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Performance Analysis of ARIMA, LSTM, and Hybrid ARIMA-LSTM in Forecasting the Composite Stock Price Index

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Abstract

This study evaluates the performance of the ARIMA, LSTM and hybrid ARIMA-LSTM models in predicting the closing and opening prices of the Indonesia Stock Exchange Composite Index (IHSG) for various periods (2007-2020, 2007-2022 and 2007-2024). For the LSTM model, a lag of 1 was chosen based on MAPE analysis, showing a strong dependence on the previous day's price. Different learning rates (0.01, 0.001, 0.0001) and batch sizes (16, 32) were tested on various network architectures. The results indicate that while ARIMA effectively captures linear patterns, LSTM consistently outperforms with lower MAPE values - 2. 27% for closing and 2. 02% for opening prices - especially with a simple architecture (1-50-1) and a learning rate of 0.001. The hybrid ARIMA(0,1,1)-LSTM(1-50-1) model showed competitive results, achieving MAPE of 2.00% for closing and 1.74% for opening prices using batch size 16. However, its success depends on ARIMA's ability to model linear components. Key findings emphasize LSTM's dominance in accuracy, the importance of parameter tuning, and the effectiveness of simple network structures. The hybrid approach holds promise when linear and nonlinear data components are clearly separable. This research offers methodological insights for optimizing stock price prediction models and practical guidance for model configuration, contributing to the advancement of financial market forecasting.

Keywords: ARIMA; LSTM; hybrid model; stock price forecasing, time series analysis

1 Introduction

The stock market is one of the main indicators of a country's economy, as it reflects overall economic conditions and financial stability [1], [2]. In Indonesia, the Indonesia Stock Exchange Composite Index (IHSG) serves as a key indicator of capital market performance, reflecting investor sentiment and overall stock market dynamics. IHSG movements are influenced by various domestic and global factors, including historical trends, market sentiment, and external economic events [3],[4],[5],[6].

With advancements in technology, data-driven approaches such as machine learning and deep learning have gained prominence in stock market forecasting. Traditional statistical models like the Autoregressive Integrated Moving Average (ARIMA) have long been used to analyze time series data and capture linear trends and seasonality [7], [8],[9] . However, these models often struggle to capture non-linear relationships and complex patterns inherent in financial data [10].

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Various approaches have been used in stock market forecasting, ranging from traditional statistical methods to artificial intelligence techniques. The ARIMA model, for example, has been used to predict the movements of IHSGs for the period 2021-2025 with accurate short-term results [11]. However, this model has limitations in capturing the non-linear and complex patterns in financial data. Meanwhile, long-short-term memory (LSTM) methods, a type of repetitive neural network (RNN), have proven effective in handling long-term dependencies in time series data. LSTM models have been implemented to predict IHSG prices and compared to ARIMA and linear regression models, with LSTM showing relatively higher accuracy, although not significantly outperforming ARIMA [12]. To improve predictive performance, several studies have proposed hybrid approaches such as ARIMA-LSTM. For example, a hybrid ARIMA-LSTM model has been used to forecast the S&P 500 index using live data, showing better results than Prophet [13].

To overcome these limitations, deep learning models such as Long Short-Term Memory (LSTM) networks have emerged as powerful tools due to their ability to learn long-term dependencies and capture non-linear dynamics in sequential data [14], [15]. However, previous studies have also identified limitations of LSTM models, including high computational complexity, difficulty in tuning hyperparameters, and a tendency to overfit when trained on limited data, which necessitate further refinement and improvement. [16], [17], demonstrated that LSTM models provide more accurate predictions of IHSG movements compared to traditional statistical methods.

In addition, hybrid approaches that combine the strengths of statistical and deep learning models have been explored to improve the accuracy of forecasting. Studies have shown that integrating models like ARIMA and LSTM can enhance prediction performance by leveraging ARIMA's strength in capturing linear components and LSTM's capability to model complex non-linear relationships. [18],[19],[20] reported promising results using a hybrid ARIMA-LSTM model for financial forecasting tasks.

Although various studies have examined the use of ARIMA and LSTM separately in stock market forecasting, there is still limited research that specifically performs a comparative analysis of ARIMA, LSTM, and ARIMA-LSTM models in the context of IHSG. Furthermore, few studies have highlighted the effectiveness of hybrid models in addressing market dynamics in emerging economies such as Indonesia.

Given the advantages of each approach, this study proposes a comparative analysis of three modeling techniques—ARIMA, LSTM, and hybrid ARIMA-LSTM—to forecast the IHSG [21], [22], [23], [24], [25] . The objective is to evaluate and compare the predictive performance of ARIMA, LSTM, and hybrid ARIMA-LSTM models for understanding stock market dynamics in Indonesia. The findings are expected to provide valuable insights for investors, analysts, and financial institutions in making informed decisions under conditions of uncertainty.

The novelty of this study lies in its comparative analysis of three forecasting models, ARIMA, LSTM, and the hybrid ARIMA-LSTM, specifically applied to the Indonesia Stock Exchange Composite Index (IHSG), which has been relatively underexplored in previous research. By evaluating these models within the context of an emerging market, this study contributes empirical evidence on their respective strengths and limitations, providing meaningful insights for selecting appropriate forecasting techniques tailored to the complexities of financial markets in developing economies such as Indonesia.

Furthermore, this research supports Sustainable Development Goal (SDG) 8 on decent work and economic growth by promoting the development of intelligent forecasting systems that contribute to a resilient and well-informed financial market ecosystem.

2 Methods

This research applies three forecasting approaches to the Indonesia Composite Index (IHSG): ARIMA for modeling linear components, LSTM for capturing nonlinear patterns, and a hybrid

ARIMA-LSTM that integrates both. The modeling process includes data preparation, model construction, and performance evaluation, as described in the following subsections.

