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# Adaptability of Statistical and Deep Learning Models to Volatile Market Conditions in Bursa Malaysia Stock Index Forecasting

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**ABSTRACT**

The stock market plays a crucial role in the financial world, yet its inherent volatility and unpredictability make forecasting future movements challenging. In recent years, deep learning has emerged as a promising approach for stock market prediction, leveraging advanced computational capabilities to analyze complex patterns within large datasets. This study investigates the forecasting performance of the Bursa Malaysia Kuala Lumpur Composite Index (KLCI), comparing the adaptability of Long Short-Term Memory (LSTM), Artificial Neural Network (ANN), and Autoregressive Integrated Moving Average (ARIMA) models across periods of high and low market volatility. Our findings reveal that the LSTM model consistently outperforms both ANN and ARIMA models, demonstrating greater robustness and accuracy during volatile phases, such as those induced by the COVID-19 outbreak and political uncertainties in Malaysia. By highlighting each model's strengths and limitations under varying market conditions, this study provides valuable insights for stakeholders aiming to select forecasting models that can adapt to the challenges of market instability.

## 1. Introduction

The stock market is a dynamic system characterized by high volatility, noise, and frequent changes. Its time series behaviour is influenced by a multitude of variables, including a company’s financial profile, market sentiment, economic conditions, and political developments. These complexities make stock value prediction a challenging task. Accurate stock market forecasting offers significant implications for both investors and policymakers. For investors, it is a critical enabler of informed portfolio management, allowing for strategic decisions on asset allocation, diversification, and timing [1]. Predictive insights can mitigate the impact of unexpected market shocks and enhance the capacity to capitalize on emerging opportunities, particularly in volatile conditions. For policymakers, stock market forecasts play a pivotal role in shaping economic strategies [2]. Stock indices often act as leading indicators of macroeconomic health, reflecting corporate performance, public sentiment, and global economic trends. By leveraging accurate forecasts, policymakers can

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anticipate disruptions, implement timely regulatory adjustments, and design targeted interventions to stabilize the financial system during periods of instability.

Stock market forecasting is not only a tool for profit maximization but also a mechanism to minimize losses by enabling stakeholders to make informed decisions in the face of uncertainty. This underscores the necessity of developing advanced techniques for predicting stock values that can effectively handle the complexity and unpredictability of financial time series. Two prominent approaches for time series analysis are statistical and computational methods, both of which have been extensively applied to tackle the challenges posed by stock market dynamics.

Statistical approaches for financial time series analysis encompass a diverse array of methods designed to understand, interpret, and forecast temporal data effectively. Key techniques include ARIMA (Autoregressive Integrated Moving Average) models, which are versatile in handling various data patterns by combining autoregressive terms (AR), differencing for stationarity, and moving averages (MA) to model the series' noise components [3-5]. Seasonal ARIMA (SARIMA) further extends this by incorporating seasonal differencing and seasonal AR and MA components, making it suitable for data with seasonal patterns. Exponential smoothing methods provide powerful tools for smoothing and forecasting by emphasizing recent observations while accounting for trends and seasonality. Decomposition methods such as seasonal decomposition break down a time series into trend, seasonal, and residual components, offering insights into the underlying structure and enabling better interpretation and forecasting.

For multivariate time series, Vector Autoregression (VAR) models generalize autoregressive models, allowing each variable to be a linear function of past values of itself and other variables in the system. GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are particularly valuable for financial time series, as they model the variance of the current error term based on past errors, capturing volatility clustering [7-9]. Advanced techniques like Kalman filtering and state space models, offer robust solutions for estimating the state of dynamic systems from noisy data, making them suitable for real-time applications. Spectral analysis provides insights into the frequency domain of time series, identifying periodicities and cyclical patterns. Each of these methods has unique strengths and is selected based on the specific characteristics and requirements of the time series data, such as stationarity, presence of trends and seasonality, and the need for real-time analysis or causal inference. The choice of method ensures accurate modelling, insightful analysis, and reliable forecasting tailored to the data's nature.

Time series forecasting has evolved with the development of computational approaches that leverage advanced algorithms and modern computing to manage complex patterns, large datasets, and non-linear relationships effectively [10,11]. Deep learning models represent a transformative advancement in computational approaches, offering unparalleled flexibility and adaptability for sequential data. Recurrent Neural Networks (RNN) are a pioneering deep learning architecture designed for temporal data, capable of capturing dependencies across sequences through their recurrent connections. Enhanced variants like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) address the limitations of traditional RNNs, such as the vanishing gradient problem, enabling them to model long-term dependencies with high accuracy [12]. These deep learning models stand out for their ability to learn complex, non-linear relationships inherent in financial data without requiring manual feature extraction.

Moreover, LSTM networks exemplify the core strengths of deep learning in stock market forecasting by leveraging hierarchical representations of data through multiple neural layers. Unlike statistical models that rely on fixed equations, LSTMs dynamically adapt to changing data patterns, capturing both short-term fluctuations and long-term trends. This adaptability is particularly beneficial in volatile market conditions, where traditional models often fall short. The prominence of deep learning models extends beyond LSTMs. Autoencoders, another deep learning framework, are widely used for unsupervised anomaly detection, identifying deviations from normal market behaviour [13]. These approaches highlight how deep learning transcends predictive accuracy, offering tools for understanding complex financial systems.

