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Enhancing Stock Index Forecasting with LSTM using Volatility-Weighted Input Features

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Abstract Today's local and global stock markets are confronted with numerous challenges, such as the difficulty in accurately predicting stock prices and extracting useful features. While many researchers have successfully employed long short-term memory (LSTM) models for stock price prediction, there is still room for improvement in enhancing their accuracy, particularly in capturing the impact of market volatility. This paper proposed an LSTM with Average True Range (ATR) weighted input features to address this limitation. By incorporating volatility-weighted features into the LSTM architecture, the model adapts its learning process to reflect the varying impact of market volatility on stock index prices. Specifically, ATR is used to construct input features that better represent volatility, allowing the LSTM to more effectively capture fluctuations in market conditions. Using Bursa Malaysia Kuala Lumpur Composite Index (KLCI) as dataset, the proposed ATR-LSTM showed accuracy improvement in forecasting stock index prices compared to classic stock price prediction models such as autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and regular LSTM models. The evaluation metrics of mean absolute error (MAE) and root mean square error (RMSE) are used to validate this model. These findings highlight the importance of incorporating volatility-driven signals in stock index forecasting models.

Keywords Average True Range; Bursa Malaysia; LSTM; Machine learning; Time series; Volatility weighted LSTM.

Mathematics Subject Classification 37M10, 62P20, 68T99, 91B84.

1 Introduction

The stock market is characterized by its dynamic nature, exhibiting significant levels of volatility, noise, and dynamic fluctuations in its time series [1]. This complexity creates significant challenges for accurate prediction. Traditional prediction techniques frequently encounter difficulties in capturing the complex patterns and non-linear correlations found in financial time series data.

The LSTM model, a variation of the recurrent neural network (RNN), has become widely recognized as an effective technique for predicting financial time series data. Its capability to capture long-term dependencies and adapt to changing market conditions makes it especially suitable for modelling the dynamic nature of stock market data. Leveraging its memory cell structure, the LSTM model can effectively learn and exploit the temporal dynamics inherent in financial time series, thereby enhancing forecasting accuracy and robustness.

However, despite advancements, challenges persist, particularly volatility clustering and sudden spikes during turbulent market periods. This can present challenges for traditional forecasting models as well as LSTM model, resulting in inaccurate predictions. Limited representation of external factors presents another challenge. Standard LSTM architectures primarily rely on historical price data for predictions, potentially overlooking essential external factors that influence market behaviors [2]. Incorporating these factors, especially market volatility, is crucial for a more comprehensive understanding of stock index movements [3].

Numerous studies have explored the importance of input features and the role of feature selection in forecasting stock market movements. One approach combined sentiment analysis with an emotion-enhanced convolutional neural network and denoising autoencoder models alongside LSTM [4]. This method utilized information from news and social media to derive a sentiment index, while the autoencoder reconstructed input data with added random noise to extract meaningful representations from corrupted input. Another study employed multilingual sentiment analysis by translating texts from non-English-speaking countries into English, integrating unstructured data from social media with structured data such as trading information and technical indicators for input into an LSTM network [5].

Moreover, other approaches have integrated news headlines and language model-generated summaries to extract semantic information and representations [6]. Summarized news titles are used to predict sentiment polarity, which is then input into the LSTM network along with technical indicators. Technical indicators such as moving averages, oscillators, volatility indicators, and volume indicators have also been incorporated as inputs in various studies [7–9]. Other works have introduced investor sentiment indices as new variables for stock price prediction [10]. Besides that, one approach expanded LSTM input variables to include proxies for investor attention alongside market data like price and volume [11]. Additionally, composite investor sentiment indices [12] have been proposed, comprising objective indicators such as funds raised and monthly return rates, along with subjective measures like the consumer confidence index.

Volatility often reflects market sentiment and the collective perception of investors. Integrating volatility into stock index forecasting allows for the identification of periods of heightened uncertainty or market stress, which in turn provides insights into investor behavior and sentiment, helping anticipate potential market trends and shifts [13]. Market volatility is closely connected to significant price movements. By integrating volatility into forecasting models, these models can more effectively capture and adjust to rapid changes in market conditions. These lead to more precise predictions, particularly during periods of increased volatility, which are crucial for timely and effective decision-making [14]. Incorporating volatility is paramount due to its multifaceted significance and profound impact on market dynamics [15]. Understanding and integrating volatility into predictive models offers several crucial benefits that contribute to more accurate, reliable, and insightful stock index forecasts.