2.1 Data

This study uses monthly time series data of the Indonesia Composite Index (IHSG) from January 2007 to December 2024. The main variables analyzed are the opening price (Open) and closing price (Close) of the IHSG, without incorporating macroeconomic factors as additional variables. The dataset consists of 216 observations, representing monthly data over 18 years. The objective of this study is to predict the closing price (Close) and opening price (Open) of the IHSG based on historical data, and to compare the performance of each model in predicting the Open and Close prices using three modeling approaches: ARIMA, LSTM, and the hybrid ARIMA-LSTM model. The ARIMA model is used to capture linear and seasonal patterns in the time series data, the LSTM model is used to identify nonlinear patterns and long-term dependencies, while the hybrid ARIMA-LSTM model combines the strengths of both approaches to improve the prediction accuracy of IHSG prices, both for the opening and closing prices.

Use tables to present data concisely and clearly. Employ the `table` and `tabular` environments, as illustrated below:

Table 1: Research Variables

Variable	Variable Name	Type	Description
Y_1	IHSG Close	Continuous	Monthly closing value of the IHSG
Y_2	IHSG Open	Continuous	Monthly opening value of the IHSG

2.2 Research Methods

The data analysis in this study was conducted using Google Colaboratory with the Python programming language. The modeling aimed to predict the Indonesia Composite Stock Price Index (IHSG) based on historical stock price data. The following are the steps carried out in the data analysis of this research:

1. Data Exploration
   Exploring the dataset by visualizing time series plots to observe the IHSG trends over time.
2. Data Selection
   The dataset was split into training and testing subsets, taking into account the similarity in data patterns from 2007–2020, 2007–2022, and 2007–2024.
3. ARIMA Modeling
   a. Testing for data stationarity was carried out both exploratively using Autocorrelation Function (ACF) plots and formally using the Augmented Dickey-Fuller (ADF) test.
   b. Differencing was applied if the data was not stationary in terms of mean and variance.
   c. Identifying candidate ARIMA models through Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Extended Autocorrelation Function (EACF).
   d. Estimating the model parameters using the Maximum Likelihood Estimation (MLE) method.
   e. Selecting the best ARIMA model based on the lowest Akaike's Information Criterion (AIC) value and the statistical significance of the parameters.
   f. Performing an overfitting test on the ARIMA model obtained in the previous step.
   g. Determining the optimal ARIMA model based on AIC and parameter significance.
   h. Conducting diagnostic tests on the best ARIMA model to ensure assumptions of residual normality, independence, and homoscedasticity are met.
4. LSTM Modeling

a. Applying MinMaxScaler transformation to standardize the data within a specified range.
b. The data is reshaped into a supervised learning format with lag=1, using the previous day's value as input and the current day's value as output to facilitate direct multi-step forecasting based on optimal lag selection.
c. Developing an LSTM model by optimizing key hyperparameters such as epoch, batch size, and learning rate.
d. Applying inverse transformation and evaluation to return the scaled predictions to their original scale after training.

5. Hybrid ARIMA-LSTM Modeling
The hybrid ARIMA-LSTM model was constructed to combine the strengths of both linear and nonlinear modeling techniques. First, the ARIMA model was applied to capture the linear patterns in the IHSG time series data. Let y_t represent the observed value, and let $\hat{L}_t$ be the linear forecast from the ARIMA model. The residual series r_t is obtained by subtracting the ARIMA output from the actual data:

$$r_t = y_t - \hat{L}_t \tag{1}$$

These residuals, which contain nonlinear structures not captured by ARIMA, are then used as input to an LSTM model. Before feeding into the LSTM, the residuals are scaled using Min-Max normalization. The input to the LSTM is a lagged sequence of residuals:

$$X_t = [r_{t-w}, r_{t-w+1}, \ldots, r_{t-1}] \tag{2}$$

The LSTM is trained to learn the nonlinear component $\hat{N}_t$ from this input:

$$\hat{N}_t = f_{\text{LSTM}}(X_t) \tag{3}$$

The final hybrid forecast $\hat{y}_t$ is obtained by summing the linear and nonlinear predictions:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{4}$$

This architecture allows the LSTM to model complex nonlinear dependencies in the residuals, thereby improving prediction accuracy beyond what either model can achieve independently.

6. Model Comparison
Comparing the performance of the ARIMA, LSTM, and Hybrid ARIMA-LSTM models using MAPE values to determine the most optimal model for predicting IHSG.

7. Forecasting
Forecasting the IHSG Close and Open using the best-performing model as determined from the model comparison step.

3 Results and Discussion

The time series of IHSG opening and closing prices from 2007 to 2024 is illustrated in Figure 1, providing a visual overview of the index's historical dynamics.

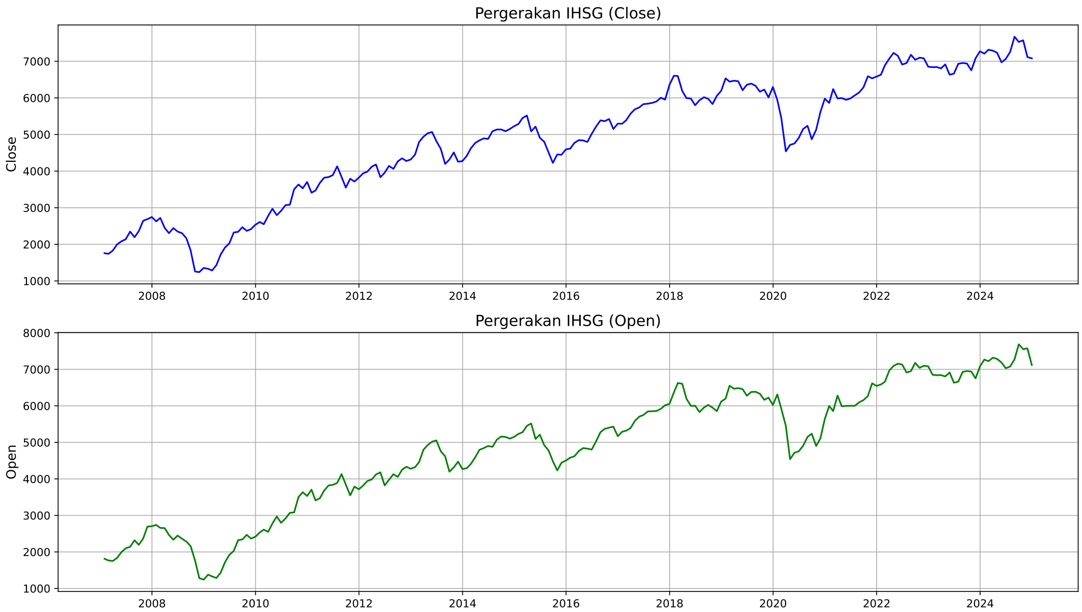
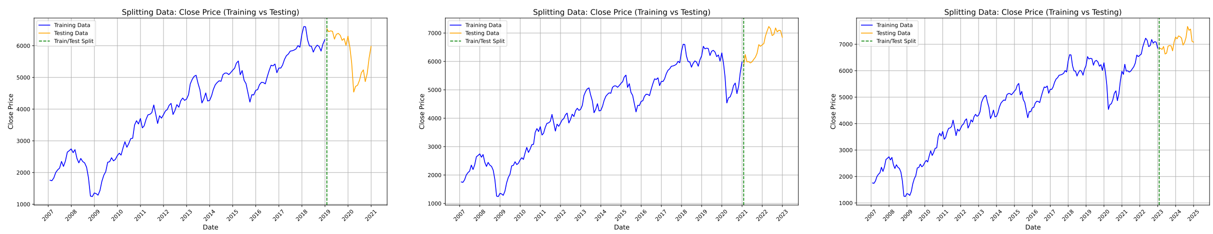