While ensemble methods like Random Forests, Gradient Boosting Machines (GBMs), and Support Vector Regression (SVR) remain integral to machine learning for time series analysis, their focus on regression and classification tasks differs fundamentally from the sequential learning capabilities of deep learning models [14]. Statistical models may provide robustness under stable conditions, but they cannot match the capacity of deep learning approaches to handle volatility and non-linear dynamics in financial markets.

In Malaysia, the Bursa Malaysia Kuala Lumpur Composite Index (KLCI) serves as a key benchmark for market performance, and its forecasting has attracted significant research attention. Traditional statistical models such as ARIMA have been widely employed due to their simplicity and interpretability. For example, previous studies [15-17] applied ARIMA to forecast the KLCI and reported satisfactory results under stable market conditions. However, these models rely on assumptions of linearity and stationarity, which limit their effectiveness in highly volatile or dynamic market environments [18].

In recent years, deep learning models, particularly LSTM networks, have gained traction for stock index forecasting due to their ability to capture non-linear relationships and long-term dependencies. Previous studies in the Malaysian context [19-21] demonstrated the potential of LSTMs to outperform statistical models like ARIMA. While these studies underscore the advancements brought by LSTM, they often overlook the variability in model performance under different market regimes, such as high volatility during political instability or economic recovery phases.

Existing research has primarily emphasized overall accuracy, often overlooking the crucial aspect of adaptability during periods of significant market turbulence. Consequently, a critical gap persists in understanding how statistical and deep learning models respond and perform under varying market conditions, particularly during phases of heightened volatility. The adaptability of models like ARIMA and LSTM during such phases remains underexplored, particularly for financial markets like Bursa Malaysia, which are subject to both global and domestic influences. Thus, this study aims to address this gap by evaluating the performance of statistical models (ARIMA), classical machine learning models known as Artificial Neural Network (ANN), and advanced deep learning models (LSTM) under distinct market conditions in Malaysia. By examining how these models respond to high and low volatility regimes, we provide insights into their robustness and adaptability, ultimately guiding practitioners in selecting the most suitable forecasting approach for varying financial contexts.

## 2. Methodology

### *2.1 Data Collection and Segmentation*

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 divided into two segments: the training set, spanning from January 2, 2018, to July 1, 2022 (90% of the data), and the testing set, covering the period from July 4, 2022, to December 30, 2022 (10% of the data).

Between 2018 and 2022, there are identifiable high and low volatility phases for the KLCI based on historical events and market behaviour as shown in Table 1.

**Table 1**
Classification of market volatility based on key events and phases in Malaysia (2018-2022)

| Year | Events | Volatility classification |
|---|---|---|
| 2018-2019 | Prior to the pandemic, the market exhibited more stable behaviour, with relatively lower volatility. The political changes during the 2018 general election did create some market reactions, but these were less pronounced compared to the pandemic period. | Low Volatility |
| 2020 | This was a period of intense volatility due to the COVID-19 pandemic. Market reactions to lockdowns, economic disruptions, and uncertainty about global recovery created significant fluctuations in the stock index. | High Volatility |
| 2021 | After the initial economic recovery measures, some level of stability returned to the markets in 2021, as vaccination efforts and economic reopening plans took shape. This period was more stable than the highly volatile 2020 phase. | Low Volatility |
| 2022 | Another high volatility phase occurred in 2022, influenced by political uncertainty in Malaysia, as well as global economic factors such as inflationary pressures and supply chain disruptions. These factors, coupled with economic recovery from COVID-19, contributed to heightened market movements. | High Volatility |

Once the data is separated into high and low volatility periods, another distinct training and testing sets are created for each regime. This step is necessary to ensure each model is evaluated on its ability to adapt to volatility-specific patterns rather than a general mix of conditions. This approach allows us to analyze and compare each model's accuracy and robustness within distinct volatility contexts, providing insights into how well ARIMA, ANN, and LSTM models adapt to changes in market stability. By redoing the data split based on volatility, we can isolate each model's performance under high-stress conditions versus more stable periods, helping to identify which model is most resilient across different market scenarios.

### *2.2 Model Selection Framework*

The methodology employs three distinct models which are ARIMA, ANN and LSTM, to assess forecasting performance under varying market conditions. These models were chosen to represent three categories of computational approaches: statistical models (ARIMA), classical machine learning models (ANN), and advanced deep learning models (LSTM). The inclusion of these models ensures a comprehensive evaluation of methodologies with increasing levels of complexity and adaptability.

#### *2.2.1 ARIMA model*

ARIMA is a well-established statistical time series model used extensively in financial forecasting. Its reliance on stationarity and linearity makes it a robust benchmark for stable market conditions, but its limitations in handling non-linear and volatile patterns necessitate comparison with more sophisticated techniques. The ARIMA model's parameters ($p, d, q$) are determined through grid search and evaluated for adequacy using autocorrelation and partial autocorrelation plots [22].

The expression for an ARIMA model is as follows:

$$(1-B)^d y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (1)$$

where,

$y_t$ represents value at time $t$
$B$ represents backshift operator
$c$ represents constant term
$\phi_1$, $\phi_1$, …., $\phi_1$ represents coefficients for the autoregressive terms (AR part)
$\theta_1$, $\theta_1$, …., $\theta_1$ represents coefficients for the moving average terms (MA part)
$\epsilon_t$ represents white noise error term
$p$ represents the quantity of autoregressive terms
$q$ represents the number of moving average terms
$d$ represents differencing

### *2.2.2 ANN model*

ANN serves as a bridge between statistical models and deep learning. Unlike ARIMA, ANN can capture non-linear relationships, making it a valuable intermediary in the evaluation. A feedforward neural network architecture is implemented, with the input layer consisting of lagged time series values and the output layer predicting the next time step [23]. The model is trained using backpropagation and optimized with a chosen activation function and gradient-based optimizer. The inclusion of ANN enables a comparison of how machine learning models fare in dynamic market environments relative to both ARIMA and LSTM.