While LSTM models have been widely applied in stock price prediction, a significant gap persists in their ability to incorporate market volatility, a critical factor influencing stock index movements. Most existing studies focus primarily on historical price data, overlooking volatility measures that could significantly enhance model accuracy. Although some research has incorporated additional input features, such as market sentiment and trading volume, none have utilized a direct measure of market volatility like the ATR. To address this limitation, this study proposed a novel approach by integrating the ATR, a widely used measure of market volatility, directly into the LSTM model as a volatility-weighted input feature.

This innovative ATR-LSTM model aims to improve predictive accuracy by capturing the dynamic relationship between market volatility and stock index movements. Hence, the objective of this study is to develop and validate the ATR-LSTM model, demonstrating its superiority in capturing the relationship between market volatility and stock index price movements. In addition to addressing the primary objectives of this study, we benchmark the proposed ATR-LSTM model against widely used forecasting models, such as ARIMA, ANN, and standard LSTM. This comparison aims to validate the effectiveness of the ATR-LSTM model in capturing stock index volatility and to provide insights into its relative strengths within the broader context of stock market forecasting research. ARIMA has been a traditional choice for time series forecasting due to its simplicity and interpretability, making it a standard baseline in stock market prediction studies. On the other hand, ANN represents a class of machine learning models widely used for their ability to capture complex non-linear relationships in data. Including these models provides a comprehensive performance comparison across traditional statistical, machine learning, and advanced deep learning approaches

2 Methodology

2.1 Data Collection and Preparation

This study utilized the daily closing prices of the KLCI from January 2, 2018, to December 30, 2022, comprising a total of 1,206 observations obtained from the Yahoo Finance website. The dataset was first preprocessed to ensure consistency and reliability. Since the KLCI is not open daily, dates without values were retained as is, as no imputation was necessary. Outlier detection was performed using the Interquartile Range (IQR) method on half-yearly segments to account for potential drastic price fluctuations while preserving temporal integrity. Normalization of the closing prices was conducted using Z-normalization to standardize the data, ensuring compatibility with the LSTM model and facilitating convergence during training.

The dataset was divided into two segments: 80% for training and 20% for testing. This split ratio is widely used in time-series forecasting studies as it provides sufficient data for model training while reserving an adequate portion for evaluation. However, to ensure robustness and reduce potential bias introduced by a single train-test split, a rolling cross-validation strategy was also considered as an alternative test. This approach involves increasing the training set while reserving a fixed testing window, enabling an assessment of model performance over multiple temporal periods.

2.2 Volatility Measure and Data Segmentation

ATR is a versatile volatility measure that assesses the average range of price movements over a specific period [16]. Unlike traditional measures that only consider closing prices, ATR incorporates both intraday price highs and lows, providing a more comprehensive view of market volatility [17]. It is particularly valuable for setting stop-loss levels and determining the potential range of price movements within a given trading session or timeframe.

ATR is calculated as the average of the true ranges over a specified period as follows:

$$\mathrm{ATR} = \frac{\sum_{i=1}^{n} \mathrm{TR}_i}{p}. \tag{1}$$

where, TR_i represents true range of each day i and p represents the number of periods.

To analyze market behavior across varying volatility conditions, the dataset was segmented into half-year periods from 2018 to 2022. For each half-year period, the average ATR was calculated to represent the overall volatility trend. This segmentation was selected to ensure an adequate number of data points for training and testing predictive models while reflecting meaningful market behavior over time. Volatility categories were assigned to each period based on the quartiles of average ATR values, with thresholds determined by the 75th percentile (high volatility), 50th percentile (medium volatility), and 25th percentile (low volatility). This approach balances statistical rigor with practical interpretability, enabling a clear analysis of model performance under different volatility regimes. The categorized periods form the basis for further comparative analysis between the baseline and proposed models.

2.3 LSTM Model

The LSTM model is a specialized type of RNN, designed to effectively capture and learn from sequential data [18]. LSTMs are particularly well-suited for tasks involving time series analysis, natural language processing, and other applications where temporal dependencies are crucial [19]. LSTMs incorporate unique memory cells that enable them to maintain information over long periods. As depicted in Figure 1, the LSTM unit contains a cell, an input gate, an output gate, and a forget gate.