Figure 1: Time series plot of the movement of IHSG close and open prices

The annual movement of IHSG from 2007 to 2024 reflects the fluctuating dynamics of Indonesia's stock market. A sharp decline occurred in 2008 due to the global financial crisis, followed by a gradual recovery and a sustained upward trend through 2019. The COVID-19 pandemic caused another significant contraction in 2020, but the IHSG began to recover in 2021 and showed more consistent stability from 2022 to 2024. In general, the movement patterns of IHSG opening (Open) and closing (Close) prices exhibited similar trends over time, reflecting market responses to macroeconomic conditions and underlying investor sentiment.

3.1 Data Selection

To assess the impact of different historical periods on model performance, the dataset was segmented into three training-testing windows. These configurations are visualized in Figure 2, which illustrates the time-based data splitting strategies applied in this study.



(a) **(b)** **(c)**

Figure 2: Splitting plot of training and testing data: (a) January 2007 to December 2020, (b) January 2007 to December 2022, and (c) January 2007 to December 2024.

The data segmentation process uses a splitting window approach over a 24-month period applied three times. In panel (a), the training data covers the longest historical period from 2007 until the end of 2018, while the testing data spans from January 2019 to December 2020. Panel (b) shows the training data extended until the end of 2020, with testing data from January 2021 to December 2022. In panel (c), the training data covers the period from 2007 to the end of 2022, and the testing data spans from January 2023 to December 2024.

At each stage, the data is split with an 80%-20% ratio for training and testing respectively, maintaining a consistent testing period across iterations. This approach aims to evaluate the model's robustness against variations in the length of historical data. The data segmentation considers market patterns from 2007 to 2024 to ensure a comprehensive representation of stock market behavior.

3.2 ARIMA

At this stage, the data will be analyzed to test for stationarity using the Augmented Dickey-Fuller (ADF) test. The decision rule states that if the p-value $\leq$ significance level ($\alpha = 5\%$), the data can be considered stationary. Conversely, if the p-value $> 5\%$, the data is considered non-stationary with respect to the mean, and therefore, differencing must be applied to transform the data into a stationary series before further modeling.

If the data becomes stationary after differencing d times, it can then be modeled using the ARIMA model. Generally, the ARIMA model is denoted as ARIMA(p, d, q), where p is the order of the autoregressive (AR) component, d is the degree of differencing, and q is the order of the moving average (MA) component.

The mathematical representation of the ARIMA(p, d, q) model is expressed as:

$$\Phi(B)(1 - B)^d(X_t - \mu) = \Theta(B)a_t \tag{5}$$

Where:

- d: differencing parameter
- t: index of observation
- μ: mean of observation
- $a_t \sim$ i.i.d. $N(0, \sigma_a^2)$

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \quad \text{(AR polynomial)} \tag{6}$$

$$\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \quad \text{(MA polynomial)} \tag{7}$$

Table 2 shows the results of the Augmented Dickey-Fuller (ADF) test conducted on the IHSG price data (both Close and Open prices) across different periods. This test is used to determine whether the time series is stationary. A p-value less than the significance level of 5% indicates that the data is stationary.

Table 2: Result of ADF Test

Data Splitting	Period	Dataset	Data Integrity	ADF	P-value
80:20	2007–2020	Close	I(0)	-0.991	0.756
			I(1)	-10.202	0.000
		Open	I(0)	-0.817	0.813
			I(1)	-5.919	0.000
	2007–2022	Close	I(0)	-1.477	0.544
			I(1)	-10.574	0.000
		Open	I(0)	-1.528	0.519
			I(1)	-10.339	0.000
	2007–2024	Close	I(0)	-1.349	0.606
			I(1)	-11.794	0.000
		Open	I(0)	-1.169	0.686
			I(1)	-11.743	0.000

The next stage in ARIMA modeling is model identification, conducted using ACF, PACF, and EACF plots to determine the (p, d, q) components based on the stationary data. Candidate models are then selected from the observed patterns in these plots.

