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Forecasting Stock Returns Using Long Short-Term Memory (LSTM) Model Based on Inflation Data and Historical Stock Price Movements

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Abstract

The stock market is crucial for economic growth and development, offering profit opportunities that attract investors worldwide. However, its inherent volatility necessitates the inclusion of macroeconomic indicators like inflation, which can affect stock valuation and investor behavior. This study explores predicting stock returns using a Long Short-Term Memory (LSTM) model by incorporating inflation data, historical stock price movements, and calculated returns as input features. The dataset was split into 80% for training and 20% for testing, with hyperparameter tuning conducted using the RMSprop optimizer under varying batch sizes and epoch settings. Experimental results show that the configuration using RMSprop with a batch size of 8 and 200 epochs delivered the best performance, achieving a Root Mean Squared Error (RMSE) of 0.0167 and a Mean Absolute Percentage Error (MAPE) of 25.89%. These results represent a significant improvement over alternative configurations and previous benchmarks. This study underscores the importance of including inflation as a predictive variable, enhancing the model's accuracy. The findings highlight the relevance of incorporating macroeconomic factors into stock return forecasting, providing valuable insights for investors and financial analysts seeking data-driven strategies in decision-making processes.

Keywords: forecasting; inflation; long short-term memory; stock forecasting; stock return

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1. Introduction

The stock market plays a crucial role in driving economic growth by providing liquidity and capital to businesses [1]. However, stock price fluctuations are heavily influenced by various external factors, including inflation, economic stability, and global market dynamics [2], [3], [4], [5]. Inflation, as one of the key macroeconomic indicators, has been shown to have a significant relationship with stock market movements.

Previous studies have highlighted that the stock market contributes to economic growth even under unstable economic conditions, such as periods of high inflation and volatility [6]. These findings emphasize the importance of incorporating inflation variables into stock market prediction analyses, particularly for more informed investment decision making.

Stock price prediction has been a widely researched topic, with various methods applied to forecast fluctuations and trends, while machine learning models and statistical methods have also been extensively used, each demonstrating unique advantages and limitations. Neural Network models, for example, have been applied successfully, achieving RMSE values as low as 19.734 in specific setups [7]. Similarly, XGBoost has proven effective for stock price prediction, particularly when hyperparameter tuning is employed, resulting in a MAPE of 4.01% in one study [8]. Support Vector Regression (SVR), known for its robustness in managing smaller datasets, has also been used to predict stock prices, achieving high precision levels[9].

Long Short-Term Memory (LSTM) networks have been recognized for their ability to model sequential data and address vanishing gradient problems[10]. Previous research on stock price prediction achieved a MAPE of 2.3% after hyperparameter tuning [11]. An advanced variant, Bidirectional LSTM (BiLSTM), has shown particular promise in capturing complex temporal patterns by incorporating bidirectional context. For example, a study that integrated public sentiment as an additional variable achieved a mean square error (MSE) of 0.094, a root mean square error (RMSE) of 0.306, and a maximum Dstat success rate of 68% [12]. These findings demonstrate BiLSTM's potential for stock price prediction, however the study focused on sentiment data and did not incorporate macroeconomic factors such as inflation, leaving room for further exploration.

In addition to these neural network-based approaches, previous studies on stock price prediction have investigated hybrid models, such as the combination of ARIMA and Neural Networks, to capture both linear and non-linear temporal patterns. A study integrated Neural Networks with net foreign flow data, achieving an RMSE of 41.119, highlighting the advantages of incorporating external factors into stock market forecasting models [13]. Furthermore, a comparison of LSTM and SVR demonstrated the superior performance of LSTM in handling temporal data for stock price prediction [14]. Recurrent Neural Networks (RNNs) with optimizations like Adaptive Moment Estimation have also shown promise in improving predictive performance for time series data [15].

Recent research has explored deep learning models to forecast volatility in the stock return volatility. A study using the Excitatory and Inhibitory Neuronal Synapse Unit (EINS) within a multifractal framework compared its performance with LSTM and GRU. The EINS model achieved a Mean Squared Error of 0.02549 and a Mean Absolute Error of 0.10999, outperforming LSTM, which recorded a Mean Squared Error of 0.02577 and a Mean Absolute Error of 0.11091 [16]. The results indicate that LSTM remains a strong approach for capturing temporal dependencies and biologically inspired models like EINS offer improvements in accuracy.

In this study, inflation and stock return are incorporated as key variables in forecasting stock returns using the Long Short-Term Memory (LSTM) model Inflation characterized by a persistent rise in the general price level over time, significantly affects the performance of the stock market by increasing business costs, reducing real investment returns, and influencing market stability [17], [18]. Additionally, stock return represents the gain or loss from an investment in a stock over a given period and is widely used as a key indicator of profitability and market performance. Stock return provides insights into the relative performance of a stock and is influenced by various factors, including macroeconomic conditions, market dynamics, and company-specific attributes [19], [20].

Previous studies have shown that inflation negatively and significantly affects stock indices such as the LQ45 in both the short and long term [21]. Similarly, stock returns are closely related to broader market conditions and play a critical role in the shaping of investment strategies and decision-making processes [22]. Despite their importance, existing forecasting models often overlook the integration of inflation and stock return variables, limiting their applicability in addressing real-world investment challenges.

This study seeks to bridge this gap by leveraging LSTM's capability to model non-linear and temporal dependencies in data. Unlike most previous studies that focused on predicting stock prices, this research shifts the perspective to forecasting stock returns, providing a more direct measure of investment profitability. Several previous studies have explored BBCA stock forecasting using different methods, such as BiLSTM, which achieved an RMSE of 0.306 [12], and linear regression, which recorded an RMSE of 0.032 when predicting BBCA stock returns [23]. These findings highlight the relevance and potential of return-based forecasting models. By focusing on daily stock returns, this study not only captures short-term profitability but also offers a flexible approach for estimating future stock prices through the accumulation of predicted returns.