The expression for an ANN model is as follows:

$$h_j = g\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \quad (2)$$

$$\hat{y} = f\left(\sum_{j=1}^{m} v_j h_j + c\right) \quad (3)$$

where,
$x_i$ represents input features
$w_{ij}$ represents weight from input $x_i$ to hidden node $j$
$b_j$ represents bias for hidden node $j$
$g(\cdot)$ represents activation function for hidden nodes
$h_j$ represents output of the hidden layer node $j$
$v_j$ represents weight from hidden node $j$ to output layer
$c$ represents bias term for the output layer
$f(\cdot)$ represents activation function for the output layer

### *2.2.3 LSTM model*

LSTM, a specialized form of Recurrent Neural Networks (RNNs), is included due to its demonstrated ability to capture long-term dependencies and dynamic patterns in sequential data [24]. As illustrated in Figure 1, the LSTM model is designed with a series of memory cells and gates that mitigate the vanishing gradient problem, enabling it to process and retain important features in financial time series data. The architecture is tailored for the study, incorporating features like multiple hidden layers, dropout regularization, and the tanh activation function to enhance model performance [25].

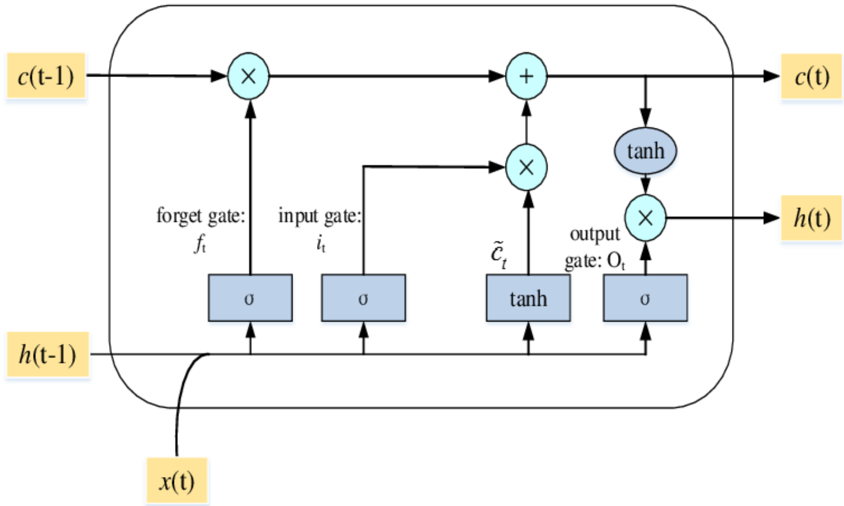



**Fig. 1.** Architecture of the LSTM unit

The equations involved in the LSTM are listed below:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{5}$$

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{6}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \tag{7}$$

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_0) \tag{8}$$

$$h_t = o_t \odot \tanh(C_t) \tag{9}$$

where,
$i_t$ is value of the input gate
$\widetilde{C}_t$ is value of the candidate cell state
$f_t$ is value of the forget gate
$C_t$ is value of the updated cell state
$O_t$ is value of the output gate
$h_t$ is value of the hidden state
$W_i$, $W_c$, $W_f$ and $W_o$ represent four distinct matrix weights
$b_i$, $b_c$, $b_f$ and $b_o$ represent the biases
$\sigma$ is the sigmoid function
$\odot$ represents the vector outer product

### *2.3 Model Evaluations*

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

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{11}$$

The true value is represented by $y_i$ while $\hat{y}_i$ denotes the estimated value. A smaller MAE and RMSE indicate a more accurate prediction model. The selection of MAE and RMSE as evaluation metrics is guided by their relevance in financial forecasting. MAE measures the average magnitude of errors in predictions without considering their direction, providing an interpretable metric for understanding overall model performance. On the other hand, RMSE penalizes larger errors more heavily due to its squared error calculation. This feature is particularly valuable in financial forecasting, where extreme deviations can have significant implications for decision-making. By combining MAE and RMSE, this study offers a comprehensive evaluation framework that captures both the average performance and the sensitivity of models to large errors, ensuring a detailed assessment of their effectiveness in volatile market conditions [26].

## 3. Results and Discussion
### *3.1 Volatility Phase Analysis*

To understand the varying market conditions, we first examined the overall performance of the KLCI from 2018 to 2022. Figure 1 displays the KLCI's closing prices during this period, highlighting key events that influenced market behaviour. The graph clearly reflects significant phases of high and low volatility, which are classified based on the events described in Table 1. The relatively stable market behaviour from 2018 to 2019 contrasts sharply with the heightened volatility in 2020 caused by the COVID-19 pandemic. While the market regained some stability in 2021 during the recovery phase, another spike in volatility emerged in 2022 due to political uncertainty in Malaysia and global economic challenges [27].

