond to sudden price swings, whereas the 50-day ATR highlights broader fluctuations and longer-term risk conditions. Including volatility information allows the Transformer model to adjust its predictions in response to market uncertainty, improving its stability during turbulent periods.

Mean-reversion indicators highlight the deviation of the current market price from a reference value, typically a long-term average, signaling potential reversion to equilibrium levels. In this study, the deviation of the current price from the 100-day SMA is used as a mean-reversion measure. When prices are significantly above or below the long-term average, the market is more likely to experience a corrective movement. This indicator is particularly valuable for long-term prediction, as it captures structural imbalances that may not be immediately apparent from short-term momentum or trend signals alone.

Table 1 summarizes the selected indicators, their categories, functions, and specific usage in this study. By combining short-term and long-term indicators across momentum, trend-following, volatility, and mean-reversion categories, the Transformer model is able to process a rich representation of market dynamics. This allows it to simultaneously account for rapid price fluctuations, sustained trends, and structural deviations, enhancing its predictive capability under both stable and highly volatile market conditions. Such a comprehensive feature set is particularly important for long-term stock market forecasting, where both immediate signals and persistent trends must be considered to produce reliable and actionable predictions.

Table 1. Details of technical indicators

Indicator	Category	Function	Usage in This Study
Relative Strength Index (RSI)	Momentum	Identifies overbought/oversold conditions and momentum strength.	14-day RSI for short-term momentum; 50-day RSI for medium-term signals.
Moving Average Convergence Divergence (MACD)	Momentum / Trend	Captures changes in momentum and trend direction, useful during market transitions.	Provides buy/sell signals during price reversals or breakouts.
Stochastic Oscillator (STOCH)	Momentum	Detects overbought/oversold conditions and short-term momentum shifts.	%K and %D lines used to identify potential reversals.
Moving Average (MA)	Trend-Following	Smooths price data to reveal underlying trend direction.	50-day SMA for medium-term trends; 100-day SMA for long-term market direction.

Average True Range (ATR)	Volatility	Measures market volatility regardless of direction.	14-day ATR for short-term volatility; 50-day ATR for broader volatility trends.
Price Difference from 100-Day MA	Mean Reversion	Measures the deviation of the current price from the long-term average.	Highlights bullish/bearish bias relative to 100-day SMA.

The selection of technical indicators was based on both their theoretical relevance and empirical validation in prior research. Indicators were chosen to represent the four principal analytical categories in financial forecasting, which are momentum, trend-following, volatility, and mean reversion, ensuring a balanced representation of market behaviors. Similar sets of indicators have been shown to enhance predictive accuracy when combined with deep learning approaches (Naik & Mohan, 2019; Chantrasmee et al., 2024; Xue et al., 2023). By integrating these indicators, the proposed Transformer model captures complementary short-term and long-term signals, aligning with evidence from previous studies that emphasize multi-indicator fusion for robust stock market prediction.

3.3. Training Procedure

The model was trained using the Adam optimizer with a learning rate $\alpha = 10\text{^}(-4)$ minimizing the Mean Squared Error (MSE) loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \quad (\hat{y}_i - y_i)^2 \tag{6}$$

Training proceeds for a maximum of 200 epochs, with early stopping (patience =10) to prevent overfitting. An adaptive learning rate scheduler (ReduceLROnPlateau) reduces the learning rate by a factor of 0.5 if the validation loss does not improve for 5 consecutive epochs. A batch size of 32 is used to balance computational efficiency and gradient stability. These strategies enhance model convergence and ensure stable performance on volatile financial time series, making the model suitable for both short-term adjustments and long-term stock market prediction.

3.4. Model Evaluation

The performance of the proposed Transformer-based stock market prediction model is evaluated against several baseline models to assess its effectiveness. The baselines include an LSTM network, a Transformer trained on OHLCV data only, a Transformer with short-term technical indicators only, and a Transformer with long-term indicators only. This comparative evaluation highlights the impact of integrating both short- and long-term technical indicators on predictive accuracy and computational efficiency. The models are evaluated using MAE, RMSE, and MAPE to measure prediction accuracy, along with training and testing times to assess computational cost. MAE provides the average magnitude of prediction errors in the same units as the stock price, RMSE emphasizes larger deviations to capture worst-case errors, and MAPE expresses error as a percentage of actual values, allowing for scale-independent comparison across datasets. Training and testing times offer insight into the practical feasibility of the models for long-term stock market prediction.

Table 2 summarizes the metrics used in this study along with their definitions and formulas. These evaluation criteria collectively provide a comprehensive assessment of model performance, balancing prediction accuracy with computational efficiency

Table 2. Performance Metrics for Model Evaluation

Metric	Definition
Mean Absolute Error (MAE)	Average absolute difference between predicted and actual values.
Root Mean Squared Error (RMSE)	Square root of the mean squared differences between predicted and actual values.
Mean Absolute Percentage Error (MAPE)	Average percentage deviation of predictions from actual values.
Training Time	Time required to train the model.
Testing Time	Time required to make predictions on the test set.