2. Methods

In this study, several stages were carried out systematically. Research stages include data collection, data merging, data preprocessing, training process, and testing process. The research method flowchart is shown in Figure 1.

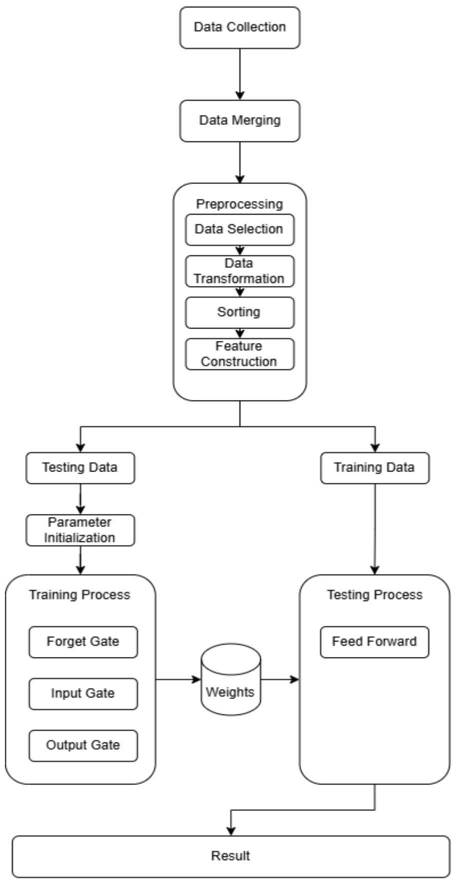

Figure 1. Research Method

The dataset comprises historical stock prices of PT Bank Central Asia Tbk (BBCA.JK) from Yahoo Finance and annual inflation data from Bank Indonesia. The stock price dataset includes attributes such as Date, Open, High, Low, Close, and Adjusted Close. Meanwhile, inflation data spanning from 2005 to 2024 were collected to examine its influence on stock return predictions. These datasets were merged to analyze the relationship between stock price movements and macroeconomic factors.

The data merging process involved combining the stock price dataset with the inflation dataset. Each stock price record was linked to the corresponding inflation rate for the same year, ensuring temporal consistency. This merging step resulted in a unified dataset that integrated historical stock prices and inflation rates, allowing for a comprehensive analysis of their relationship during the modeling phase.

Data preprocessing was performed to ensure the quality and consistency of the dataset. The process began with data selection, where irrelevant attributes, such as dividend data, and records containing missing values were eliminated to preserve data integrity. Subsequently, data transformation was applied to convert all attributes into their appropriate formats, ensuring that date-related fields were recognized as temporal data and numerical attributes were correctly structured for further analysis. The dataset was then sorted in chronological order, as the original dataset was initially arranged in descending order. This reordering was necessary to maintain the correct temporal sequence required for time-series analysis using the LSTM model.

A key aspect of the preprocessing stage was feature construction, where daily stock returns were calculated as the percentage change in adjusted closing prices using Equation 1.

$$\text{SR} = \frac{\text{Adj. Close}_t - \text{Adj. Close}_{t-1}}{\text{Adj. Close}_{t-1}} \times 100 \quad (1)$$

t represents the current time period and $t-1$ refers to the previous time period. This calculation, as defined by Formula (1), produced a new variable, Stock Return (SR), which served as the target output for the LSTM model. Feature construction was then performed to derive key features essential for stock return prediction, including Date, Open, High, Low, Close, Adjusted Close, Stock Return, and Inflation Rate. The dataset underwent data selection to remove irrelevant attributes, such as dividend data, and to discard records with missing values. Following this, data transformation ensured that all attributes were appropriately formatted, with date fields recognized as temporal data, and numerical values correctly processed. The data were then sorted in chronological order to maintain the proper temporal sequence, since initial dataset was arranged in reverse chronological order.

After preprocessing, the dataset was split into training and testing subsets to ensure that the model could be evaluated on unseen data. Subsequently, parameter initialization was conducted on the training data, preparing the LSTM model for the training process. With all preprocessing steps completed, the data was structured and ready for input into the LSTM model, ensuring that the dataset was relevant, correctly formatted, and appropriately organized to support effective model training and evaluation.

The LSTM model was selected due to its effectiveness in handling sequential data and its ability to capture long-range dependencies, an essential feature for analyzing time-series data like stock prices and inflation rates. The structure of the LSTM network, depicted in Figure 2, comprises the Forget Gate, Input Gate, and Output Gate.

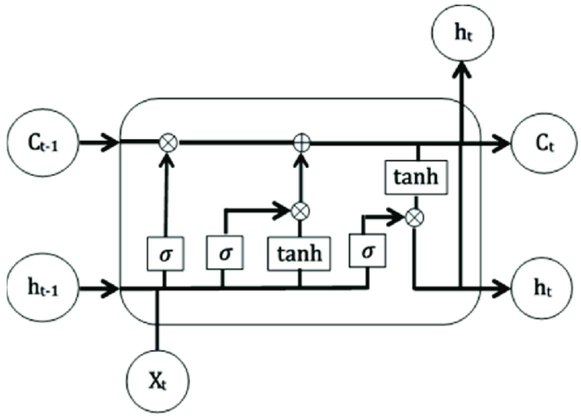

Figure 2. LSTM Architecture [24]

As shown in Figure 2, the architecture of the LSTM cell illustrates the flow of information within the network. The Forget Gate, Input Gate, and Output Gate collaboratively manage the cell state C_t and the hidden state h_t allowing the model to selectively preserve, modify, or discard information over time steps.