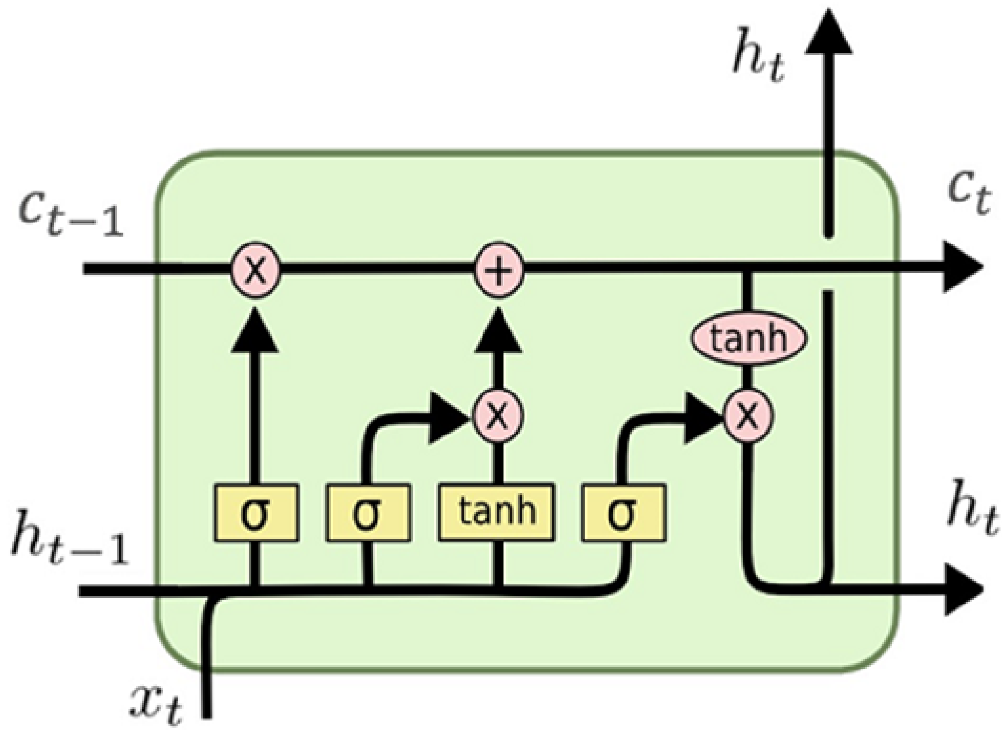

Figure 1: Structure of the LSTM cell.

The forget gate f_t dictates the degree to which the previous cell state c_{t-1} is discarded, computed as $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$, using the sigmoid function. The input gate i_t determines what new information is retained in the cell state, given by $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$, and the candidate cell state $\widetilde{C}_t$ is calculated using $\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$, with hyperbolic tangent function. The current cell state C_t is updated using the formula $C_t = f_t \bigodot C_{t-1} + i_t \bigodot \widetilde{C}_t$. Finally, the output gate o_t governs the output of the LSTM cell, calculated as $o_t = \sigma(W_o \bigodot [h_{t-1}, x_t] + b_0)$, and the hidden state h_t is derived from $h_t = o_t \bigodot \tanh(C_t)$.

2.4 ATR-LSTM Model

Incorporating ATR as input to LSTM model requires creating a function that assigns weights at different time steps based on their associated volatility [20,21]. Let X_t be the original time series at time t and A_t be the corresponding ATR measures at time t. The ATR values are used to adjust X_t by applying a weighting function based on volatility.

A function that assigns weights to different time steps based on their associated volatility is defined as follows:

$$W = f(\beta \cdot A_t). \tag{2}$$

where, β represents hyperparameter controlling the sensitivity of the weighting to ATR.

A_t represents the ATR values at time t, and f is a function that maps volatility to weights

Subsequently, the adjusted time series can be denoted as:

$$X_t^* = W \cdot X_t. \tag{3}$$

where, X_t^* represents the modified series.

The resulting series is then fed into the LSTM model, represented by the equation:

$$h_t = LSTM(X_t^*, h_{t-1}). \tag{4}$$

The process of incorporating ATR into the LSTM model through volatility-weighted input features can be visualized in Figure 2.

2.5 Model Evaluation

The forecasting models were evaluated using two performance measures: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_l|. \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_l)^2}. \tag{6}$$

The total number of observations is represented by n, where y_i denotes the actual observed value and $\hat{y}_l$ refers to the forecasted value. These performance metrics will be utilized to evaluate the forecasted values generated by the LSTM model for the out-of-sample data.