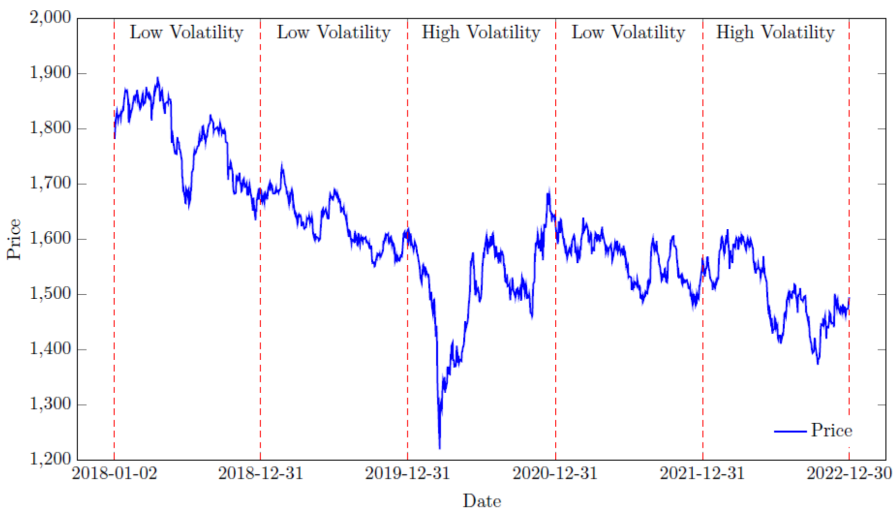


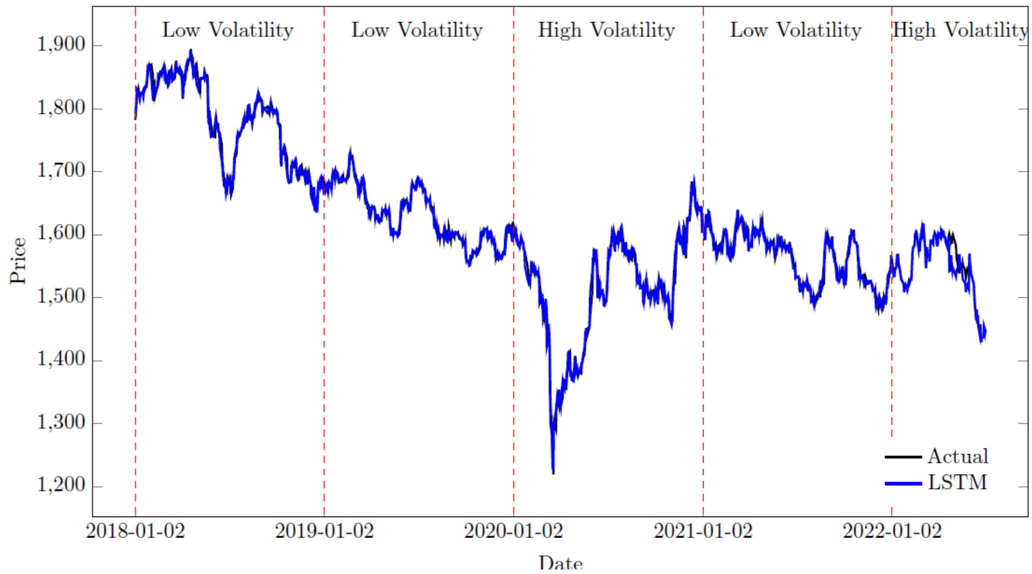

**Fig. 2.** KLCI Closing Prices from 2018 to 2022

### *3.2 Model Performance Evaluation*

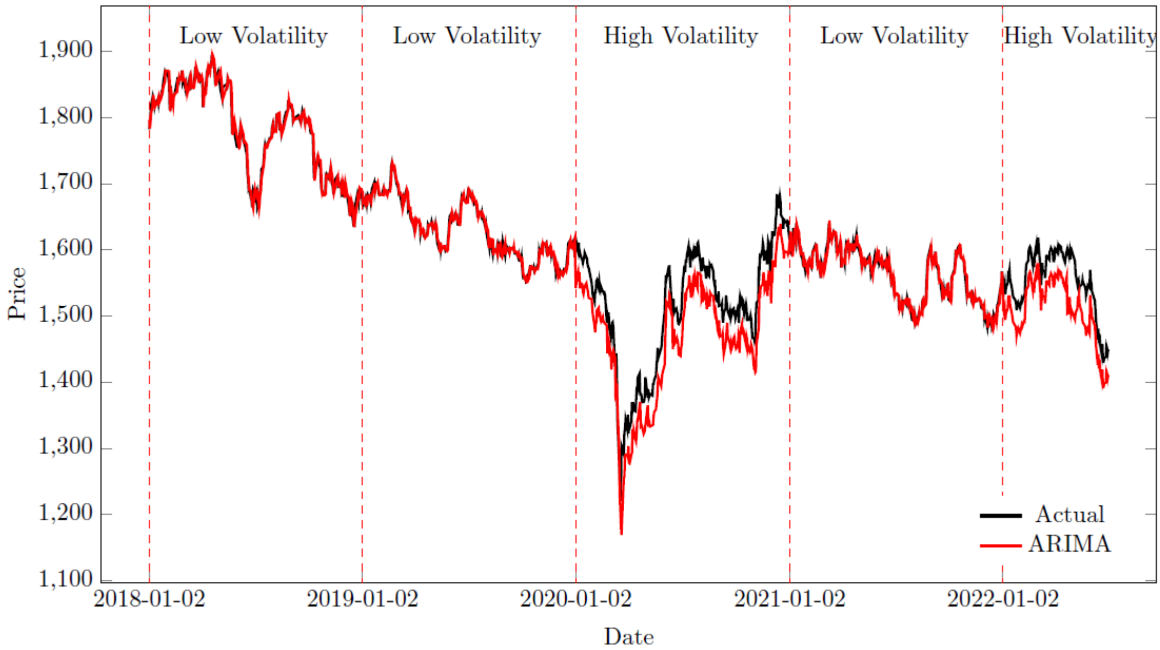
The predictive accuracy of ARIMA, ANN, and LSTM models was assessed across the identified volatility phases using MAE and RMSE as evaluation metrics. The results are presented in Table 2, highlighting the strengths and weaknesses of each model under both stable and turbulent conditions. During low-volatility periods, ARIMA performed well due to its strength in capturing linear patterns. However, its accuracy declined significantly in high-volatility phases, where non-linearities and rapid market shifts became more pronounced. ANN demonstrated moderate performance across all phases, benefiting from its ability to handle non-linearity but struggling with sequential dependencies. In contrast, LSTM consistently outperformed both ARIMA and ANN, particularly during high-volatility periods, due to its capability to capture temporal dependencies and long-term patterns. Figure 3 illustrate the actual vs. predicted prices for each model, underscoring LSTM's superior adaptability to volatile market conditions.