The Forget Gate is responsible for identifying which components of the previous cell state C_{t-1} should be preserved or eliminated. This mechanism is governed by a sigmoid activation function that produces output values ranging from 0 to 1, indicating the extent of information retention. This process is mathematically represented in Equation 2.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

The term f_t denotes the output of the Forget Gate, W_f represents the weight matrix corresponding to the Forget Gate, h_{t-1} indicates the hidden state from the prior timestep, x_t signifies the input at the current timestep, and b_f is the bias term.

The Input Gate determines the new information to be stored in the cell state. It consists of two parts: the gate vector i_t , calculated using a sigmoid function, and the candidate cell state $\widetilde{C_t}$ calculated using a tanh activation function. These are represented in Equations 3 and 4.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\widetilde{C_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

The updated cell state C_t is computed by combining the retained information from the Forget Gate and the newly selected information from the Input Gate, as shown in Equation 5.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \quad (5)$$

Lastly, the Output Gate governs the hidden state h_t, which functions as the LSTM cell's output for the current timestep. The hidden state is calculated by applying a sigmoid activation function to the gate vector o_t, followed by modulating the updated cell state C_t with a hyperbolic tanh function. This computation is formally represented in Equations 6 and 7.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (7)$$

o_t is the Output Gate activation, W_o is the weight matrix, b_o is the bias, and h_t is the final hidden state or output of the cell.

After training the LSTM model, the testing process involved feeding unseen data (testing data) into the trained model through the feed-forward mechanism. During this process, the model predicted stock returns for each timestep based on historical stock prices and inflation rates provided in the input. The feed-forward process ensured that the trained weights were applied to the testing data without further updates, maintaining the integrity of the learned patterns.

After the LSTM model produced the predicted stock return percentage, the next step was to estimate the predicted stock price for the next trading day. This transformation was crucial for interpreting the model's predictions in a practical financial context. The predicted closing price at time t $(\widehat{C_t})$ was derived from the adjusted closing price of the previous day (C_{t-1}) using Equation 8.

$$\widehat{C_t} = C_{t-1} \times \left(1 + \widehat{R_t}\right) \quad (8)$$

$\widehat{R_t}$ represents the predicted stock return at time t expressed as a decimal value. This conversion allowed for direct comparison between predicted and actual closing prices, providing further insight into the applicability of the model to real-world stock price forecasting.

Subsequently, the predicted closing prices were used to evaluate the effectiveness of the model in forecasting stock price movements. When these estimated prices were compared with actual closing prices, the accuracy of the model predictions was assessed. This step was essential in determining whether the model captured meaningful patterns in stock return fluctuations and provided reliable future price estimates.

The accuracy of the trained LSTM model was evaluated using four performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are employed to assess prediction precision and quantify the differences between actual and predicted values.

The MAE, which calculates the average magnitude of errors, is defined in Equation 9.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \quad (9)$$

The MSE, which measures the average squared differences between the actual and predicted values, is shown in Equation 10.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \quad (10)$$

The RMSE, which emphasizes larger errors, is given in Equation 11.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \quad (11)$$

MAPE, which expresses errors as a percentage of actual values, is defined in Equation 12.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \times 100\% \quad (12)$$

In these equations, y_i represents the actual value, $\widehat{y_i}$ denotes the predicted value, and n refers to the total number of observations. Lower values of these evaluation metrics indicate better model performance, demonstrating the effectiveness of the LSTM model in predicting stock returns using historical stock prices and inflation data.

3. Results and Discussions

The dataset used in this study covers the period from January 2005 to December 2024, providing a comprehensive 19-year overview of stock price fluctuations and inflation trends. The stock price data capture market dynamics influenced by a range of macroeconomic factors, including inflation. By integrating inflation data with stock price movements, this study enables a deeper analysis of their relationship—particularly in assessing how macroeconomic trends impact stock returns.

Figure 3 illustrates the closing price movement of BBCA stock from 2005 to 2024, where the horizontal axis represents the date, and the vertical axis denotes the price in IDR. The graph reveals a significant long-term upward trend with periodic fluctuations over time. Meanwhile, Figure 4 presents the average annual closing price of BBCA stock over the same period. This figure indicates a consistent increase in the average closing price, reaching its highest value of approximately 10,000 IDR in 2024. The observed upward trajectory in both figures reflects the sustained growth and resilience of BBCA over time, which is crucial for developing a predictive model that leverages historical price patterns and seasonal trends.

Understanding the historical price movement of BBCA stock is essential for build an accurate forecasting model. The long-term upward trend observed in Figures 3 and 4 suggests consistent growth, making BBCA a strong candidate for investment analysis. However, short-term fluctuations indicate the influence of market dynamics and macroeconomic factors. These patterns not only provide insight into past performance but also serve as valuable input for time series models. By recognizing both stability and volatility in the data, the model can better adapt to real-world financial behavior.

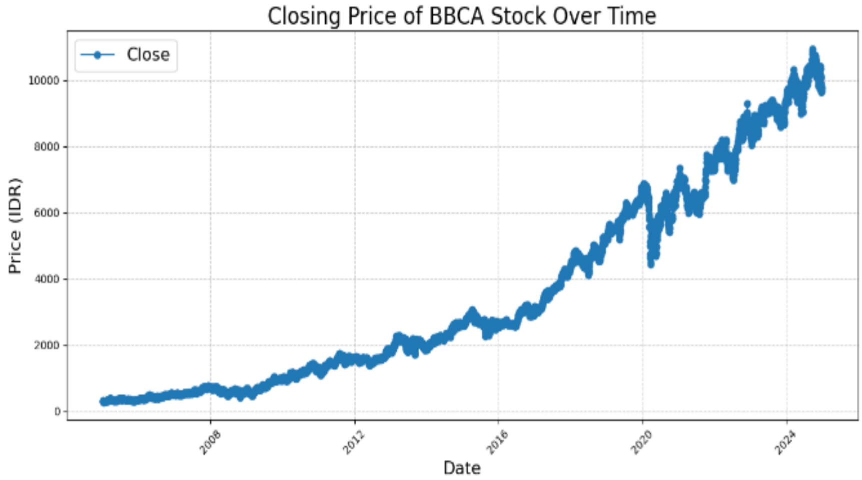

Figure 3. Closing Price of BBCA Stock Over Time (2005-2024)