3 Results and Discussion

3.1 Volatility Phases and Data Characteristics

To understand the dynamics of the KLCI under varying market conditions, the dataset was segmented into volatility phases based on ATR trends. The ATR values for each half-year period from 2018 to 2022 were calculated, and the average ATR for each period was used as a representative measure of market volatility. These values were categorized into three distinct volatility levels (high, medium, and low) based on quartile thresholds. The 75th percentile and 25th percentile of the average ATR values served as cutoffs, defining high and low volatility periods, respectively, while values between these thresholds represented medium volatility. To provide context, significant economic or political events were associated with each half-year period to explain the observed volatility patterns. These events include market shocks, political developments, or global financial trends influencing market behavior. Table 1 summarizes the segmentation, highlighting the average ATR, corresponding volatility level, and key events during each period.

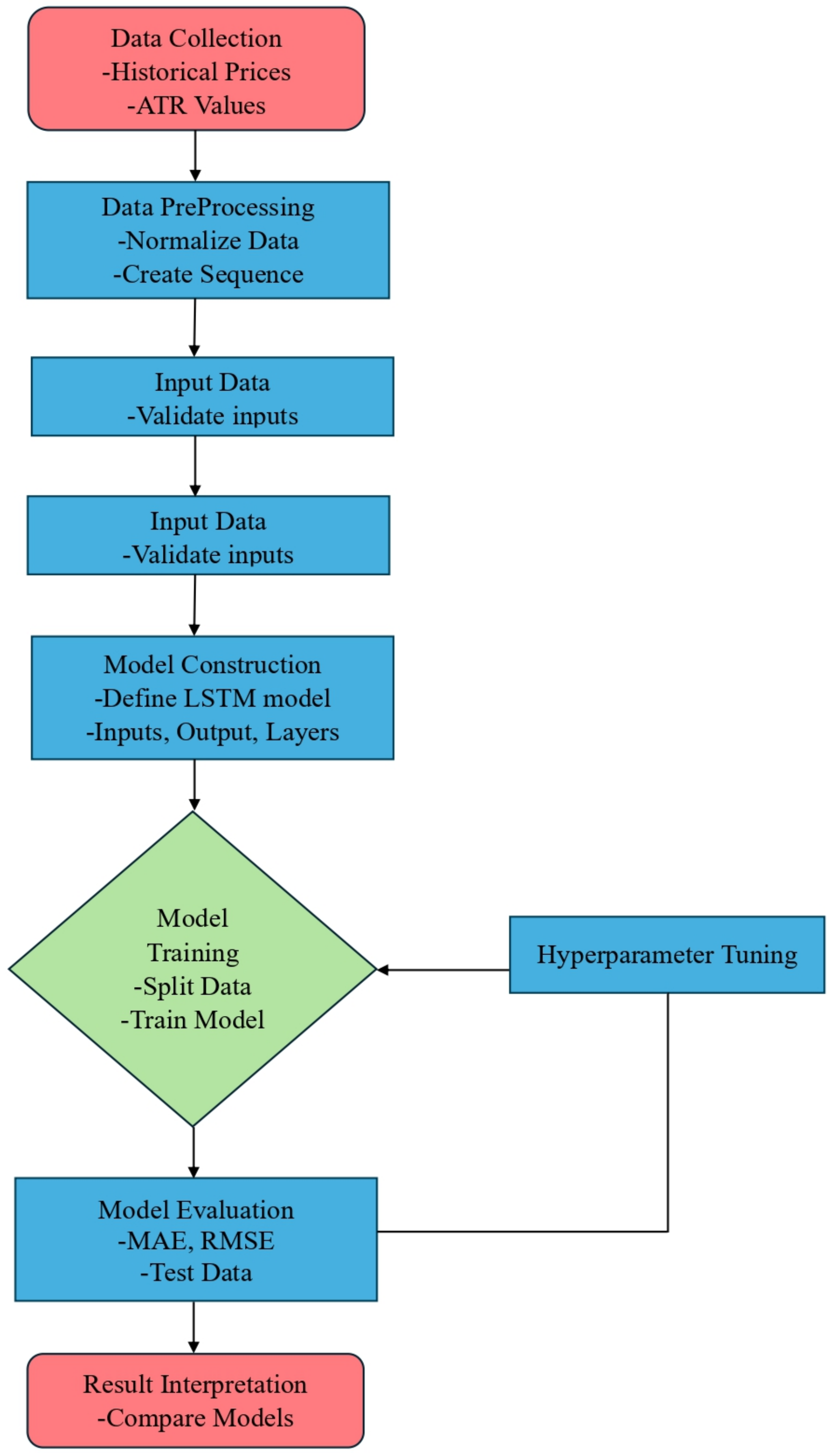

Figure 2: Workflow of the ATR-LSTM Model using Volatility-Weighted Input Features.