**Table 2**
Model Performance Across Segmented Datasets

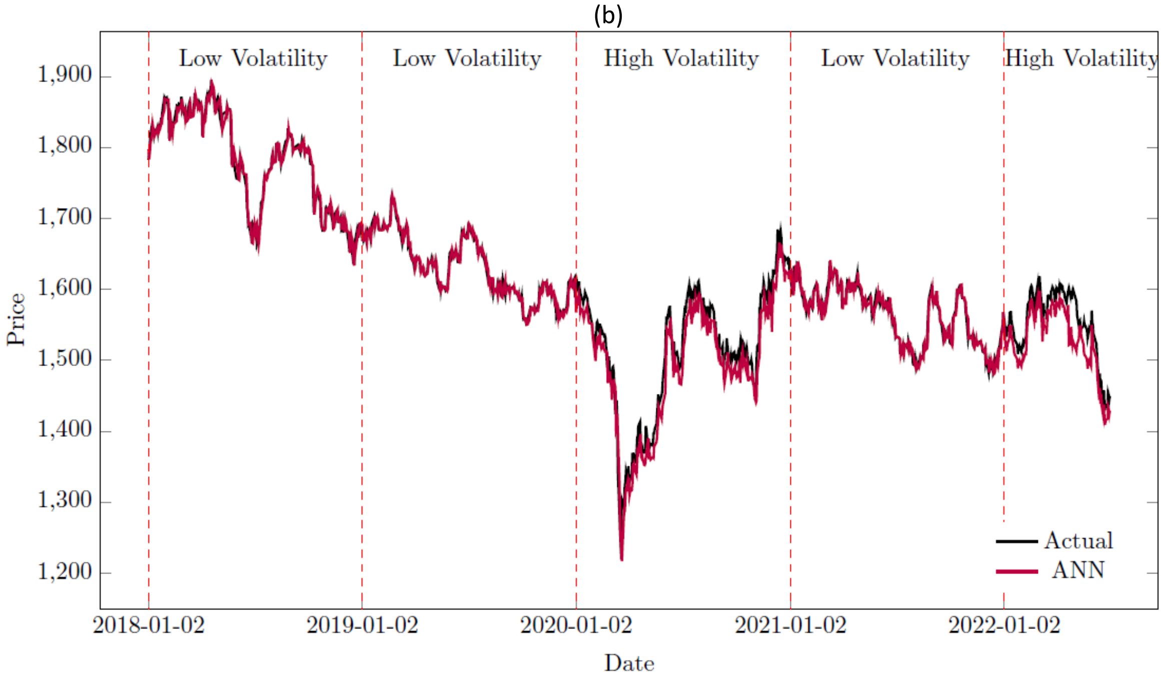
| Year and Volatility Phase | Evaluation Metrics | ARIMA (0,1,0) | ANN (3,1,1) | LSTM (3 input, 1 LSTM layer, 64 units) |
|---|---|---|---|---|
| 2018-2019 | MAE Training | 9.2648 | 12.655 | 9.3248 |
| Low Volatility | RMSE Training | 8.9703 | 12.3742 | 9.0422 |
| | MAE Testing | 9.0218 | 12.3431 | 9.14 |
| | RMSE Testing | 9.43 | 12.8513 | 9.1081 |
| 2020 | MAE Training | 12.0963 | 9.073 | 8.9427 |
| High Volatility | RMSE Training | 12.4697 | 10.7431 | 9.2333 |
| | MAE Testing | 12.3119 | 9.7262 | 9.1536 |
| | RMSE Testing | 12.3162 | 9.334 | 9.2227 |
| 2021 | MAE Training | 8.9648 | 12.0536 | 9.2142 |
| Low Volatility | RMSE Training | 8.7908 | 11.9721 | 9.0737 |
| | MAE Testing | 8.774 | 11.9213 | 9.1702 |
| | RMSE Testing | 8.8379 | 11.9287 | 9.2048 |
| 2022 | MAE Training | 12.6553 | 9.745 | 8.8459 |
| High Volatility | RMSE Training | 12.7278 | 10.1123 | 9.0163 |
| | MAE Testing | 12.2218 | 9.069 | 8.8645 |
| | RMSE Testing | 12.9609 | 10.7922 | 8.8873 |



(a)




(b)




(c)

**Fig. 3.** Actual vs. Predicted Values on Training Dataset Across Models: (a) LSTM, (b) ARIMA, and (c) ANN

During the high-volatility phase of the testing dataset, the graph comparing the actual prices with the predictions of ARIMA, ANN, and LSTM models (Figure 4) reveals key insights into their performance under turbulent market conditions. The actual prices exhibit sharp and frequent fluctuations, an indicator of high market volatility. These rapid movements highlight the market's sensitivity to external factors and the challenge of accurately predicting price trajectories in such an unstable environment.