Table 3: Comparison of the goodness of fit for the tentative ARIMA models

Period	Dataset	Model	Parameter	P-value	AIC	BIC
2007–2020	Close	ARIMA(1,1,4)	MA(1)	0.979	1882.832	1903.571
			MA(2)	0.985		
			MA(3)	0.973		
			MA(4)	0.972		
			AR(1)*	0.000		
	Open	ARIMA(0,1,1)	MA(1)*	0.010	1873.916	1882.804
	Open	ARIMA(1,1,0)	AR(1)*	0.020	1874.255	1883.143
2007–2022	Close	ARIMA(0,1,1)	MA(1)*	0.010	2243.633	2252.987
	Close	ARIMA(1,1,0)	AR(1)*	0.004	2243.321	2252.675
	Open	ARIMA(0,1,1)	MA(1)*	0.004	2232.727	2242.081
	Open	ARIMA(1,1,0)	AR(1)*	0.002	2232.492	2241.846
2007–2024	Close	ARIMA(0,1,1)	MA(1)*	0.030	2559.412	2569.169
	Close	ARIMA(1,1,0)	AR(1)*	0.016	2559.137	2568.894
	Open	ARIMA(0,1,1)	MA(1)*	0.015	2551.167	2560.924
	Open	ARIMA(1,1,0)	AR(1)*	0.007	2550.820	2560.577

*Significance level 5%

The selection of the best ARIMA model was adjusted based on the data period used. For the 2007–2020 period, the optimal models were ARIMA(1,1,4) for close data and ARIMA(0,1,1) for open data. In the 2007–2022 period, ARIMA(1,1,0) was found to be the best model for both datasets. For the 2007–2024 period, ARIMA(1,1,0) remained the best model for close data, while ARIMA(0,1,1) was selected for open data as it fulfilled all assumptions and had statistically significant parameters, despite a slightly higher AIC value. These baseline models were then used to construct overfitted models for further testing.

Table 4: *Overfitting* Model ARIMAX

Period	Dataset	Model	Parameter	P-value	AIC	BIC
2007–2020	Close	ARIMA(2,1,4)	MA(1)	0.887	1884.833	1908.536
			MA(2)	0.927		
			MA(3)	0.868		
			MA(4)	0.851		
			AR(1)	0.092		
			AR(2)	0.990		
	Open	ARIMA(1,1,1)	MA(1)*	0.009	1872.630	1884.481
	Open	ARIMA(1,1,0)	AR(1)*	0.000		
2007–2022	Close	ARIMA(1,1,1)	MA(1)	0.560	2245.296	2257.768
			AR(1)	0.886		
	Open	ARIMA(1,1,1)	MA(1)	0.533	2234.483	2246.955
			AR(1)	0.916		
2007–2024	Close	ARIMA(1,1,1)	MA(1)	0.565	2561.045	2574.054
			AR(1)	0.796		
	Open	ARIMA(1,1,1)	MA(1)	0.460	2552.688	2565.697
			AR(1)	0.716		

*Significance level 5%

After establishing the base ARIMA model, overfitting tests were conducted by alternately adding AR and MA parameters to explore alternative models. For the 2007–2020 period, the best model for the close data was ARIMA(1,1,4), while ARIMA(1,1,1) performed best for the open data.

In the 2007–2022 period, ARIMA(1,1,0) demonstrated superior performance for both close and open data, with lower AIC and BIC values and more significant parameters. For the 2007–2024 period, ARIMA(1,1,0) for the close data and ARIMA(0,1,1) for the open data outperformed the overfitted models.

Diagnostic checks showed that the residuals were independent and homoscedastic, although not normally distributed. However, due to the large sample size, the normality assumption can be disregarded according to the Central Limit Theorem. The best models were then used to generate forecasts on the test data, with performance evaluated using the MAPE value.

3.3 LSTM

The modeling process begins by separating the data into two main variables: Close and Open prices. Unlike a multivariate approach, this study employs a univariate LSTM model applied separately to each variable. One model is used to predict the Close price based on its historical values, and another model is used to predict the Open price using its own historical data. The dataset is then split into training and testing subsets. To ensure consistent scaling across variables, each series is individually normalized to a range between 0 and 1 using the MinMaxScaler method. As shown in Figure 1, the Close price generally exhibits a stable upward trend with minor fluctuations, particularly after 2015. The Open price follows a similar pattern, though with slight differences due to daily price variations. This approach allows each LSTM model to focus more effectively on the temporal patterns of the respective variable, thereby improving prediction accuracy.

Table 5: Characteristics of the developed model

Characteristic	**Specification**
Optimizer	Adam
Loss Function	Mean Squared Error
Batch Size	16, 32
Epoch	300

Following model selection as shown in Table 5, the next step involves converting the data into a supervised learning format. In this approach, lagged values (lag $= 1$) are used as input (X), and the current value $(t + 1)$ is used as the output (Y). This method, known as multi-step prediction, allows the model to forecast multiple steps ahead directly, rather than iteratively. This approach differs from the method used by [26], who adopted a sliding window or recursive forecast (rolling prediction) technique. In their method, predictions are made sequentially, where the previously predicted values (e.g., $\hat{y}_1$ to $\hat{y}_{t2}$) are used as inputs to forecast the next value $(\hat{y}_{t3})$. While commonly used, this method is prone to error propagation, as each prediction depends on previous forecast outputs. In contrast, this study adopts a multi-step direct forecasting strategy to mitigate error accumulation. Each predicted value is directly linked to its target step without relying on previous predictions. This approach is considered more effective in maintaining model stability over longer forecasting horizons and is better suited to datasets with stable trends and minor fluctuations in values like the Close and Open prices.

The choice of lag $= 1$ was made based on model performance evaluation using the Mean Absolute Percentage Error (MAPE). Compared to lag values of 6 and 12, using lag $= 1$ yielded the lowest MAPE of 2.31%, while lag $= 6$ and lag $= 12$ resulted in MAPE values of 8.67% and 17.13%, respectively, on the best-performing model. This indicates that the current Close IHSG price is heavily influenced by the previous day's closing value $(t - 1)$, suggesting that short-term dependencies are more dominant. As the lag increases, model accuracy significantly declines, further indicating that IHSG exhibits non-seasonal behavior and is more affected by short-term dynamics. A similar pattern was also observed in the Open price data, where lag $= 1$ consistently provided the most accurate forecasts compared to longer lags.

Table 5 presents the performance evaluation of various LSTM model architectures in predicting the IHSG closing price across three different time periods: 2007–2020, 2007–2022, and 2007–2024. The evaluation was conducted using the Mean Absolute Percentage Error (MAPE) metric for each combination of architecture, learning rate (LR), and batch size (16 and 32). The results show that models with architectures 1-50-1 and 1-128-64-32-1 using a learning rate of 0.001 and batch size of 32 demonstrated the best performance, achieving notably low MAPE values, such as 2.27% for the 1-50-1 architecture in the 2007–2022 period and 2.07% for the 1-128-64-32-1 architecture in the 2007–2024 period. These findings indicate that moderately complex architectures and a balanced learning rate can yield more accurate predictions for IHSG closing price data.