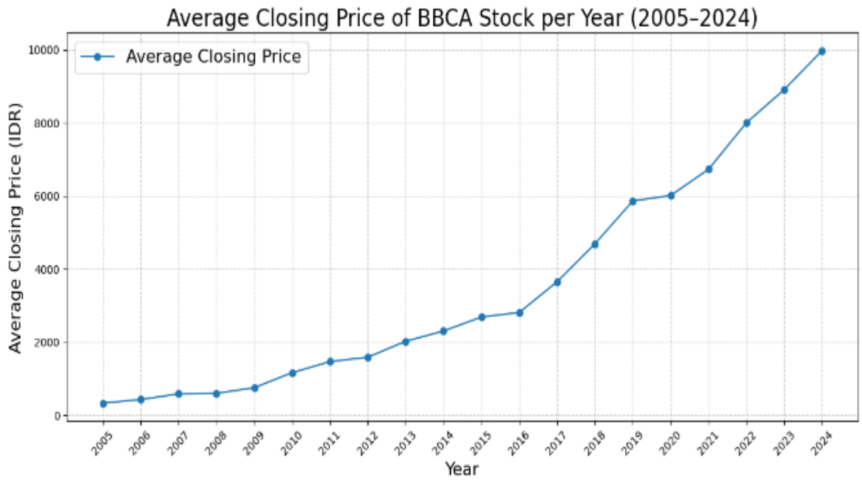

Figure 4. Average Closing Price of BBCA Stock per Year (2005-2024)

Figure 5 illustrates the daily stock return fluctuations of BBCA from 2005 to 2024, while Figure 6 presents the average annual stock return over the same period. Unlike stock prices, which exhibit a clear upward trend, stock returns show significant volatility, characterized by sharp spikes and declines at various points. This variability highlights the challenges in predicting stock returns compared to stock prices, as returns are inherently more sensitive to short-term market movements and external economic factors. In particular, Figure 6 reveals an inconsistent pattern in average annual returns, with periods of high returns followed by declines, demonstrating the dynamic nature of the behavior of stock returns.

Figure 7 illustrates the annual average inflation rate in Indonesia over the same period (2003–2024). The horizontal axis denotes the year, whereas the vertical axis indicates the average inflation rate, expressed as a percentage. The graph indicates that inflation has fluctuated significantly over the years, with a peak of 12% in 2004 and a decline to 2% in recent years. Understanding the relationship between inflation and stock prices is essential, as inflation can influence investor behavior and market trends. Macroeconomic variables, particularly inflation, often have a cascading effect on stock market performance. High inflation reduces purchasing power, deters investments, and impacts stock prices, while a low and stable inflation environment fosters investor confidence and promotes market growth.

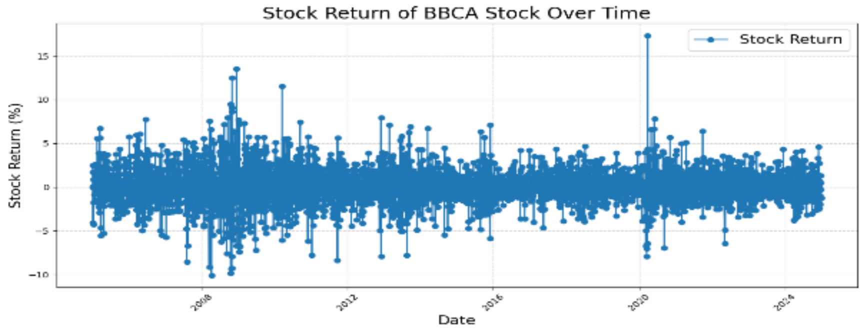

Figure 5. Stock Return of BBCA Stock Over Time (2005-2024)

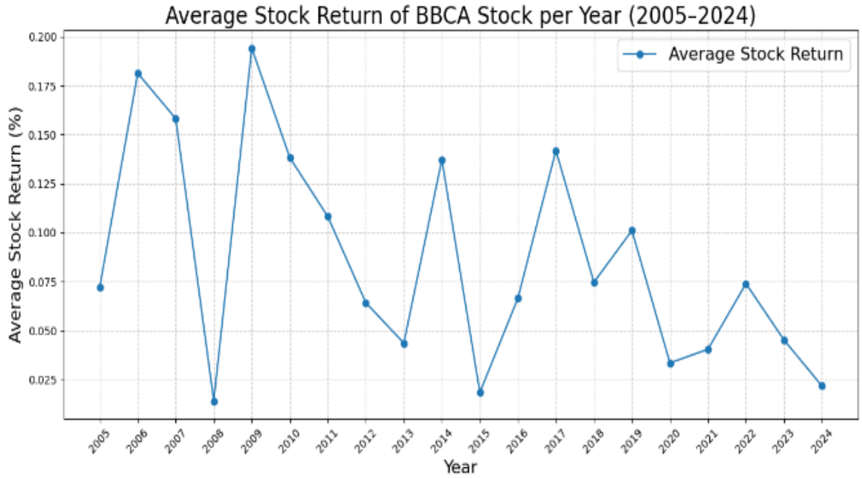

Figure 6. Average Stock Return of BBCA Stock per Year (2005-2024)

Figure 7. Average Inflation Rate in Indonesia per Year (2003-2024)

As shown in Figure 5 and Figure 7, the volatility in stock returns and the downward trend in inflation rates suggest that macroeconomic stability plays a vital role in shaping investor sentiment and stock market behavior. By linking micro-level stock behavior with macroeconomic trends, this study incorporates inflation as a key variable to develop more accurate forecasting frameworks.

