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FORECASTING THE JAKARTA COMPOSITE INDEX USING LSTM BASED ON INDONESIAN MARKET DATA

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Abstract: The capital market plays an important role in describing the economic conditions of a country, and the IHSG is used as the main indicator to observe the movement of all stocks on the Indonesia Stock Exchange. Because stock data is volatile and non-linear, the forecasting process becomes challenging, requiring methods that can capture historical patterns more accurately. This study aims to predict IHSG movements using the Long Short-Term Memory (LSTM) model to generate stable short-term predictions. Historical IHSG data was used to train the model, and accuracy was evaluated using Mean Squared Error (MSE). The results show that the model obtained an MSE 6784.0207, RMSE 82.3652 and MAPE 0.88%, indicating a relatively low prediction error rate. The visualization shows that the model's predictions are very close to the actual data, and the 60-day forecasting results show a potential increase in the IHSG of 1.05%. Thus, the LSTM model is capable of providing fairly accurate IHSG predictions and can be a useful tool for investors in analyzing short-term market movements.

Keywords: forecasting; JCI; long short term memory

Abstrak: Pasar modal memiliki peran penting dalam menggambarkan kondisi ekonomi suatu negara, dan IHSG digunakan sebagai indikator utama untuk melihat pergerakan seluruh saham di Bursa Efek Indonesia. Karena data saham bersifat fluktuatif dan tidak linear, proses peramalan menjadi tantangan, sehingga dibutuhkan metode yang mampu menangkap pola historis secara lebih akurat. Penelitian ini bertujuan memprediksi pergerakan IHSG menggunakan model Long Short-Term Memory (LSTM) untuk menghasilkan prediksi jangka pendek yang stabil. Data historis IHSG digunakan untuk melatih model, kemudian akurasi dievaluasi menggunakan Mean Squared Error (MSE). Hasil penelitian menunjukkan bahwa model memperoleh nilai MSE 6784.0207, RMSE 82.3652 dan MAPE 0.88% yang menandakan tingkat kesalahan prediksi relatif rendah. Visualisasi menunjukkan bahwa prediksi model sangat mendekati data aktual, dan hasil forecasting 60 hari ke depan memperlihatkan potensi kenaikan IHSG sebesar 1,05%. Dengan demikian, model LSTM mampu memberikan prediksi IHSG yang cukup akurat dan dapat menjadi alat bantu bagi investor dalam menganalisis pergerakan pasar jangka pendek.

Kata kunci: forecasting; JCI; memory jangka pendek

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INTRODUCTION

The capital market plays a crucial role in a country's economic development, reflecting financial stability and investor confidence. In Indonesia, the Composite Stock Price Index (IHSG) serves as the main indicator of overall stock market performance [1]. However, IHSG movements are influenced by various domestic and global factors, such as macroeconomic conditions, exchange rates, and commodity prices, resulting in highly volatile and non-linear behavior that is difficult to predict using traditional statistical approaches [2][3][4].

Accurate IHSG forecasting is therefore essential to support investment decisions and risk management [5], yet conventional models often fail to capture the complex dynamics of this time-series data effectively [6][7][8]. Although adaptive approaches have been proposed to model non-linear patterns [9][10], previous studies still have limitations in developing IHSG prediction models that can optimally capture market complexity and volatility, particularly when applied to recent data and changing market conditions. This condition highlights the urgent need for a more accurate and adaptive IHSG forecasting model to support decision making in the Indonesian capital market.

Several recent works have explored deep learning models, especially LSTM, for stock market prediction, reporting that LSTM can outperform traditional models such as ARIMA in handling volatile stock data and learning long-term dependencies [11][12][13][14]. Several variants, including bidirectional LSTM, embedded LSTM with autoencoders, and modified activation functions, have demonstrated improved prediction accuracy across different markets, including the Shanghai index and Indonesian blue-chip stocks [15][16][17].

However, most previous studies still focus on individual stocks using daily data, while studies that specifically discuss JCI predictions using weekly data for the medium term are still very limited. Therefore, this study offers a novel approach by developing an LSTM-based JCI prediction model that utilizes weekly data to forecast JCI movements over the next 60 days. The selection of a 60-day prediction period aims to represent medium-term prediction needs, which are more relevant to investors and policymakers because they provide a more stable picture of market trends compared to short-term predictions.