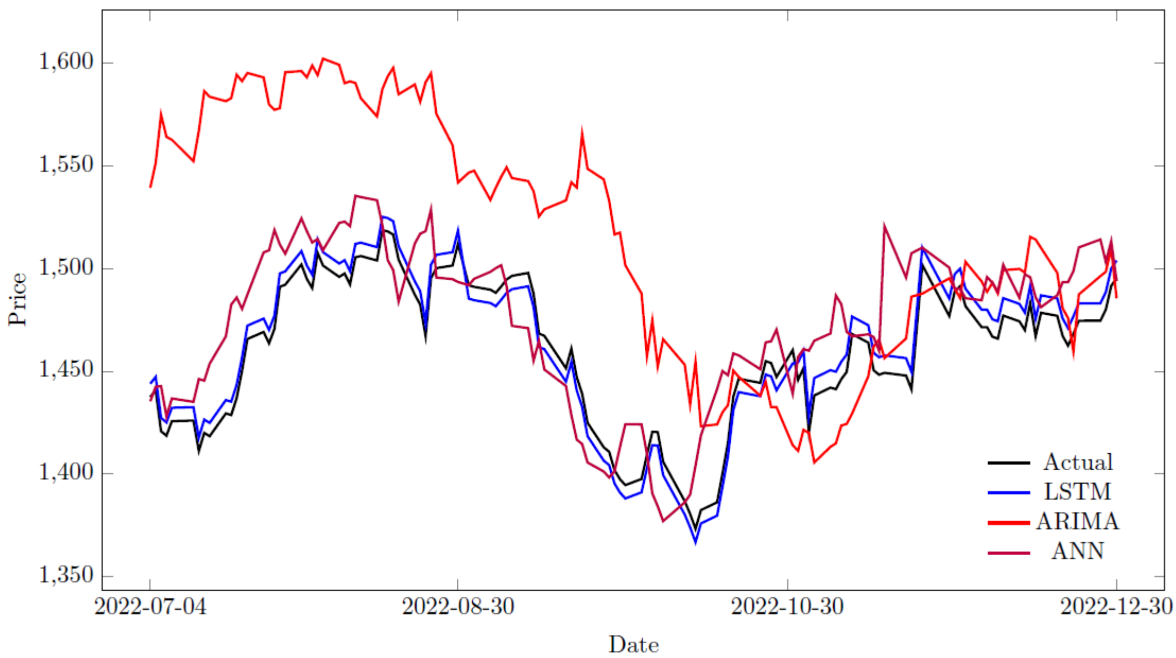



**Fig. 4.** Actual vs. Predicted Values on Testing Dataset Across Models

### *3.3 Model Limitations and Performance Contexts*

ARIMA, being a statistical model, shows a significant deviation from the actual prices, particularly during periods of abrupt market transitions. Its reliance on linear assumptions and inability to adapt to non-linear and dynamic patterns make it ill-suited for capturing the frequent and sharp fluctuations characteristic of high-volatility phases [28]. As a result, ARIMA produces smoother predictions that fail to reflect the rapid market movements, demonstrating its limitations under these conditions.

ANN, as a non-linear machine learning model, performs moderately better than ARIMA but still exhibits noticeable deviations from the actual prices during high-volatility periods. While ANN's non-linear architecture allows it to capture general trends, it lacks the sequential memory required to effectively track abrupt changes in the data [29]. Consequently, ANN often lags behind in responding to sudden price movements, leading to delayed or overly smoothed predictions that deviate significantly from the actual market behaviour.

In contrast, LSTM, designed specifically for sequential data, demonstrates the strongest performance in this high-volatility scenario [30]. Its ability to learn and retain temporal dependencies enables it to adapt to sudden market movements with remarkable accuracy. The LSTM predictions align closely with the actual prices, effectively capturing both the magnitude and frequency of fluctuations. While minor deviations may occur due to the inherent unpredictability of the market, LSTM consistently outperforms the other models, showcasing its robustness and adaptability to dynamic financial forecasting tasks.

This comparison underscores the limitations of statistical and shallow machine learning models like ARIMA and ANN in volatile markets, while showcasing LSTM's superior capability to navigate complex and unpredictable market behaviours.

### *3.4 Generalizability and Future Applications*

The adaptability of forecasting models to different market conditions is critical not only for their application in the Malaysian stock market but also for their broader usability in other financial markets. While this study focused on the Bursa Malaysia, the findings have potential implications for other emerging and developed markets with varying levels of volatility and economic structures.

Future research can explore the applicability of the evaluated models in markets with unique characteristics, such as higher frequency trading or prolonged economic instability. Additionally, integrating region-specific factors, such as macroeconomic indicators, political stability, and policy shifts, could enhance the robustness of these models when deployed in other contexts. Another avenue for generalizability lies in testing these models across different asset classes, such as bonds, commodities, or cryptocurrencies, where volatility patterns may differ significantly from equity markets. By doing so, researchers can determine whether the observed adaptability of LSTM models to volatile conditions extends beyond stock indices to other financial instruments.

Finally, while the study demonstrated the effectiveness of LSTM in handling high-volatility periods, incorporating global datasets or multi-market data might reveal its capability to predict interdependent market movements. Such an approach could establish LSTM's role in global financial forecasting and further validate its performance across diverse economic conditions.