Table 1: Volatility Analysis of KLCI: Average ATR and Significant Events by Half-Year Period (20182022).

Year	Period	Average ATR	Volatility Level	Significant Event
2018	H1	9.40	High	General election (GE14) causing market uncertainty
2018	H2	8.28	Medium	Transition to new government, economic adjustments
2019	H1	6.60	Low	Stable political landscape, modest market growth
2019	H2	5.66	Low	Trade tensions ease, market steadiness
2020	H1	13.83	High	COVID-19 outbreak and global economic shocks
2020	H2	11.66	High	Recovery phase, political instability
2021	H1	9.08	Medium	Vaccine rollout, intermittent market optimism
2021	H2	7.53	Medium	Recovery from pandemic-induced market shocks
2022	H1	9.64	High	Inflation concerns, geopolitical tensions
2022	H2	8.73	Medium	Post-pandemic economic adjustments

The inclusion of significant events provides context for understanding the underlying drivers of volatility. For instance, the high volatility in 2020 corresponds to the onset of the COVID-19 pandemic, which caused drastic market movements globally. Similarly, high volatility during the first half of 2022 aligns with inflation concerns and geopolitical tensions.

The graph in Figure 3 below illustrates the ATR values over the study period (2018-2022) for the KLCI, segmented into half-year periods. The ATR values are plotted on the y-axis, while the x-axis represents the timeline from 2018 to 2022.

From the graph, it is evident that the ATR values fluctuate significantly across different periods, reflecting the varying levels of market volatility. The spikes in ATR values, particularly in 2020, correspond to significant economic and political events such as the outbreak of the COVID-19 pandemic, which triggered a global market downturn. In contrast, periods with lower ATR values, such as the second half of 2019 and 2021, indicate relatively stable market conditions. These lower ATR values align with periods of economic recovery and political stability, where the market experienced more gradual movements.

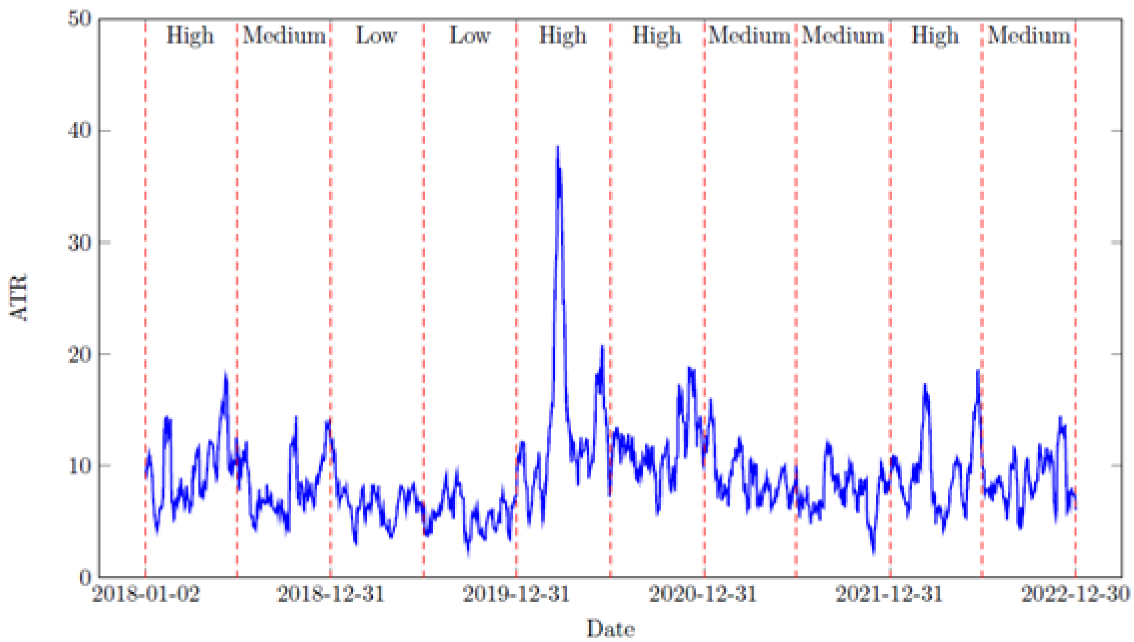

Figure 3: Volatility Trends in KLCI: ATR Values Over Time (20182022).