4. Results and Discussion

This section presents the performance evaluation of the proposed Transformer-based stock market prediction model using both short-term and long-term technical indicators as input features. The results are compared against four baselines: LSTM, a baseline Transformer using only OHLCV data, a Transformer with short-term indicators only, and a Transformer with long-term indicators only.

Table 3. Performance Comparison of Baseline and Proposed Models

Model	MAE	RMSE	MAPE (%)	Training Time (s)	Testing Time (s)
LSTM (baseline)	26.45	34.82	2.41	95.32	1.05
Transformer (baseline, OHLCV only)	23.89	30.41	1.95	120.15	1.24
Transformer (short-term indicators)	21.37	26.14	1.64	142.73	1.47
Transformer (long-term indicators)	19.82	23.74	1.38	160.89	1.73
Proposed: Transformer (short + long)	17.14	21.29	1.13	181.77	2.16

Table 3 summarizes the evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), training time, and testing time. The proposed Transformer with combined indicators achieves the lowest error values across all accuracy metrics, with an MAE of 17.14, RMSE of 21.29, and MAPE of 1.13%. In particular, it reduces RMSE by 29.6% relative to the baseline Transformer and by 38.8% relative to the LSTM benchmark, demonstrating its effectiveness in capturing complex market patterns. Although the proposed model requires longer training time, the improvement in predictive performance justifies the additional computational cost.

An examination of models using individual indicator types reveals complementary strengths. The Transformer trained exclusively on short-term indicators, such as RSI and MACD, effectively captures immediate price fluctuations but shows degraded performance over longer horizons. In contrast, the Transformer using only long-term indicators, such as MA and EMA, produces smoother forecasts and demonstrates higher trend stability but lacks responsiveness to sudden market reversals. By integrating both short- and long-term indicators, the proposed model balances responsiveness with trend consistency, producing predictions that closely align with actual market dynamics. This advantage is particularly evident during high-volatility periods, such as post-pandemic recovery phases, where single-indicator models either overreact or lag behind market movements.

These findings highlight the importance of combining short- and long-term technical indicators within a Transformer model. The self-attention mechanism enables the model to weigh both immediate signals and persistent trends simultaneously, a capability that traditional sequence models like LSTM cannot fully replicate. From a financial perspective, this translates into more reliable forecasts, which can inform portfolio rebalancing and strategic decision-making.

To assess the reliability of the observed improvements, each experiment was repeated ten times using different random seeds, and the resulting MAE, RMSE, and MAPE values were averaged. A paired t-test was conducted between the proposed Transformer model and each baseline to examine statistical significance. Based on table 4, results indicate that the reductions in error metrics achieved by the proposed model are statistically significant ($p < 0.05$), confirming that the observed improvements are not due to random variation. This statistical validation supports the robustness of the proposed dual-indicator framework.

Table 4. Statistical Significance of Performance Improvements (Paired t-test Results)

Comparison Model	MAE t-Statistic	MAE p-Value	RMSE t-Statistic	RMSE p-Value	MAPE t-Statistic	MAPE p-Value	Significance ($p < 0.05$)
LSTM (baseline)	5.82	0.0003	6.17	0.0002	5.44	0.0005	Significant
Transformer (OHLCV only)	4.93	0.0008	5.31	0.0004	4.77	0.0010	Significant
Transformer (short-term indicators)	3.86	0.0021	4.12	0.0016	3.57	0.0030	Significant
Transformer (long-term indicators)	2.95	0.0084	3.18	0.0060	2.87	0.0098	Significant