Moreover, models with overly simple architectures (e.g., 1-32-1) or excessively deep architectures (e.g., 1-256-128-64-1) tend to produce higher MAPE values, particularly when trained with suboptimal learning rates (0.01 and 0.0001). These results suggest that the choice of model configuration greatly influences prediction performance. Additionally, while model performance tends to decline with longer time periods (such as 2007–2024), certain architectures are capable of maintaining predictive accuracy over extended timeframes. Overall, this table highlights the critical importance of selecting appropriate model architectures and hyperparameters to optimally capture the temporal patterns in closing price data.

Table 6: Comparison of LSTM model architectures based on MAPE Dataset Close

Period	**Architecture**	**MAPE of LR Batch Size 16(%)**			**MAPE of LR Batch Size 32(%)**		
		0.01	0.001	0.0001	0.01	0.001	0.0001
2007–2020	1-32-1	27.33	27.44	85.12	27.41	27.24	48.11
	1-50-1	**4.38**	5.10	79.53	4.22	4.83	22.66
	1-128-1	28.76	27.45	78.60	27.16	27.46	22.54
	1-64-32-1	10.12	6.39	77.67	13.54	6.22	24.01
	1-128-64-1	8.54	6.69	78.02	16.89	5.69	24.72
	1-64-32-16-1	28.29	14.93	78.11	26.64	17.64	22.85
	1-128-64-32-1	29.00	**4.08**	77.99	29.70	**4.11**	23.76
	1-256-128-64-1	29.33	4.67	79.53	26.88	5.29	9.48
2007–2022	1-32-1	33.89	34.21	27.85	33.48	34.15	30.71
	1-50-1	**2.86**	**2.40**	11.27	2.72	**2.27**	4.80
	1-128-1	35.22	32.93	29.99	35.20	34.72	32.53
	1-64-32-1	15.57	9.46	27.66	10.07	10.69	25.64
	1-128-64-1	12.30	8.49	27.26	10.05	7.65	23.54
	1-64-32-16-1	35.79	21.36	26.74	35.14	20.65	12.34
	1-128-64-32-1	35.97	3.02	13.59	33.99	3.28	7.32
	1-256-128-64-1	34.71	7.30	5.24	34.23	4.69	4.92
2007–2024	1-32-1	34.72	34.71	34.10	35.09	35.39	28.74
	1-50-1	**6.87**	2.49	2.44	4.05	**2.38**	17.85
	1-128-1	34.70	34.38	33.94	34.13	34.85	27.36
	1-64-32-1	6.85	6.91	16.89	9.97	9.93	30.13
	1-128-64-1	13.14	8.36	12.17	9.95	9.58	28.82
	1-64-32-16-1	34.92	21.62	3.86	35.05	20.72	29.78
	1-128-64-32-1	39.62	**2.07**	6.88	36.87	5.18	26.02
	1-256-128-64-1	35.22	8.32	3.38	33.68	5.33	9.32

Table 6 illustrates the evaluation results of the LSTM model for predicting the IHSG opening price, using the same approach as in Table 6. Overall, the performance trends are *relatively consistent*, where architectures such as 1-50-1, 1-64-32-1, and 1-128-64-32-1 combined with a learning rate of 0.001 and a batch size of 32 provided highly *accurate* results. For instance, the lowest MAPE of 2.02% was achieved by the 1-50-1 architecture for the 2007–2024 period. This *indicates* that models with moderate complexity and *properly tuned* hyperparameters are highly effective in predicting opening prices in the stock market.

However, some differences in performance were *observed* compared to the models for closing prices. For example, certain architectures that performed well in closing price prediction, such as

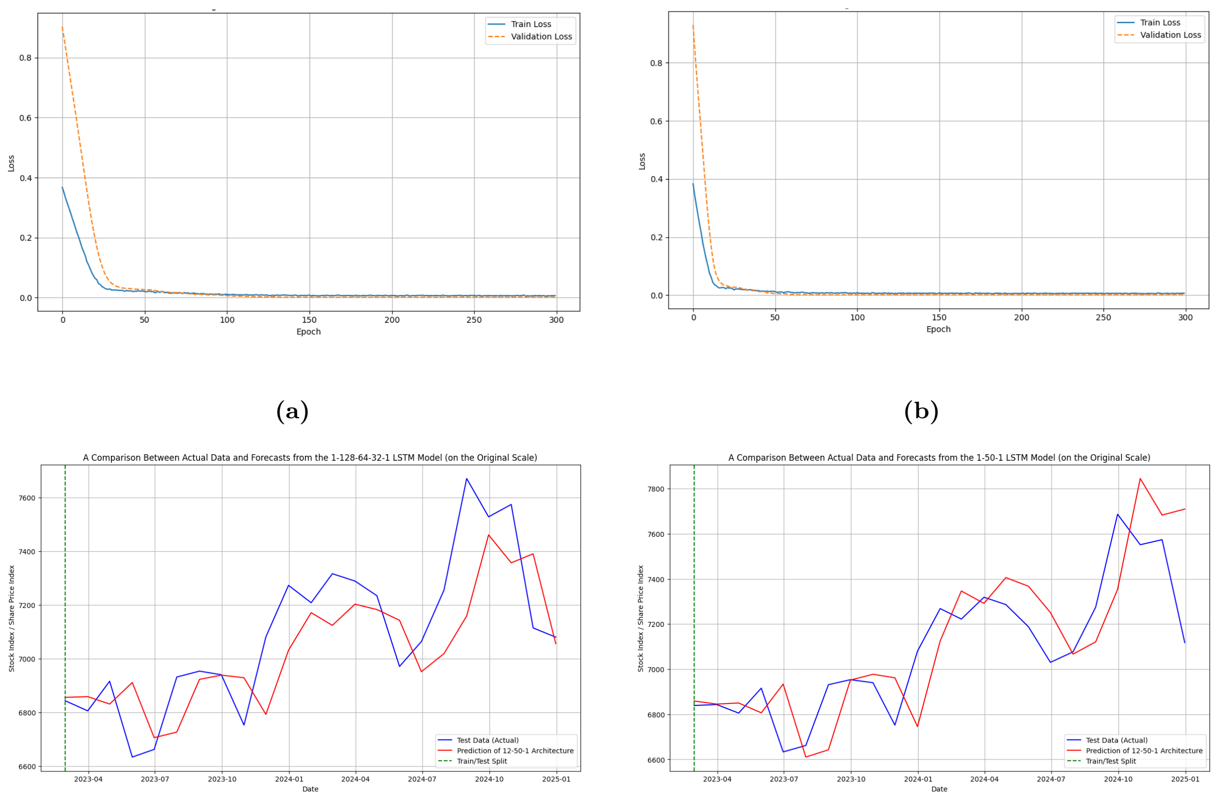
1-256-128-64-1, showed less *optimal* results for opening price, as reflected in higher MAPE values. Additionally, the model *appeared to be more sensitive* to changes in batch size and learning rate when applied to opening price data, as *evidenced* by significant MAPE fluctuations in specific combinations. These findings *emphasize* that despite the structural similarities in the data, LSTM models must be specifically customized for each price type to achieve optimal predictive performance.