3.2 Hyperparameter Optimization Strategies

The hyperparameters of the LSTM and ATR-LSTM models were optimized using a combination of manual tuning and grid search to achieve superior performance during the training phase. The process began with manually identifying a reasonable range for each hyperparameter based on literature and initial experiments. A grid search was then applied within these ranges to systematically evaluate combinations and their impact on model performance.

The following hyperparameters were fine-tuned:

- Number of Hidden Layers: Tested values included 1, 2, and 3 layers. The final choice of 2 layers balances model complexity and performance

- Number of Neurons per Layer: Ranges from 50 to 200 were explored. The optimal setting was 100 neurons per layer.

- Dropout Rate: Values between 0.1 and 0.5 were considered to mitigate overfitting. A rate of 0.2 was selected for its effectiveness in preventing overfitting without significant loss of information.

- Timestep: A range of 5 to 20 timesteps was tested to capture temporal dependencies effectively. A timestep of 10 demonstrated superior predictive accuracy.

- Batch Size: Explored values were 32, 64, and 128. A batch size of 64 was chosen for its balance between computational efficiency and convergence.

- Epochs: Models were tested for 30 to 100 epochs. Convergence analysis determined that 50 epochs were sufficient for stable performance.

- Activation Function: The hyperbolic tangent (tanh) activation function was chosen for its ability to handle normalized data effectively.
- Recurrent Function: The sigmoid function was retained for its compatibility with the tanh activation in capturing dependencies.
- Optimizer: The Adam optimizer was selected after testing alternatives (SGD and RMSprop) due to its adaptive learning rate and robust convergence.
- Loss Function: The mean squared error (MSE) was used as the loss function for its suitability in regression tasks.

The evaluation criteria for selecting the final hyperparameter settings were based on validation loss trends, with the configuration minimizing validation loss while avoiding overfitting chosen for testing. Cross-validation was used to ensure robustness across different data splits, further validating the selected hyperparameter configuration.

3.3 Model Performance on Testing Data

The predictive accuracy of the models was assessed using the testing dataset, which comprised 20% of the original data split. The evaluation metrics used were MAE and RMSE, providing a comprehensive measure of model performance. These metrics were calculated for all models under consideration, including standard LSTM, ATR-LSTM, and benchmark models like ARIMA and ANN. The results are summarized in Table 2, showcasing how each model generalizes to unseen data. The findings highlight the superior performance of the ATR-LSTM model, particularly in capturing complex patterns in the KLCI dataset, as reflected in its lower error values compared to baseline models. The results of this study are consistent with previous research that identified LSTM as the most effective model for predicting the KLCI, outperforming both ANN and ARIMA in terms of predictive accuracy [22–24].

Table 2: Performance Metrics for Various Models on the Testing Dataset.

Model	MAE	RMSE
ARIMA (0,1,0)	9.05	11.83
ANN (3,1,1)	8.99	11.71
Regular LSTM	8.98	11.74
ATR-LSTM	8.94	9.21

Additionally, Figure 4 visualizes the actual vs. predicted closing prices for each model on the testing data. This graph highlights the alignment between predicted and actual trends, emphasizing the ATR-LSTM model's ability to capture fluctuations in market movements more accurately than the benchmarks.