With a 60-day time frame, the influence of random short-term fluctuations can be reduced, allowing the prediction results to serve as a reference in investment decision-making, risk management, and strategy planning within the Indonesian capital market. Forecasting is carried out to estimate the direction of future price movements based on historical data so that investors can anticipate risks in making decisions to buy or sell shares [18]. Accordingly, this study aims to identify the most accurate LSTM model through a systematic process that includes data collection, preprocessing, model training, performance evaluation, forecasting, and result interpretation.

By utilizing recent IHSG data and structured analysis procedures, this study is expected to contribute to the

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financial forecasting literature and provide practical insights for market participants and investment decision makers in Indonesia.

METHOD

In completing this research, several stages were carried out, starting from Data Collection, Pre-Processing, Modeling, Evaluation, Forecasting, and Analysis (Image 1).

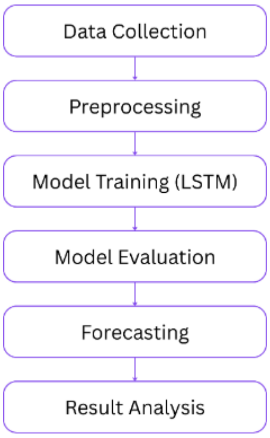

Image 1. Proposed model

Data Collection

The first stage is collecting JCI closing price data using the yfinance library. Data is retrieved via ticker (^JKSE) with a time range from January 1, 2017 to November 24, 2025. This process ensures that all historical data needed to build the prediction model is available and complete.

Image 2. JCI Closing Price History

Image 2. is a graph of closing price history from December 2016 to December 2025. There was a sharp decline in prices at the beginning of 2020, followed by a significant upward trend that peaked at 8419.92 towards the end of the period.

Pre-processing

After the data was obtained, preprocessing was carried out, which included cleaning the data by removing irrelevant columns such as Dividends and Stock Splits.

Date	Open	High	Low	Close	Volume
2025-11-17 00:00:00+07:00	8397.835938	8452.329102	8391.995117	8416.881836	382110500
2025-11-18 00:00:00+07:00	8427.398438	8442.865234	8341.903320	8361.925781	374837900
2025-11-19 00:00:00+07:00	8384.362305	8426.632812	8375.575195	8406.577148	394548300
2025-11-20 00:00:00+07:00	8449.541992	8491.427734	8419.916992	8419.916992	319147400
2025-11-21 00:00:00+07:00	8403.901367	8432.602539	8361.271484	8414.351562	288992600

Image 3. JCI Data Preprocessing

The JCI closing price data is then normalized using MinMaxScaler so that all price values are within the range of 0-1. Normalization is performed because the LSTM model is sensitive to data scale; large differences in scale can hinder the learning process and slow down convergence. This normalization process converts the original JCI price values into measurable values on a small scale (0-1) so that price change patterns are easier for the LSTM network to learn. The normalization results are numerical arrays that represent the JCI price in the form of scaled data. The MinMaxScaler formula can be seen in equation (1).

$$x' = \frac{(x - x_{min})}{x_{max - x\_min}} \tag{1}$$

In Equation 1, x' is the value resulting from the normalization process. This value is calculated from the difference between the data value to

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be normalized x and the minimum value in the dataset (x_{min}), then divided by the difference between the maximum value (x_{max}) and the minimum value (x_{min}) in the entire dataset. Thus, each data value is converted to a scale of 0 to 1, making it easier for the LSTM model to learn data patterns.

Model Training (LSTM)

At this stage, the LSTM model is constructed using a layered architecture consisting of two LSTM layers, a dropout layer, and a dense layer (Image 4). The input data is in the form of a weekly IHSG time series with five input features. The use of two stacked LSTM layers is intended to enable hierarchical feature learning, where the first LSTM layer captures short-term temporal patterns and local fluctuations in the IHSG data, while the second LSTM layer learns higher-level and longer-term dependencies from the extracted sequence representation.