Table 7: Comparison of LSTM model architectures based on MAPE Dataset Open

Period	Architecture	MAPE of LR Batch Size 16 (%)			MAPE of LR Batch Size 32 (%)		
		0.01	**0.001**	**0.0001**	**0.01**	**0.001**	**0.0001**
2007–2020	1-32-1	29.00	27.85	23.96	28.12	27.73	25.42
	1-50-1	4.53	4.84	11.25	4.89	**4.66**	6.81
	1-128-1	28.40	28.17	24.60	28.52	28.25	27.10
	1-64-32-1	5.41	7.78	23.16	8.54	4.78	22.25
	1-128-64-1	13.13	6.99	24.21	12.44	7.83	27.05
	1-64-32-16-1	29.80	16.95	27.22	29.78	20.83	8.00
	1-128-64-32-1	26.94	6.81	18.39	26.94	7.35	5.10
	1-256-128-64-1	30.11	**3.85**	5.81	29.32	6.96	6.81
2007–2022	1-32-1	35.36	34.00	28.50	35.42	33.90	30.93
	1-50-1	2.32	**2.27**	12.15	2.10	2.44	4.44
	1-128-1	35.10	33.83	29.83	33.81	33.35	32.49
	1-64-32-1	6.89	9.64	27.04	4.41	2.99	24.21
	1-128-64-1	13.18	10.46	27.01	7.65	5.26	23.46
	1-64-32-16-1	34.01	23.86	26.92	34.64	21.79	14.33
	1-128-64-32-1	14.17	3.74	10.53	34.84	5.12	7.08
	1-256-128-64-1	34.22	7.82	6.76	33.51	3.82	5.01
2007–2024	1-32-1	36.29	34.54	29.78	35.69	35.17	31.98
	1-50-1	6.38	**2.26**	10.25	**2.02**	2.55	3.30
	1-128-1	34.68	34.00	31.38	35.57	35.09	34.22
	1-64-32-1	2.82	6.03	27.68	3.61	6.27	24.34
	1-128-64-1	3.38	6.64	28.62	10.84	9.06	24.44
	1-64-32-16-1	35.68	19.80	31.69	34.88	17.69	25.82
	1-128-64-32-1	40.18	3.95	8.14	39.35	3.79	6.75
	1-256-128-64-1	35.98	7.85	5.32	35.02	9.38	4.64

In terms of data volume, the results presented in Table 6 and Table 7 suggest that using datasets with longer time spans (such as the 2007–2024 period) *generally leads* to better predictive performance compared to shorter datasets (2007–2020). This *is evident* in the reduced MAPE values for several of the best-performing architectures, particularly when used with *optimal* hyperparameter settings. This phenomenon aligns with fundamental machine learning principles, where the availability of richer historical data helps models capture more complex temporal patterns and improves generalization. Nevertheless, this improvement is highly dependent on the suitability of the model architecture, as some configurations experienced overfitting or increased error with more data. This *indicates* that a larger dataset does not necessarily guarantee better accuracy unless accompanied by an appropriately designed model.

Figure 3(a) and 3(b) present the training and validation loss curves for two different LSTM architectures: 1-128-64-32-1 and 1-50-1, respectively. Both figures *exhibit* a similar pattern where the losses decrease significantly in the early epochs, *indicating* an efficient learning process during the *initial* training phase. In Figure 3(a), the validation loss shows slight fluctuations compared to the training loss but *ultimately stabilizes*, *demonstrating a relatively stable* generalization performance. Meanwhile, in Figure 3(b), the training and validation loss curves closely follow each other and converge near zero, implying that the model effectively avoids overfitting and is *able to maintain* consistent performance across training and unseen data. These patterns *indicate* that both architectures are capable of learning meaningful patterns from the data, with the 1-50-1 model exhibiting slightly smoother convergence.



(a) **(b)**

(c) **(d)**

Figure 3: (a–b) Training and validation loss using LSTM with architectures 1-128-64-32-1 and 1-50-1, respectively; (c–d) Actual vs predicted closing prices on test data using the same architectures.

Figure 3(c) and (d) provide visual comparisons between actual and predicted closing prices of the Jakarta Composite Index (JCI) for the two respective LSTM architectures. In Figure 3(c), the 1-128-64-32-1 model captures the overall trend of the JCI but *exhibits* a noticeable deviation in certain regions, suggesting potential overfitting or insufficient generalization. In contrast, Figure 3(d) shows that the 1-50-1 model delivers more *accurate* and stable predictions, with the red prediction line closely aligning with the actual blue line, especially after the train/test split *indicated* by the green dashed line. This improved alignment is *supported* by the *relatively low* prediction error and better tracking of directional trends. Overall, the 1-50-1 architecture *demonstrates* superior performance in terms of both training stability and predictive accuracy, making it more suitable for forecasting the JCI closing price.