As detailed in Table 1, the dataset includes comprehensive daily trading information of BBCA stock over 19 years, serving as the basis for predictive modelling in this study. The attributes of the data set include the opening, highest, lowest, closing and adjusted closing prices of BBCA stock, as well as the corresponding stock return percentage and annual inflation rate for each trading day. This combination of data provides a comprehensive view of both stock market performance and macroeconomic conditions, which is crucial for understanding their relationships and building predictive models.

Table 1. Summary of Key Attributes in the Dataset

Date	Open	High	Low	Close	Adj. Close	Stock Return(%)	Inflation Rate(%)
2005-01-03	295.0	295.0	292.5	295.0	197.74	-0.8424	6.4
2005-01-04	295.0	302.5	295.0	300.0	201.09	1.694	6.4
2005-01-05	300.0	315.0	300.0	307.5	206.12	2.501	6.4
…………..	……….	……….	………	………	……….	…….	…..
2024-10-29	10525.0	10575.0	10500.0	10500.0	10447.89	-0.943	1.71
2024-10-30	10275.0	10400.0	10275.0	10350.0	10298.63	-1.428	1.71

To facilitate predictive modeling, the dataset is partitioned into training and testing subsets, employing an 80:20 split ratio. The training subset, comprising 3,981 rows, represents data from January 2005 to April 2021, while the testing subset, consisting of 995 rows, covers the period from May 2021 to December 2024. The details of this split are summarized in Table 2.

Table 2. Split Dataset

Split Percentage	Total Data
80%	3,981
20%	995

This division ensures a balanced approach, allowing the model to capture historical patterns while evaluating performance on recent data, reflecting current market conditions.

Ensuring the representativeness of the dataset is essential in developing an accurate forecasting model. The choice of an 80:20 split provides sufficient data for training while retaining a portion for evaluation, allowing the model to generalize effectively. Additionally, the selected period encompasses various market conditions, including economic downturns and recoveries, making the dataset well-suited for assessing the model's robustness in different scenarios.

Implementation of the LSTM model is conducted in Python 3.8 using the Keras library. ADAM and RMSprop optimizers are applied to minimize errors and optimize weight adjustments during training. Mean Squared Error (MSE) serves as the loss function, aiming to reduce prediction errors. This study employs a data partitioning strategy in which 80% of the dataset is used for training, while the remaining 20% is allocated for testing. Execution takes place on a device equipped with an Intel i5-11400H CPU, 16GB of RAM, and an NVIDIA RTX 3050 GPU. CUDA Python is used to utilize GPU acceleration, significantly enhancing training efficiency and performance.

The training process involves hyperparameter optimization with batch sizes of 4, 8, 16, and 32, and epochs set to 100, 200, and 300. The architecture of the LSTM model comprises two hidden layers, each containing 50 units, and a single output node for predicting stock returns. Dropout regularization with a rate of 0.2 is applied to mitigate overfitting. The overall learning process and the model architecture are illustrated in Figure 8.

As shown in Figure 8, the model receives an input sequence of 30 time steps, which approximately represents one month of trading data, an interval commonly adopted in financial time series forecasting due to its ability to capture short-term trends and cyclical market behavior. Each sequence, consisting of features such as historical stock prices and inflation data, is processed through two stacked LSTM layers with 50 units each, allowing the model to learn both immediate and longer-term temporal dependenciesThe output of the final LSTM layer is fed into a fully connected dense layer comprising a single neuron, which executes the regression task to produce a one dimensional prediction of stock return. This architecture allows the model to extract meaningful patterns from sequential data and produce accurate forecasts using both financial and macroeconomic indicators.

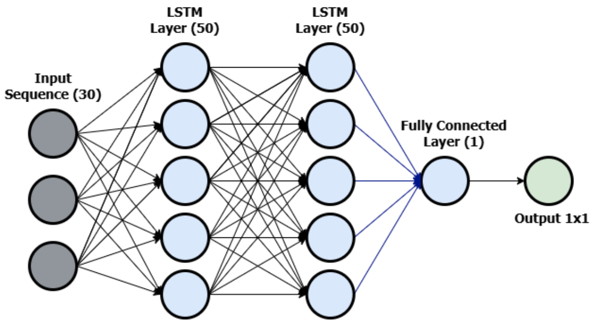

Figure 8 Model Learning Process

Model performance is evaluated using four key metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Collectively, these metrics provide a comprehensive assessment of the model's predictive accuracy and overall reliability.

Summaries of the training and testing results for different epochs are presented in Table 3, Table 4, and Table 5, which show performance metrics for each combination of hyperparameters.

As shown in Table 3, Table 4, and Table 5, the performance of the models varies depending on the hyperparameter settings. The results show that the choice of optimizer, batch size, and number of epochs significantly affects the accuracy of the predictions. The RMSprop optimizer consistently shows better performance compared to the Adam optimizer across different epoch settings and batch sizes.

In terms of model evaluation, the best overall performance is achieved with 200 epochs, using the RMSprop optimizer and a batch size of 8, resulting in the lowest RMSE (0.0167), MSE (0.0002), MAE (0.0129), and MAPE (25.89%). These metrics suggest that this configuration provides the most accurate and efficient model. The train and validation loss curves for this model, as shown in Figure 9.