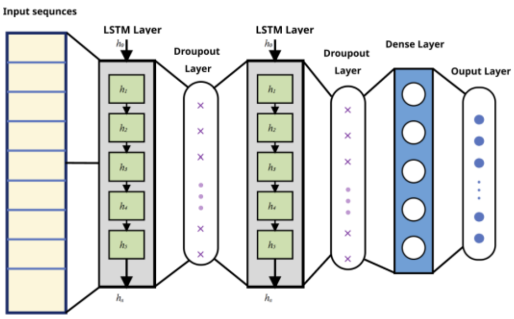

Image 4. Architecture of the Proposed Stacked LSTM Model

The first LSTM layer functions to pass time sequence information to the next layer, while the second LSTM layer produces the final representation of the data. To reduce overfitting, a dropout layer is used. Next, the output is processed by a dense layer and one output neuron to generate the IHSG prediction value. Through the gate mechanism in LSTM (input gate, forget gate, and output gate), the model is able to retain important information in the long term and ignore irrelevant information, making it effective in capturing non-linear patterns in IHSG movements.

Model Evaluation

To measure accuracy, the MSE, RMSE, and MAPE methods are used. The trained model is then tested using test data generated from the previous preprocessing process. Mean Squared Error (MSE) is used to measure the extent to which the prediction results are close to the actual data. A lower MSE value indicates that the forecasting model has more accurate prediction capabilities, making it reliable for data-based decision making. The MSE equation is as follows (2).

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \qquad (2)$$

Description:
$\hat{Y}_1, \hat{Y}_2, \ldots, \hat{Y}_n$ = predicted values.
$Y_1, Y_2, \ldots, Y_n$ = observed values.
n = amount of data observed.

Root Mean Square Error (RMSE) is a method for measuring the magnitude of the error between the actual value and the value predicted by a model. The RMSE calculation is performed by summing the squares of each difference between the actual value and the predicted value, then dividing the result by the number of times or forecasting periods, and taking the root of the result. The RMSE value is used to see how far the model's error is from the linear regression line. In addition, RMSE is also able to dampen or reduce the effect of sudden large

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changes in the data. The calculation formula is shown in equation (3).

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{n}} \quad (3)$$

Description:
$\hat{Y}_1, \hat{Y}_2, \ldots, \hat{Y}_n$ = predicted values.
$Y_1, Y_2, \ldots, Y_n$ = observed values.
n = amount of data observed.

Mean Absolute Percentage Error (MAPE) is a measure used to see how large the prediction error is in percentage form. MAPE calculates the difference between the actual value and the predicted value, then takes the absolute value so that there are no negative values. After that, the difference is compared to the actual value and converted into a percentage. The MAPE value shows how large the average prediction error is compared to the actual data. The smaller the MAPE value, the better the quality of the predictions produced by the model. The calculation formula is shown in equation (4).

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-\hat{F}_t}{A_t}\right|\times 100\% \quad (4)$$

Description:
A_t : actual value.
F_t : forest value.
n : sample size.
t : (time-step).

Forecasting

The next step is to predict the JCI price for the next 60 days. The prediction process is carried out iteratively using the sliding window method, which uses the previous day's prediction results as part of the input for the next day's prediction. The prediction results are stored in a Data-Frame complete with the prediction date.

Result Analysis

The final stage is the analysis of the prediction results. At this stage, a graph is visualized between the actual price, the model prediction price, and the 60-day forecasting results. In addition, the percentage increase or decrease in price is calculated based on the latest price prediction compared to the latest actual closing price, so that it can be determined whether the JCI is expected to experience an upward or downward trend.

RESULTS AND DISCUSSION

This study uses closing price data from the Composite Stock Price Index (IHSG) that has undergone preprocessing before being used in the model training process, with 80% of the data used as training data. The results of the model performance evaluation are shown in Image 5. The results obtained show that the LSTM model is able to capture the movement patterns of the IHSG well. This indicates that the proposed stacked LSTM model is capable of learning complex temporal dependencies in the IHSG time series, which is characterized by non-linear and volatile behavior.

This finding is in line with previous studies, which state that the LSTM model is more effective in modeling stock market data that is non-linear and volatile compared to traditional statistical methods [16]. In addition, similar performance improvements using LSTM-based models for stock market prediction have also been reported in prior studies

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[13][14]. In this study, stock closing price data (^JKSE) that has undergone preprocessing is used for model training, with 80% of the data used for training.