## 4. Conclusions

This study explored the adaptability of forecasting models under varying market volatility conditions, focusing on the Bursa Malaysia Stock Index. By evaluating statistical and deep learning approaches, it was found that while ARIMA and ANN models exhibit reasonable performance during stable market phases, their accuracy and robustness deviate significantly under high-volatility conditions. In contrast, LSTM demonstrated superior adaptability, effectively capturing complex patterns and dependencies in volatile market environments. These findings underscore the importance of integrating advanced deep learning models, particularly for financial forecasting in markets characterized by dynamic and unpredictable behaviours. LSTM's capability to handle both low and high-volatility regimes highlights its potential as a reliable tool for investors and policymakers seeking to navigate uncertain economic landscapes. While this research provides valuable insights, it also reveals areas for further exploration. Extending the analysis to other financial markets, asset classes, or incorporating additional macroeconomic factors could enhance the understanding of model generalizability. Furthermore, incorporating hybrid approaches that blend statistical and deep learning methodologies may offer even greater accuracy and robustness.

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## References
[1] Nahar, Janifer, Md Shakawat Hossain, Md Mostafizur Rahman, and Md Arif Hossain. "Advanced Predictive Analytics For Comprehensive Risk Assessment In Financial Markets: Strategic Applications And Sector-Wide Implications." *Global Mainstream Journal of Business, Economics, Development & Project Management* 3, no. 4 (2024): 39-53. https://doi.org/10.62304/jbedpm.v3i4.148

[2] Khan, Muhammad Atif, Hammad Ali, Hira Shabbir, Fatima Noor, and Muhammad Dawood Majid. "Impact of Macroeconomic Indicators on Stock Market Predictions: A Cross Country Analysis." *Journal of Computing & Biomedical Informatics* (2024). https://doi.org/10.56979/801/2024

[3] Adebiyi, Ayodele Ariyo, Aderemi Oluyinka Adewumi, and Charles Korede Ayo. "Comparison of ARIMA and artificial neural networks models for stock price prediction." *Journal of Applied Mathematics* 2014, no. 1 (2014): 614342. https://doi.org/10.1155/2014/614342
[4] Suripto, S. "Decision-making model to predict auto-rejection: An implementation of ARIMA for accurate forecasting of stock price volatility during the COVID-19." *Decision Science Letters* 12, no. 1 (2023): 107-116. https://doi.org/10.5267/j.dsl.2022.10.002
[5] Albeladi, Khulood, Bassam Zafar, and Ahmed Mueen. "Time Series Forecasting using LSTM and ARIMA." *International Journal of Advanced Computer Science and Applications* 14, no. 1 (2023): 313-320. https://doi.org/10.14569/ijacsa.2023.0140133
[6] Ayoub, Fadi, George Sammour, and Abdulrahman Hashem. "Stock Market Value Estimation: An ARIMA Approach Sub-Sector Analysis at Amman Stock Exchange." *Calitatea* 24, no. 192 (2023): 18-26. https://doi.org/10.47750/qas/24.192.03
[7] Bhowmik, Roni, Gouranga Chandra Debnath, Nitai Chandra Debnath, and Shouyang Wang. "Emerging stock market reactions to shocks during various crisis periods." *Plos one* 17, no. 9 (2022): e0272450. https://doi.org/10.1371/journal.pone.0272450
[8] Kumaraswamy, Sumathi, Yomna Abdulla, and Shrikant Krupasindhu Panigrahi. "Will Gold Prices Persist Post Pandemic Period? An Econometric Evidence." *International Journal of Financial Studies* 11, no. 1 (2022): 8. https://doi.org/10.3390/ijfs11010008
[9] Zhang, Yuruixian, Wei Chong Choo, Yuhanis Abdul Aziz, Choy Leong Yee, Cheong Kin Wan, and Jen Sim Ho. "Effects of Multiple Financial News Shocks on Tourism Demand Volatility Modelling and Forecasting." *Journal of Risk and Financial Management* 15, no. 7 (2022): 279. https://doi.org/10.3390/jrfm15070279
[10] Roondiwala, Murtaza, Harshal Patel, and Shraddha Varma. "Predicting stock prices using LSTM." *International Journal of Science and Research (IJSR)* 6, no. 4 (2017): 1754-1756. https://doi.org/10.21275/art20172755
[11] Moghar, Adil, and Mhamed Hamiche. "Stock market prediction using LSTM recurrent neural network." *Procedia computer science* 170 (2020): 1168-1173. https://doi.org/10.1016/j.procs.2020.03.049
[12] Sadon, Aida Nabilah, Shuhaida Ismail, and Azme Khamis. "Gated Recurrent Unit Model with Untrained Heteroscedasticity Element in Modelling Forecast of Bursa Malaysia Stock Return Volatility." *Journal of Advanced Research in Applied Sciences and Engineering Technology* (2024): 13-27.https://doi.org/10.37934/araset.61.2.1327
[13] Usmani, Usman Ahmad, Ari Happonen, and Junzo Watada. "A review of unsupervised machine learning frameworks for anomaly detection in industrial applications." In *Science and Information Conference*, pp. 158-189. Cham: Springer International Publishing, 2022. https://doi.org/10.1007/978-3-031-10464-0_11
[14] Zhang, Yuzhen, Jingjing Liu, and Wenjuan Shen. "A review of ensemble learning algorithms used in remote sensing applications." *Applied Sciences* 12, no. 17 (2022): 8654. https://doi.org/10.3390/app12178654
[15] Zakaria, Syazana, Badrina Nur Yasmin Badrul Azhar, Intan Nadia Azvilla Maulad Mohamad Rawi, and Noreha Mohamed Yusof. "Performance of Kuala Lumpur composite index stock market." *Malaysian Journal of Computing (MJoC)* 5, no. 2 (2020): 553-562. https://doi.org/10.24191/mjoc.v5i2.9495
[16] Firdaus, Mohamad, Nur Arina Bazilah Kamisan, Nur Arina Bazilah Aziz, and Chan Weng Howe. "Modelling Stock Market Exchange By Autoregressive Integrated Moving Average, Multiple Linear Regression And Neural Network." *Jurnal Teknologi* 84, no. 5 (2022): 137-144. https://doi.org/10.11113/jurnalteknologi.v84.18487
[17] Ibrahim, Nurul'Izzumi Nadhirah, and Nurul Nisa'Khairol Azmi. "Modelling and Forecasting the Volatility and Price of Malaysian Stock Market." *International Journal of Academic Reserach in Economics and Management Sciences* 11, no. 2 (2022). https://doi.org/10.6007/ijarems/v11-i2/12304
[18] Samah, Khyrina Airin Fariza Abu, Nurul Azifah Mohd Khalid, Jamaluddin Jasmis, Noor Afni Deraman, Lala Septem Riza, and Zainab Othman. "Autoregressive Integrated Moving Average (ARIMA) Algorithm Adaptation for Business Financial Forecasting." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 38, no. 1 (2024): 37-47. https://doi.org/10.37934/araset.38.1.3747
[19] Ho, M. K., Hazlina Darman, and Sarah Musa. "Stock price prediction using ARIMA, neural network and LSTM models." In *Journal of Physics: Conference Series*, vol. 1988, no. 1, p. 012041. IOP Publishing, 2021. https://doi.org/10.1088/1742-6596/1988/1/012041
[20] Malim, Tengku Nurul Aimi Balqis Tengku, Saadi Ahmad Kamarudin, Nor Aishah Ahad, and Nor Azura Md Ghani Mamat. "Prediction of FTSE Bursa Malaysia KLCI Stock Market using LSTM Recurrent Neural Network." In *2022 IEEE International Conference on Computing (ICOCO)*, pp. 415-418. IEEE, 2022. https://doi.org/10.1109/icoco56118.2022.10031901
[21] Khalil, Mohd Ridzuan Ab, and Azuraliza Abu Bakar. "A Comparative Study of Deep Learning Algorithms in Univariate and Multivariate Forecasting of the Malaysian Stock Market (Kajian Perbandingan Algoritma Pembelajaran Mendalam dalam Peramalan Univariat dan Multivariat Pasaran Saham Malaysia)." *Sains Malaysiana* 52, no. 3 (2023): 993-1009. https://doi.org/10.17576/jsm-2023-5203-22