Table 3. Calculation Result using Epoch = 100

Model	Optimizer	Batch Size	RMSE	MSE	MAE	MAPE (%)
1	adam	4	0.0220	0.0004	0.0185	36.51
2	adam	8	0.0254	0.0006	0.0224	4334
3	adam	16	0.0285	0.0008	0.0258	49.43
4	adam	32	0.0301	0.0009	0.0274	52.34
5	rmsprop	4	0.0220	0.0004	0.0183	35.73
6	rmsprop	8	0.0316	0.0010	0.0291	55.16
7	rmsprop	16	0.0269	0.0007	0.0239	46.03
8	rmsprop	32	0.0219	0.0004	0.0184	36.10

Table 4. Calculation Result using Epoch = 200

Model	Optimizer	Batch Size	RMSE	MSE	MAE	MAPE (%)
9	adam	4	0.0263	0.0004	0.0245	46.46
10	adam	8	0.0224	0.0005	0.0192	37.72
11	adam	16	0.0219	0.0004	0.0188	36.81
12	adam	32	0.0268	0.0007	0.0245	46.88
13	rmsprop	4	0.0218	0.0004	0.0195	36.94
14	**rmsprop**	**8**	**0.0167**	**0.0002**	**0.0129**	**25.89**
15	rmsprop	16	0.0204	0.0004	0.0171	33.46
16	rmsprop	32	0.0204	0.0004	0.0169	32.94

Table 5. Calculation Result using Epoch = 300

Model	Optimizer	Batch Size	RMSE	MSE	MAE	MAPE (%)
17	adam	4	0.0263	0.0006	0.0230	42.30
18	adam	8	0.0462	0.0021	0.0441	80.62
19	adam	16	0.0255	0.0006	0.0241	45.19
20	adam	32	0.0417	0.0017	0.0393	70.18
21	rmsprop	4	0.0262	0.0006	0.0242	45.60
22	rmsprop	8	0.0240	0.0005	0.0224	41.98
23	rmsprop	16	0.0312	0.0009	0.0296	55.13
24	rmsprop	32	0.0247	0.0006	0.0226	42.75

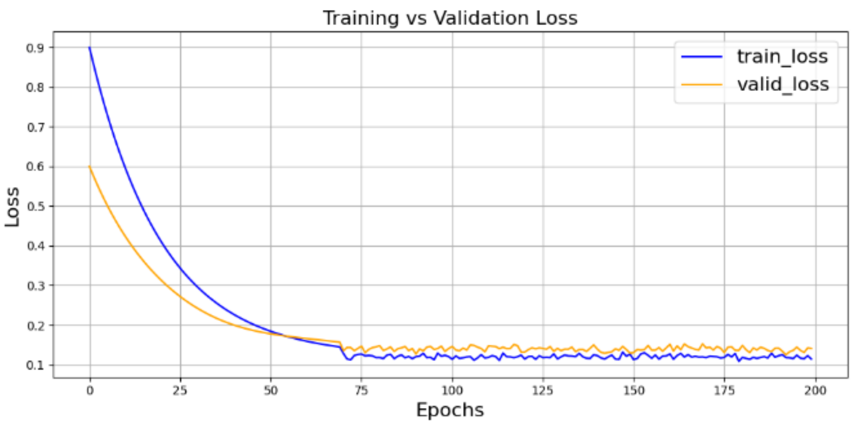

Figure 9. Training and Validation Loss with RMSprop, Batch Size 8 and Epoch 200

For 100 epochs, the RMSprop optimizer with a batch size of 4 also shows strong results, achieving an RMSE of 0.0220, MSE of 0.0004, MAE of 0.0183, and MAPE of 35.73%. Additionally, for 300 epochs, the RMSprop optimizer with a batch size of 8 performs well, with an RMSE of 0.0240, MSE of 0.0005, MAE of 0.0224, and MAPE of 41.98%. These findings confirm the consistent effectiveness of the RMSprop optimizer and underscore the importance of carefully selecting hyperparameters for optimal prediction accuracy.

The performance of the best model in this study, RMSprop with a batch size of 8 and 200 epochs, is significantly better than previous studies. For example, a study using BiLSTM to forecast stock returns achieved an RMSE of 0.306 [12], while a linear regression model for BBCA stock returns resulted in an RMSE of 0.032 [23]. In contrast, this study achieved a significantly lower RMSE of 0.0167, demonstrating the superior accuracy of the LSTM model in forecasting stock returns.

The results also indicate that the RMSprop optimizer generally performs better than the ADAM optimizer, particularly for smaller batch sizes and higher epochs. This suggests that RMSprop may be more effective in handling volatility and sequential dependencies inherent in stock return prediction. Additionally, smaller batch sizes tend to provide better accuracy, as seen in the consistently lower error metrics for batch sizes of 4 and 8 across all epochs.

Based on the evaluation of various hyperparameter configurations (as shown in Table 3, Table 4, and Table 5), the RMSprop optimizer with a batch size of 8 and 200 epochs was identified as the best-performing model. This configuration achieved the lowest RMSE (0.0167), MSE (0.0002), MAE (0.0129), and MAPE (25.89%), demonstrating its superior predictive accuracy and ability to handle sequential dependencies in stock return data. Alongside this, the second-best model (RMSprop with 100 epochs and batch size of 4) and the third-best model (RMSprop with 300 epochs and batch size of 8) were also employed to predict the average stock return of BBCA for the period from 2025 to 2027, ensuring robust and comparative analysis.

Figures 10, 12, and 14 present the prediction results of average stock returns from 2005 to 2024 using the three best-performing models. Figure 10 illustrates the prediction from the RMSprop optimizer with a batch size of 8 and 200 epochs, highlighting its ability to capture overall trends and provide stable future projections. Similarly, Figure 12 shows the results from the RMSprop optimizer with a batch size of 4 and 100 epochs, while Figure 14 presents the predictions using the RMSprop optimizer with a batch size of 8 and 300 epochs. These figures demonstrate the consistency of the LSTM model in generating reliable projections across different hyperparameter settings.