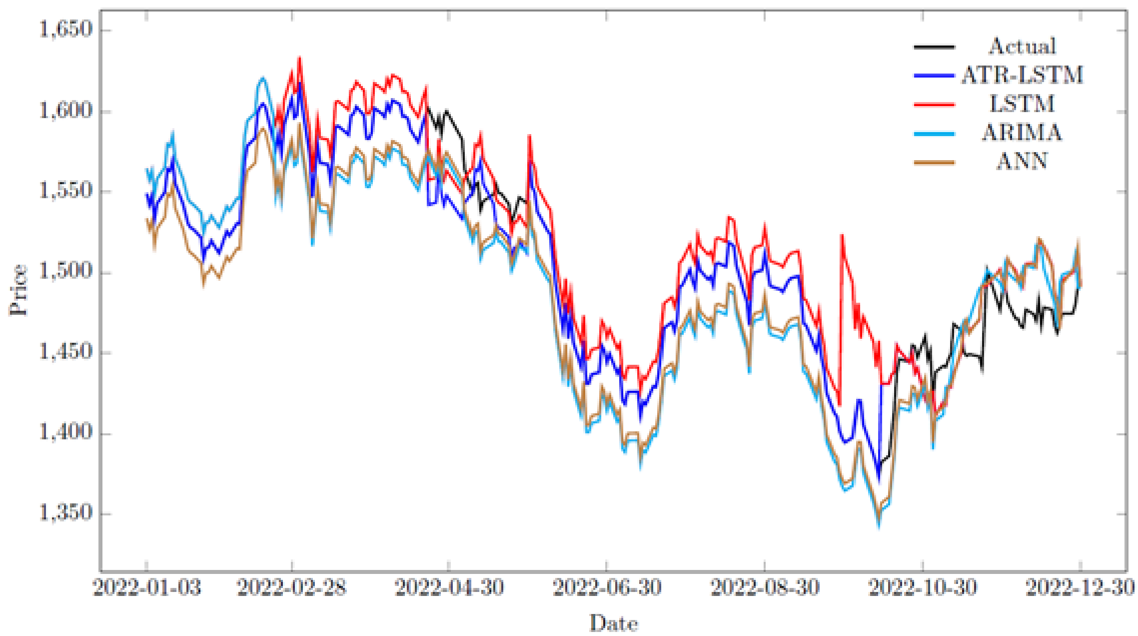

Figure 4: Comparison of Actual vs. Predicted Closing Prices for Different Models on the Testing Dataset.

3.4 Model Performance Under Different Volatility Levels

To evaluate the robustness of the models under varying market conditions, their predictive performance was analyzed across different volatility levels. The dataset was segmented into half-year periods based on ATR values, as detailed earlier. Each segment was categorized into low, medium, or high volatility levels to investigate the models performance under distinct market scenarios. The results, including MAE and RMSE values for ARIMA, ANN, LSTM, and ATR-LSTM models, are summarized in Table 3 and Table 4.

Table 3: MAE of All Models Under Different Volatility Levels.

Year	Period	Volatility Level	ARIMA	ANN	LSTM	ATR-LSTM
2018	H1	High	14.8	12.6	10.3	9.2
2018	H2	Medium	13.7	11.8	9.6	8.4
2019	H1	Low	8.2	8.3	8.7	7.5
2019	H2	Low	8.4	8.5	8.9	7.6
2020	H1	High	15.4	13.1	10.7	9.5
2020	H2	High	15.0	12.8	10.5	9.3
2021	H1	Medium	13.2	11.5	9.2	8.0
2021	H2	Medium	13.4	11.6	9.4	8.2
2022	H1	High	15.7	13.4	11.1	9.7
2022	H2	Medium	13.9	12.0	9.8	8.5

Table 4: RMSE of All Models Under Different Volatility Levels.

Year	Period	Volatility Level	ARIMA	ANN	LSTM	ATR-LSTM
2018	H1	High	17.2	15.0	12.7	11.3
2018	H2	Medium	16.1	13.8	11.9	10.1
2019	H1	Low	10.6	10.4	10.7	9.2
2019	H2	Low	10.8	10.6	10.9	9.3
2020	H1	High	18.0	15.7	13.2	11.8
2020	H2	High	17.6	15.3	13.0	11.5
2021	H1	Medium	15.8	13.6	11.4	10.0
2021	H2	Medium	16.0	13.8	11.5	10.1
2022	H1	High	18.4	16.1	13.7	12.1
2022	H2	Medium	16.3	14.1	12.1	10.5

The findings highlight a significant disparity in model performance across volatility levels. For low-volatility periods, ARIMA and ANN models performed relatively well, demonstrating their effectiveness in stable market conditions. However, as volatility increased, the predictive accuracy of these traditional models diminished, as evidenced by rising MAE and RMSE values. Conversely, the ATR-LSTM model consistently delivered lower error rates, showcasing its ability to adapt to fluctuating market conditions. The results also indicate that the ATR-LSTM model particularly excelled during high-volatility periods. This improvement can be attributed to its integration of ATR-based features, which provided it with the contextual information necessary to model abrupt market changes.

Table 5 illustrates the directional accuracy (DA) achieved by ARIMA, ANN, LSTM, and ATR-LSTM models under different volatility levels. DA measures the percentage of instances where the model correctly predicts the direction of price movement (increase or decrease). This metric provides critical insights into the practical applicability of the models, particularly in scenarios where decision-making depends on accurate trend prediction

Table 5: Directional Accuracy (%) Across Volatility Level.