3.4 Hybrid ARIMA-LSTM

The ARIMA model captures linear patterns in time series but often has high errors due to nonlinearities it cannot model. To address this, a hybrid approach is used in which residuals from the ARIMA model are passed to an LSTM network to capture the remaining nonlinear dynamics. After training the ARIMA models and extracting the residuals, the LSTM was applied to model the nonlinear component. The results of various LSTM architectures for hybrid modeling are summarized below.

Table 8: Comparison of Hybrid ARIMA-LSTM model architectures based on MAPE for each learning rate (Batch Size 16)

Period	Architecture	MAPE of LR Dataset Close (%)			MAPE of LR Dataset Open (%)		
		0.01	**0.001**	**0.0001**	**0.01**	**0.001**	**0.0001**
2007–2020	1-32-1	17.25	16.50	8.69	17.36	16.52	8.63
	1-50-1	17.49	11.92	**8.04**	17.35	12.07	**8.57**
	1-128-1	17.27	17.17	10.17	17.08	17.06	10.16
	1-64-32-1	17.25	17.53	12.24	17.38	17.27	12.13
	1-128-64-1	17.23	17.49	13.76	17.09	13.77	13.51
	1-64-32-16-1	17.48	17.39	15.77	17.45	17.19	15.77
	1-128-64-32-1	17.12	17.31	17.01	16.79	17.25	17.10
	1-256-128-64-1	17.56	17.39	17.31	17.42	17.41	17.34
2007–2022	1-32-1	8.29	8.33	6.72	7.62	7.79	6.30
	1-50-1	8.18	8.32	**6.17**	7.31	6.99	**5.38**
	1-128-1	8.41	8.19	7.19	7.66	7.60	6.53
	1-64-32-1	8.26	8.25	8.53	7.72	7.86	8.15
	1-128-64-1	8.17	8.51	8.34	7.67	7.82	7.81
	1-64-32-16-1	8.20	8.29	8.30	8.24	7.90	7.75
	1-128-64-32-1	8.44	8.13	8.25	7.88	7.72	7.74
	1-256-128-64-1	8.22	8.35	8.27	7.68	7.44	7.75
2007–2024	1-32-1	5.01	4.75	2.86	4.91	4.81	3.20
	1-50-1	5.07	4.66	**2.00**	4.42	4.51	**1.74**
	1-128-1	5.04	4.98	3.60	5.12	4.72	7.46
	1-64-32-1	4.81	4.80	4.39	4.97	4.89	4.34
	1-128-64-1	4.82	5.09	4.56	5.05	4.91	7.39
	1-64-32-16-1	4.97	5.02	4.89	4.96	5.05	7.41
	1-128-64-32-1	4.94	4.86	4.95	5.01	4.94	4.87
	1-256-128-64-1	4.83	4.56	4.90	4.80	4.68	7.41

Table 8 shows that the architecture **1-50-1** with a learning rate of 0.0001 consistently produced the lowest MAPE values for both closing and opening prices across all time periods. For example, in the 2007–2024 period, the model yielded a MAPE of 2.00% for Close and 1.74% for Open, significantly outperforming deeper and more complex architectures.

These findings indicate that simpler LSTM architectures with fewer hidden layers are more effective in modeling the nonlinear residuals of ARIMA forecasts. Furthermore, a batch size of 16 was deliberately chosen based on initial experiments, as a larger batch size (e.g., 32) led to noticeably higher error rates. Smaller batches improve model sensitivity to short-term fluctuations, which is vital for financial time series prediction.

The ARIMA models used in the hybrid modeling were selected based on performance criteria such as AIC and parameter significance. Specifically, ARIMA(1,1,4) was used for IHSG Close and ARIMA(1,1,1) for Open in the 2007–2020 period; ARIMA(1,1,0) for both in the 2007–2022 period; and ARIMA(1,1,0) for Close and ARIMA(0,1,1) for Open in the 2007–2024 period.

3.5 Selection of the Best Model

Table 9 presents the performance evaluation of ARIMA, LSTM, and Hybrid ARIMA-LSTM models for two key market variables: *closing price (Close)* and *opening price (Open)*. Overall, the LSTM model consistently outperforms both ARIMA and the hybrid model in minimizing the Mean Absolute Percentage Error (MAPE) across almost all time periods.

For instance, during the 2007–2022 period, LSTM with the architecture 1-50-1 achieves a MAPE of 2.27% (Close) and 2.02% (Open), which is significantly lower than ARIMA's 4.83% and 7.69% respectively. This highlights the strength of LSTM in capturing nonlinear patterns and temporal dependencies in financial data, which are *not well addressed* by the linear ARIMA model.

Table 9: Evaluation model ARIMA, LSTM and Hybrid ARIMA-LSTM

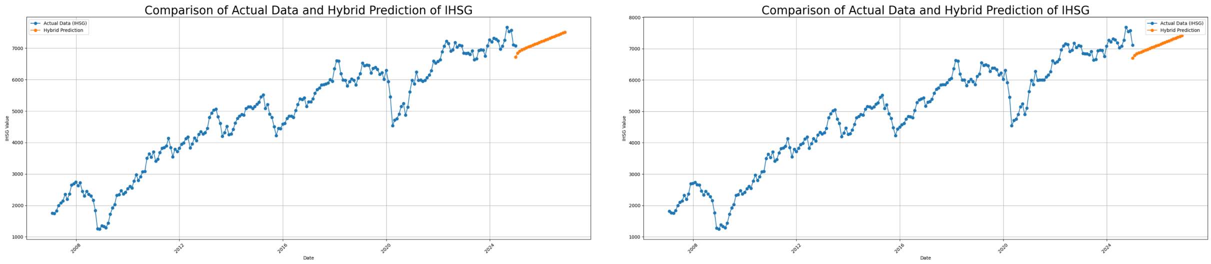
Period	Dataset	Model	MAPE (%)
2007–2020	Close	ARIMA(0,1,1)	17.46
		LSTM (1-128-64-32-1)	4.08
		HYBRID ARIMA(0,1,1)-LSTM(1-50-1)	8.04
	Open	ARIMA(1,1,1)	16.41
		LSTM (1-256-128-64-1)	3.85
		HYBRID ARIMA(1,1,1)-LSTM(1-50-1)	8.57
2007–2022	Close	ARIMA(1,1,0)	4.83
		LSTM (1-50-1)	2.27
		HYBRID ARIMA(0,1,1)-LSTM(1-50-1)	6.17
	Open	ARIMA(1,1,0)	7.69
		LSTM (1-50-1)	2.02
		HYBRID ARIMA(1,1,0)-LSTM(1-50-1)	5.38
2007–2024	Close	ARIMA(1,1,0)	2.14
		LSTM (1-128-64-32-1)	2.02
		HYBRID ARIMA(0,1,1)-LSTM(1-50-1)	**2.00**
	Open	ARIMA(0,1,1)	4.96
		LSTM (1-50-1)	2.10
		HYBRID ARIMA(0,1,1)-LSTM(1-50-1)	**1.74**