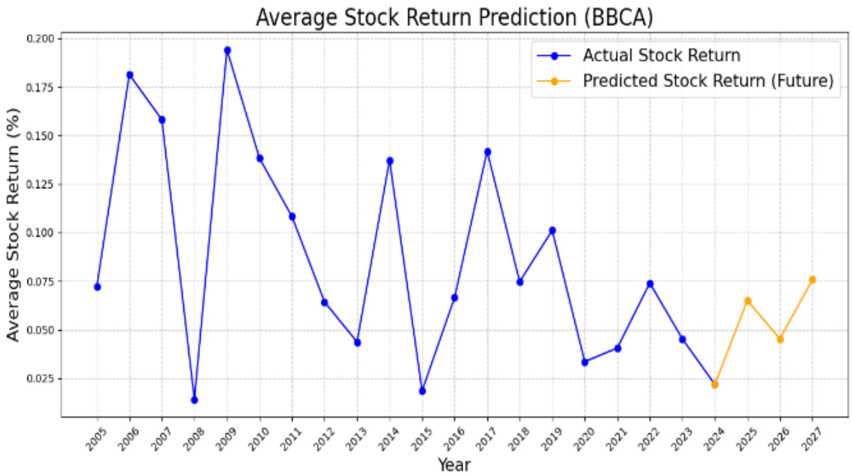

Figure 10. Average Stock Return Prediction with RMSprop, Batch Size 8 and Epoch 200

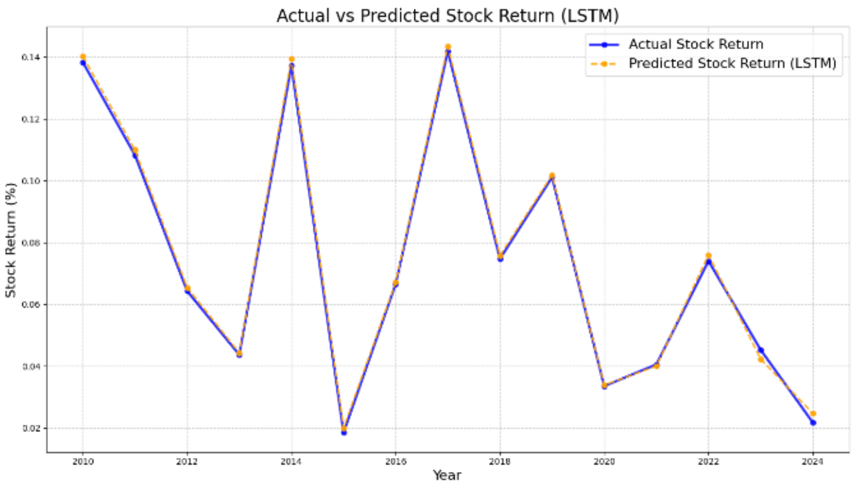

Figure 11. Actual and Predicted Stock Return (LSTM) with RMSprop, Batch Size 8 and Epoch 200

Figures 11, Figure 13, and Figure 15 compare the actual stock returns with the predicted values generated by the three best-performing models during the test period. Figure 11 focuses on the RMSprop optimizer with a batch size of 8 and 200 epochs, illustrating its accuracy in capturing historical stock return patterns. Similarly, Figure 13 evaluates the configuration with a batch size of 4 and 100 epochs, while Figure 15 presents the comparison for the configuration with a batch size of 8 and 300 epochs. These graphs effectively demonstrate the models' ability to approximate fluctuations and general trends, with minor deviations observed in certain periods. Overall, the predicted values align closely with the actual returns, validating the reliability of the LSTM models.

Although evaluation comparisons between models are limited in the number, the differences in prediction results are significant. These findings highlight the varying strengths of each model configuration in capturing stock return dynamics, emphasizing the importance of careful hyperparameter tuning. By utilizing multiple configurations, the study demonstrates the robustness of the LSTM model in generating accurate and reliable forecasts for stock returns.

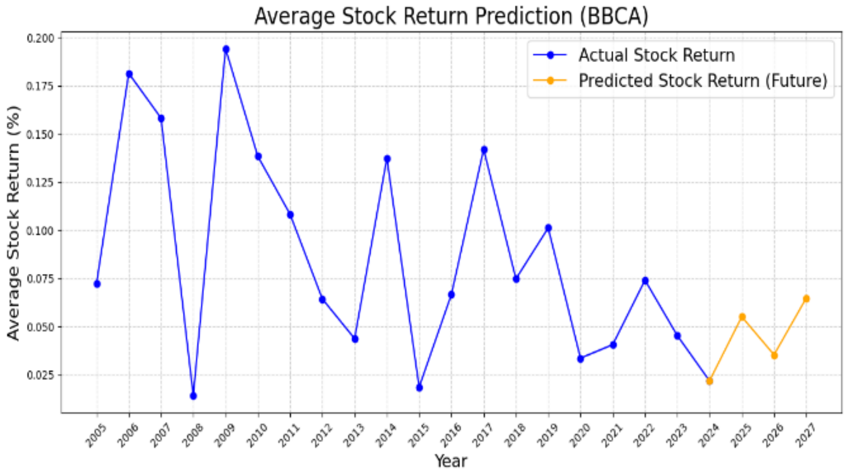

Figure 12 Average Stock Return Prediction with RMSprop, Batch Size 4 and Epoch 100

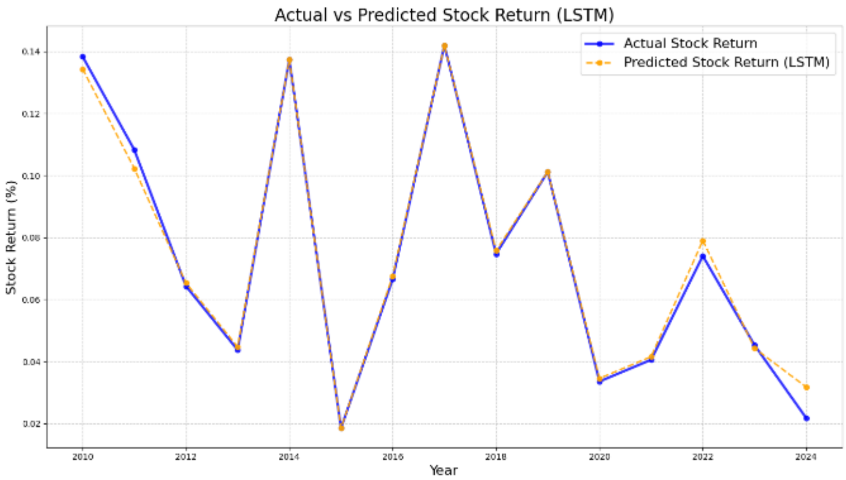

Figure 13 Actual and Predicted Stock Return (LSTM) with RMSprop, Batch Size 4 and Epoch 100