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=== Model Evaluation ===
MSE  : 6784.0207
RMSE : 82.3652
MAPE : 0.88%
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Image 5. Model Evaluation

The evaluation results show an MSE value of 6784.0207, an RMSE of 82.3652, and a MAPE of 0.88%. A MAPE value below 1% indicates that the average prediction error is very small, so the LSTM model has a very good level of accuracy in predicting JCI movements. This high accuracy is related to the non-linear and fluctuating characteristics of the IHSG data, which makes it difficult to model using traditional methods that tend to assume a linear relationship. The LSTM model is able to capture these patterns because it has a gate mechanism that allows the model to store important information in the long term and ignore less relevant information. With two LSTM layers, the model can learn short-term and long-term dependencies more effectively.

In addition, the use of weekly data helps reduce noise in the data, while the application of dropout improves the model's generalization ability and reduces the risk of overfitting. The combination of the layered LSTM architecture and the characteristics of the data used are the main factors that cause the low prediction error value, specifically MAPE of 0.88%. This value also supports the visual proximity between the actual line and the prediction line in the previous graph in Image 5.

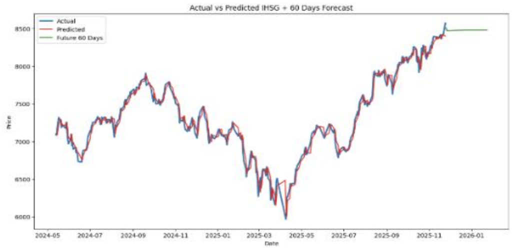

Image 5. Comparison of Actual JCI Prices, Model Predictions and the Next 60-Day Forecast

The image Shows the results of a prediction graph comparing the actual JCI price (blue line) and the model's predicted JCI price (red line) over a certain period of time. In general, the two lines appear very close to each other, indicating that the model is able to learn the JCI movement patterns quite well. The model can follow the index's ups and downs, including during sharp declines and recoveries.

At the end of the graph, there is a green line that shows the JCI prediction for the next 60 days. This prediction shows a stable upward trend, without major fluctuations. This indicates that the model predicts that the JCI will continue to move positively in the short term. Image 6 shows the predicted JCI price for each date.

```
...  0   2025-11-25 00:00:00+07:00   8510.244140625
     1   2025-11-26 00:00:00+07:00   8472.18359375
     2   2025-11-27 00:00:00+07:00   8477.103515625
     3   2025-11-28 00:00:00+07:00   8471.662109375
     4   2025-11-29 00:00:00+07:00   8471.853515625
     ...
     55  2026-01-19 00:00:00+07:00   8480.0908203125
     56  2026-01-20 00:00:00+07:00   8480.0908203125
     57  2026-01-21 00:00:00+07:00   8480.08984375
     58  2026-01-22 00:00:00+07:00   8480.0888671875
     59  2026-01-23 00:00:00+07:00   8480.087890625
```

Image 6. JCI Price Prediction

Image 6 shows the predicted IHSG price values for each date. The calculation results show that the IHSG prediction for the next 60 days will increase by 1.05%. This percentage is calculated based on the difference between the IHSG value at the beginning of the prediction period and the value at the end of the prediction period. Thus, the model predicts potential positive growth in the short term.

CONCLUSION

This research successfully identified a Long Short-Term Memory (LSTM) model that accurately predicts movements in the Composite Stock Price Index (IHSG). Based on testing and evaluation results, the LSTM model used in this study proved to be the model with the best performance, with a Mean Absolute Percentage Error (MAPE) value of 0.88%, indicating an average prediction error rate of less than 1%. This result indicates that the model is able to follow the historical patterns of the IHSG very well. The visualization results show that the predicted values are close to the actual values, and the 60-day forecast indicates a potential short-term positive trend with an increase of around 1.05%. Thus, the proposed LSTM model can be concluded as an accurate model in this study, and has the potential to provide practical benefits for investors and decision makers in understanding the direction of the IHSG movement. This study also confirms that the deep learning approach is effective for capital market analysis in Indonesia.

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