[22] Box, George EP, Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015. https://doi.org/10.1057/9781137291264_6

[23] Khan, Md Ashikur Rahman, Md Furkan Uzzaman, Ishtiaq Ahammad, Ratul Prosad, Zayed Us Salehin, Tanvir Zaman Khan, Md Sabbir Ejaz, and Main Uddin. "Stock market prediction in bangladesh perspective using artificial neural network." *International Journal of Advanced Technology and Engineering Exploration* 9, no. 95 (2022): 1397. https://doi.org/10.19101/ijatee.2021.875852

[24] Mienye, Ibomoiye Domor, Theo G. Swart, and George Obaido. "Recurrent neural networks: A comprehensive review of architectures, variants, and applications." *Information* 15, no. 9 (2024): 517. https://doi.org/10.20944/preprints202408.0748.v1

[25] Hochreiter, S. "Long Short-term Memory." *Neural Computation MIT-Press* (1997). https://doi.org/10.1162/neco.1997.9.8.1735

[26] Oyewole, Adedoyin Tolulope, Omotayo Bukola Adeoye, Wilhelmina Afua Addy, Chinwe Chinazo Okoye, Onyeka Chrisanctus Ofodile, and Chinonye Esther Ugochukwu. "Predicting stock market movements using neural networks: a review and application study." *Computer Science & IT Research Journal* 5, no. 3 (2024): 651-670. https://doi.org/10.51594/csitrj.v5i3.912

[27] Shakawi, Abang Mohammad Hudzaifah Abang, and Ani Shabri. "Improving Prediction of Bursa Malaysia Stock Index Using Time Series and Deep Learning Hybrid Model." In *International Conference of Reliable Information and Communication Technology*, pp. 119-128. Cham: Springer Nature Switzerland, 2023. https://doi.org/10.1007/978-3-031-59711-4_11

[28] Dezhkam, Arsalan, Mohammad Taghi Manzuri, Ahmad Aghapour, Afshin Karimi, Ali Rabiee, and Shervin Manzuri Shalmani. "A Bayesian-based classification framework for financial time series trend prediction." *The Journal of supercomputing* 79, no. 4 (2023): 4622-4659. https://doi.org/10.1007/s11227-022-04834-4

[29] Kim, Hyun-jung, and Kyung-shik Shin. "A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets." *Applied Soft Computing* 7, no. 2 (2007): 569-576. https://doi.org/10.1016/j.asoc.2006.03.004

[30] Tian, Bu, Tianyu Yan, and Hong Yin. "Forecasting the Volatility of CSI 300 Index with a Hybrid Model of LSTM and Multiple GARCH Models." *Computational Economics* (2024): 1-31. https://doi.org/10.1007/s10614-024-10785-0