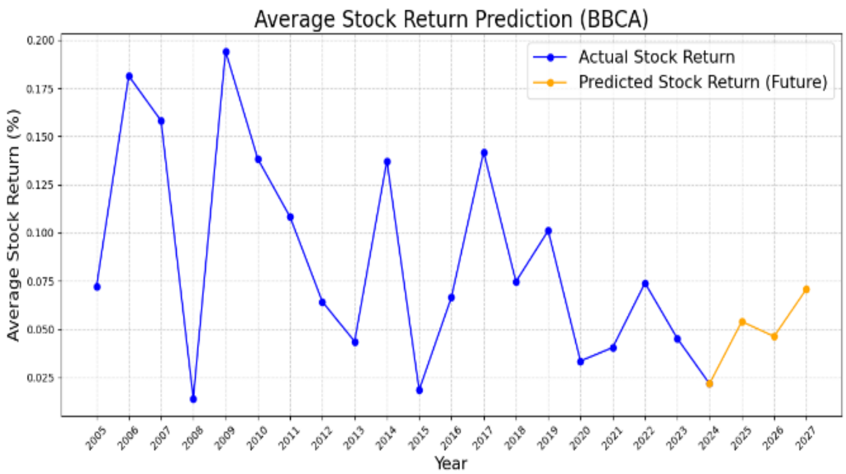

Figure 14 Average Stock Return Prediction with RMSprop, Batch Size 8 and Epoch 300

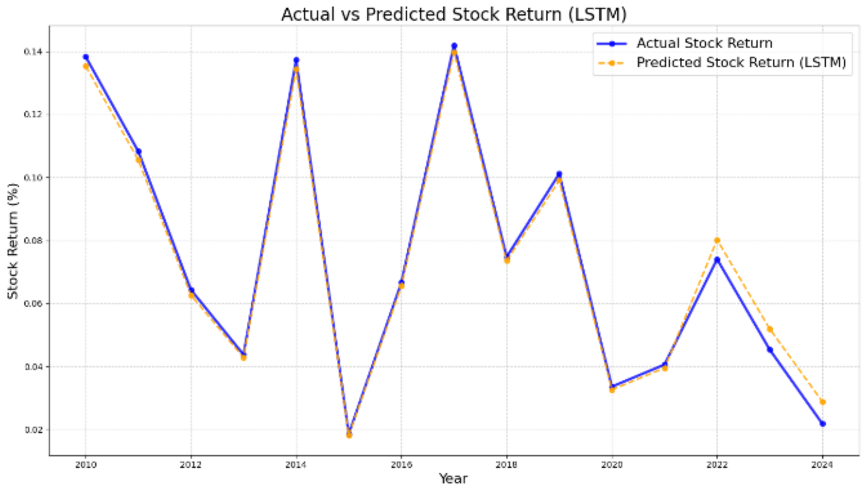

Figure 15 Actual and Predicted Stock Return (LSTM) with RMSprop, Batch Size 8 and Epoch 300

These results validate the efficacy of the selected configuration in predicting stock returns, emphasizing the importance of hyperparameter tuning in achieving optimal performance. By integrating macroeconomic factors such as inflation and leveraging historical stock data, the model provides a robust framework for analyzing and forecasting stock market dynamics, offering valuable insights for investors and stakeholders.

Despite the promising results achieved by the LSTM model, it is important to recognize its limitations. The model's performance heavily depends on the quality and quantity of historical data, and its reliance on past trends may reduce its ability to anticipate sudden market disruptions or black swan events. Additionally, hyperparameter tuning, while effective, adds computational complexity, which may not always be feasible for larger datasets or real-time predictions. Future work could explore the integration of additional variables, such as interest rates or geopolitical indicators, to enhance predictive accuracy further.

4. Conclusions

This research demonstrates the effectiveness of the Long Short-Term Memory (LSTM) model in predicting stock returns through the integration of historical stock prices and inflation rates. The results indicate that adding inflation as a macroeconomic factor not only improves stock return prediction accuracy but also enhances ability of then model to forecast stock prices. In particular, this study surpasses previous research that using biologically inspired models for stock return forecasting, demonstrating superior predictive capability of LSTM. These findings underscore the strength of LSTM in capturing complex temporal dependencies, further validating its effectiveness for financial time series prediction. The optimal model configuration, using the RMSprop optimizer, a batch size of 8, and 200 epochs, achieved an RMSE of 0.0167, MSE of 0.0002, MAE of 0.0129, and MAPE of 25.89%, effectively modeling sequential dependencies and capturing stock market volatility. Beyond its impressive predictive capabilities, the model holds significant practical value for investment decision-making, offering dependable forecasts for both short-term and long-term strategies. In the short term, predicting stock returns enables investors to anticipate daily price fluctuations and refine their trading strategies. Meanwhile, in the long term, the model's capacity to integrate macroeconomic factors such as inflation aids investors in evaluating broader market trends and potential risks, resulting in more informed portfolio management decisions.

Future research could explore the integration of additional macroeconomic variables, such as interest rates and GDP growth, to further refine the model's predictive power. Additionally, experimenting with alternative deep learning architectures, such as GRU or attention-based models, may provide further improvements in financial forecasting accuracy and adaptability to dynamic market conditions.

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