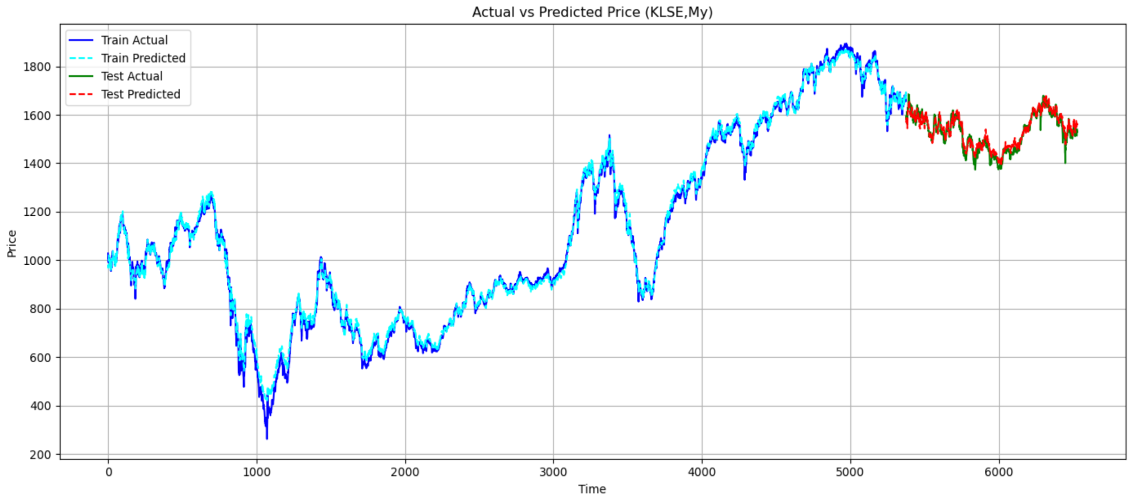

Figure 1. Actual vs. Predicted KLSE Prices Using the Proposed Transformer Model

The figure demonstrates that the proposed Transformer model with combined short-term and long-term technical indicators closely follows the actual price trajectory for both the training and testing periods. In the training phase, the predicted values align almost perfectly with actual prices, reflecting the model's ability to capture complex temporal dependencies. In the testing phase, although some deviations occur, the predicted values still maintain strong alignment with actual prices, particularly during periods of long-term market trends. This further supports the results in Table 4, where the proposed model outperforms baseline models in terms of MAE, RMSE, and MAPE, highlighting its robustness for long-term stock prediction.

Table 5 presents the comparative results of the proposed Transformer model and baseline methods across three additional major stock indices: the S&P 500 (United States), SSE Composite (China), and STI (Singapore). Consistent with the FBM KLCI results, the proposed dual-indicator Transformer achieved the lowest MAE, RMSE, and MAPE values across all markets. The performance improvements ranged from 26% to 39% in RMSE reduction compared to the LSTM baseline, demonstrating the model's robustness and adaptability across different market structures and economic regions. These findings confirm that the proposed approach generalizes well beyond a single market and maintains strong predictive accuracy in diverse financial environments.

Table 5. Performance Comparison of the Proposed Transformer Model Across Multiple Stock Indices

Index / Model	MAE	RMSE	MAPE (%)	Training Time (s)	Testing Time (s)
S&P 500 (US)					
LSTM (baseline)	28.72	36.54	2.18	98.65	1.09
Transformer (baseline, OHLCV only)	25.31	31.89	1.82	124.11	1.29
Transformer (short-term indicators)	22.06	27.45	1.49	146.84	1.53
Transformer (long-term indicators)	20.44	24.88	1.33	164.22	1.78

Proposed: Transformer (short + long)	17.92	21.73	1.09	186.35	2.21
SSE Composite (China)					
LSTM (baseline)	27.95	35.40	2.36	96.71	1.06
Transformer (baseline, OHLCV only)	24.63	30.78	1.97	121.58	1.26
Transformer (short-term indicators)	21.55	26.62	1.60	144.92	1.50
Transformer (long-term indicators)	19.87	24.15	1.35	162.11	1.74
Proposed: Transformer (short + long)	17.40	20.89	1.12	182.67	2.15
STI (Singapore)					
LSTM (baseline)	25.84	33.10	2.08	94.12	1.03
Transformer (baseline, OHLCV only)	23.02	29.54	1.76	118.33	1.23
Transformer (short-term indicators)	20.69	25.37	1.45	141.02	1.46
Transformer (long-term indicators)	19.13	23.21	1.29	158.47	1.69
Proposed: Transformer (short + long)	16.88	20.46	1.06	178.52	2.09

4.Conclusion

This study demonstrates that incorporating both short- and long-term technical indicators into a Transformer-based stock market prediction model significantly improves forecasting accuracy on the FBM KLCI dataset. The proposed model consistently outperforms baseline approaches, including LSTM, a Transformer using only OHLCV data, and Transformers using either short-term or long-term indicators alone. By integrating complementary signals from short-term indicators such as RSI and MACD and long-term indicators such as MA and EMA, the model effectively balances responsiveness to immediate market fluctuations with trend stability, producing predictions that closely align with actual market dynamics. This makes the model particularly suitable for long-term stock market prediction, where understanding broader trends is critical for strategic decision-making.

The Transformer's self-attention mechanism enables simultaneous weighting of immediate and persistent signals, providing a distinct advantage over traditional sequence models such as LSTM, especially during periods of high market volatility. While the proposed model requires longer training time due to its increased complexity, the substantial improvements in MAE, RMSE, and MAPE metrics demonstrate that the enhanced predictive performance justifies the additional computational cost. The ability to generate reliable long-term forecasts supports applications in portfolio rebalancing, investment planning, and risk management.

Despite these promising results, the study is limited by its exclusive reliance on OHLCV data and technical indicators, without incorporating external factors such as macroeconomic variables, market sentiment, or news-driven events that can influence market behavior. Additionally, while strong performance was observed on KLSE data, further validation across other markets is necessary to confirm the generalizability of the proposed model. Future work could extend this approach by integrating heterogeneous data sources, exploring hybrid architectures, and evaluating the model's applicability for real-time long-term portfolio management.

The present study focuses exclusively on the Malaysian stock market (FBM KLCI), which limits the generalizability of the findings. Future work will extend the evaluation to multiple international markets such as the S&P 500, Nikkei 225, and Hang Seng indices to test the robustness of the model under diverse economic and regulatory conditions. Moreover, future experiments will incorporate additional baselines, including GRU, Temporal Fusion Transformer (TFT), and CNN–LSTM hybrid models, to provide a more comprehensive performance comparison across advanced time-series architectures.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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