Although the hybrid ARIMA-LSTM model theoretically combines the predictive strengths of ARIMA and LSTM, its performance is not consistently better than that of pure LSTM. In some cases, such as the 2007–2024 period for the *Close* variable, the hybrid ARIMA(0,1,1)-LSTM(1-50-1) model slightly outperforms LSTM with a MAPE of 2.00% versus 2.02%. However, in other periods such as 2007–2022, the hybrid model yields a higher error (6. 17% for Close) compared to LSTM (2.27%).

This suggests that the effectiveness of the hybrid model is heavily dependent on the degree to which the ARIMA model captures the linear components of the data. If ARIMA does not model the linear patterns effectively, the residuals passed to the LSTM become more complex and can reduce the overall prediction accuracy of the hybrid model. This finding is consistent with other studies that highlight that the successful decomposition of data into linear and nonlinear components is key to the performance of hybrid ARIMA-LSTM models[27].

The relationship between the *Close* and *Open* variables is evident in the relatively consistent error patterns *observed* across all models. For all methods, the MAPE differences between Open and Close are *generally small*, indicating that these two variables share similar temporal characteristics and can be *modeled* using similar approaches. For example, in the LSTM model for the period 2007–2024, the MAPE for Close is 2.02% and for Open it is 2. 10%, reflecting the stability of the model in handling both types of prices. However, ARIMA tends to perform worse in the Open variable, suggesting that opening prices may be *more influenced by external factors* or contain more noise than linear models cannot capture. In general, the selection of the best model depends on the specific prediction goals, where LSTM is favored for higher accuracy, and the hybrid approach is useful when separating linear and non-linear components is beneficial. Figure 4 shows the prediction results using the best-performing model for each variable.

The prediction results using the *optimal HYBRID ARIMA(0,1,1)-LSTM(1-50-1)* model show a close alignment with the actual trends for both Close and Open prices. The model successfully captures the upward movement pattern in the time series, *indicating strong predictive performance*. This confirms the hybrid model's effectiveness in combining linear and nonlinear components for accurate financial forecasting.



(a) Close price

(b) Open price

Figure 4: Predictions of Close (a) and Open (b) prices using the optimal HYBRID ARIMA(0,1,1)-LSTM(1-50-1) model

3.6 Discussion

This study shows that the hybrid ARIMA-LSTM model with a simple architecture (1-50-1) provides highly accurate IHSG predictions, achieving MAPE of 2.00% (Close) and 1.74% (Open) during 2007–2024. It outperforms ARIMA and most pure LSTM models, confirming that separating linear and nonlinear components enhances forecasting performance.

These results align with prior work [28], which utilized ARIMA residuals to improve LSTM-based stock predictions. Similar approaches have also outperformed traditional strategies on global indices such as the S&P 500 and FTSE 100 [29], highlighting the strength of hybrid models in capturing complex market behavior.

In Indonesia, combining ARIMA-LSTM with Lowess regression has improved accuracy in forecasting sharia stocks [30], supporting this study's findings on the IHSG. Other studies have emphasized that well-designed hybrid models outperform deeper or more complex architectures [31], consistent with the increased error found in overly deep LSTM variants here.

Overall, this research reinforces the practical and theoretical value of ARIMA-LSTM hybrids, offering an effective solution for financial forecasting in both local and global contexts while addressing key gaps in emerging market studies.

4 Conclusion

The analysis demonstrates that while ARIMA effectively captures linear patterns in IHSG price data, LSTM consistently outperforms both ARIMA and hybrid ARIMA-LSTM models in most scenarios, achieving superior accuracy (e.g., MAPE of 2.27% for Close and 2.02% for Open during 2007–2022) due to its ability to model nonlinear dependencies. The hybrid model, though occasionally competitive (e.g., MAPE of 2.00% for Close in 2007–2024), relies heavily on ARIMA's linear fitting quality, where deficiencies can hinder LSTM's residual learning.

These findings position LSTM (particularly with 1-50-1 architectures) as the preferred choice for stock forecasting, with hybrids serving as alternatives for data exhibiting clear linear-nonlinear patterns. However, this study is limited by its univariate focus, excluding external factors (e.g., macroeconomic indicators) and advanced architectures like Transformers. Future work should pursue multivariate integration, alternative hybrid configurations, and robustness testing across market regimes to enhance model generalizability and practical adoption.

CRediT Authorship Contribution Statement

Mahda Al Maidah: Conceptualization, Methodology, Formal Analysis (ARIMA), Data Curation, Software, Visualization, Writing – Original Draft, Writing – Review & Editing. **Andi Illa Erviani Nensi**: Conceptualization, Formal Analysis (LSTM and Hybrid), Software, Visualization, Resources, Writing – Original Draft, Writing – Review & Editing. **Khairil Anwar**

Notodiputro, Yenni Angraini, Laily Nissa Atul Mualifah: Supervision, Validation, Project Administration.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist in language refinement and technical clarification. All content was reviewed and verified by the authors, who take full responsibility for its accuracy and integrity.

Declaration of Competing Interest

The authors declare that there is no known competing financial interest or personal relationship that could have influenced the work reported in this paper.

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Data and Code Availability

The IHSG time series data used in this study is publicly available via the Indonesia Stock Exchange and Yahoo Finance. The Python code for ARIMA, LSTM, and hybrid modeling is available upon reasonable request from the corresponding author.

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