Year	Period	Volatility Level	ARIMA	ANN	LSTM	ATR-LSTM
2018	H1	High	55.4	60.3	68.1	72.5
2018	H2	Medium	58.2	63.7	70.5	75.8
2019	H1	Low	60.1	65.4	73.2	78.6
2019	H2	Low	59.9	65	72.8	78.2
2020	H1	High	54.7	59.6	66.9	71.4
2020	H2	High	55.0	60.1	67.5	72
2021	H1	Medium	58.9	64.2	71.6	76.2
2021	H2	Medium	58.7	64.0	71.3	75.9
2022	H1	High	53.9	58.8	65.7	70.2
2022	H2	Medium	57.5	62.6	69.8	74.4

The DA results in Table 5 highlight significant differences in the predictive capabilities of the models under varying volatility conditions. ATR-LSTM consistently demonstrates the highest DA, particularly under high and medium volatility levels, indicating its robustness in capturing market dynamics. LSTM follows closely, outperforming both ARIMA and ANN across all levels, showcasing its ability to adapt to nonlinear and temporal relationships in the data. In contrast, ARIMA struggles with high volatility periods, achieving the lowest DA due to its reliance on linear relationships and lag-based modeling. ANN performs moderately better than ARIMA but still falls short of LSTM-based approaches, particularly under high volatility conditions.

3.5 Model Validation and Diagnostic Analysis

To validate the ATR-LSTM model's robustness, a rolling-window cross-validation was conducted, dividing the dataset into training and testing periods incrementally. Performance metrics (MAE and RMSE) were calculated for each fold to ensure consistent predictive capability. As shown in Table 6, the ATR-LSTM model achieved stable performance across folds, with low variability in errors, indicating strong generalizability.

Table 6: Extended Cross-Validation Results for the ATR-LSTM model.

Fold	Training Period	Testing Period	MAE	RMSE
1	Jan 2018 Dec 2018	Jan 2019 Jun 2019	9.34	12.78
2	Jan 2018 Jun 2019	Jul 2019 Dec 2019	8.99	12.34
3	Jan 2018 Dec 2019	Jan 2020 Jun 2020	10.23	13.45
4	Jan 2018 Jun 2020	Jul 2020 Dec 2020	11.12	14.89
5	Jan 2018 Dec 2020	Jan 2021 Jun 2021	10.89	13.98
6	Jan 2018 Jun 2021	Jul 2021 Dec 2021	9.76	12.89
7	Jan 2018 Dec 2021	Jan 2022 Jun 2022	10.45	13.67
8	Jan 2018 Jun 2022	Jul 2022 Dec 2022	8.94	9.21

To further assess the model's reliability, the residuals were analyzed for autocorrelation using the Ljung-Box test. The p-values in Table 7 indicate no significant autocorrelation, suggesting that the residuals are random and that the model effectively captures underlying temporal patterns. Together, these results demonstrate the robustness and reliability of the ATR-LSTM model for stock index forecasting.

Table 7: Ljung-Box Test Results for Residuals Autocorrelation Analysis of the ATR-LSTM Model.

Lag	Q-Statistics	p-value
1	0.953	0.329
5	3.874	0.567
10	8.243	0.684

The incorporation of volatility weighting enables the model to assign greater importance to periods of high volatility and adjust its forecasts accordingly. This adaptive mechanism is particularly crucial in volatile and uncertain market conditions, where traditional forecasting models may struggle to capture the underlying trends and patterns [25]. By leveraging the informational content embedded within market volatility, the proposed ATR-LSTM framework offers a more nuanced and responsive approach to stock index forecasting, thereby enhancing predictive accuracy and robustness.

4 Conclusion

In conclusion, this study has underscored the significance of integrating volatility as an input feature in LSTM models for enhancing stock index forecasting. By leveraging the dynamic relationship between market volatility and asset prices, ATR-LSTM models can adaptively adjust their forecasts to better capture the complexities of financial markets. Comprehensive empirical analyses demonstrate the efficacy of volatility-based LSTM frameworks in enhancing predictive accuracy and robustness, particularly under volatile market conditions. The findings also highlighted the potential of incorporating market volatility measures into machine learning-based forecasting models to unlock new avenues for innovation and improve decision-making processes in finance. Moving forward, further research in this direction could deepen the understanding of market dynamics and pave the way for the development of more sophisticated forecasting methodologies tailored to the complexities of modern financial markets.

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