STOCK PRICE PREDICTION FOR BANK SYARIAH INDONESIA USING BIDIRECTIONAL LONG SHORT-TERM MEMORY (BI-LSTM)

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ABSTRAK

The evolution of global financial markets has heightened the demand for accurate stock price prediction methods, particularly in the Islamic banking sector, which operates under unique principles of Sharia compliance. This study aims to predict the stock prices of Bank Syariah Indonesia (BSI) using a Bidirectional Long Short-Term Memory (Bi-LSTM) model. The dataset comprises daily closing prices from January 2022 to June 2024. The model is optimized through systematic hyperparameter tuning, including configurations for the number of layers, neurons, batch size, learning rate, and optimizers. Evaluation using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) identifies the Adam optimizer with a learning rate of 0.001 and batch size of 16 as the optimal configuration. The results highlight that while increasing the number of neurons or layers reduces minimum error, it increases model instability. This research provides novel insights into the application of Bi-LSTM for predicting Islamic banking stock prices, supporting data-driven decision-making in the Islamic financial sector.

Keyword : *Bank Syariah Indonesia (BSI), Bidirectional Long Short-Term Memory (Bi-LSTM), Financial Time Series Forecasting, Hyperparameter Optimization, Islamic Banking Stock Prediction.*

1. INTRODUCTION

The global financial landscape has witnessed significant transformations in recent decades, with the stock market playing an increasingly pivotal role in economic development and investment strategies. Within this evolving context, the Islamic banking sector has emerged as a rapidly growing segment, attracting attention from investors, researchers, and policymakers alike [1], [2]. Bank Syariah Indonesia (BSI), formed through the merger of three state-owned Islamic banks in 2021, stands as a prominent entity in this domain, representing a significant portion of Indonesia's Islamic banking assets [3]. As the largest Islamic bank in Indonesia, BSI's stock performance is of particular interest to various stakeholders, necessitating accurate and reliable prediction methods for its stock prices.

The prediction of stock prices has long been a challenging endeavor due to the inherent complexity and non-linear nature of financial markets [4]. Traditional forecasting methods, such as time series analysis and statistical models, have often fallen short in capturing the intricate dynamics of stock price movements [5]. This limitation has spurred the development and application of more sophisticated approaches, particularly in the realm of machine learning and artificial intelligence [6].

In recent years, deep learning techniques have gained significant traction in the field of financial forecasting, offering promising results in various prediction tasks [7]. Among these techniques, Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have demonstrated remarkable capabilities in processing sequential data and capturing long-term dependencies [8]. LSTM's ability to selectively retain or discard information over extended periods makes it particularly well-suited for time series prediction tasks, including stock price forecasting [9].

Building upon the success of LSTM, the Bidirectional Long Short-Term Memory (Bi-LSTM) architecture has emerged as an even more powerful tool for sequence modeling [10]. Bi-LSTM processes input sequences in both forward and backward directions, allowing the model to capture context from both past and future states at any given point in the sequence [11]. This bidirectional processing enables Bi-LSTM to potentially uncover more complex temporal patterns and relationships in the data, which is particularly valuable in the context of stock price prediction [12].

The application of Bi-LSTM in stock price forecasting has been explored in various markets and sectors. For instance, Yan and Ouyang [13] employed a Bi-LSTM model to predict stock prices in the Chinese market, demonstrating superior performance compared to traditional LSTM and other machine learning models. Similarly, Sagheer and Kotb [14] proposed a deep Bi-LSTM approach for predicting petroleum production, showcasing the model's effectiveness in capturing complex time-dependent patterns.

However, despite the growing body of research on Bi-LSTM applications in financial forecasting, there remains a notable gap in the literature regarding its application to Islamic banking stocks, particularly in the context of Bank Syariah Indonesia. The unique characteristics of Islamic banking, which operates under Sharia principles, present distinct challenges and opportunities in stock price prediction [15]. These principles, including the prohibition of interest (riba), profit-and-loss sharing mechanisms, and ethical investment criteria, may influence stock performance in ways that differ from conventional banking stocks [16].

Moreover, the Indonesian stock market, as an emerging market, exhibits unique characteristics that may impact the effectiveness of prediction models [17]. Factors such as market volatility, regulatory environment, and macroeconomic conditions specific to Indonesia need to be considered when developing and evaluating stock price prediction models for BSI [18].

The integration of fundamental analysis with technical indicators in Bi-LSTM models presents another avenue for enhancing prediction accuracy. While technical indicators focus on historical price and volume data, fundamental analysis considers broader economic factors and company-specific information [19]. By incorporating both types of inputs, Bi-LSTM models may capture a more comprehensive view of the factors influencing BSI stock prices [20].

Furthermore, the potential of ensemble methods, combining Bi-LSTM with other machine learning algorithms or traditional statistical models, remains largely unexplored in the context of Islamic banking stocks [21]. Such hybrid approaches could potentially leverage the strengths of different methodologies to improve overall prediction accuracy and robustness [22].

Through this research, we aim to advance the understanding of deep learning applications in Islamic finance and provide a robust framework for predicting BSI stock prices, ultimately contributing to more informed decision-making in this important sector of the global financial system.

2. LITERATURE REVIEW

2.1. Stock Price Prediction Methods

The prediction of stock prices has been a subject of extensive research in finance and economics, with methodologies evolving significantly over time. Traditional approaches to stock price forecasting have included statistical methods such as autoregressive integrated moving average (ARIMA) models [23], exponential smoothing [24], and regression analysis [25]. While these methods have provided valuable insights, they often struggle to capture the complex, non-linear dynamics inherent in financial markets [26].

In recent years, machine learning techniques have gained prominence in stock price prediction due to their ability to handle non-linear relationships and large datasets [27]. Support Vector Machines (SVM) [28], Random Forests [29], and Artificial Neural Networks (ANN) [30] have demonstrated improved predictive performance compared to traditional statistical methods. However, these approaches often face limitations in capturing long-term dependencies and temporal patterns in time series data [31].

2.2. Deep Learning in Financial Forecasting

The advent of deep learning has opened new avenues for stock price prediction. Convolutional Neural Networks (CNN) have been applied to extract features from financial time series data [32], while Recurrent Neural Networks (RNN) have shown promise in capturing sequential patterns [33]. Long Short-Term Memory (LSTM) networks, a specialized form of RNN, have emerged as particularly effective for financial time series forecasting due to their ability to capture long-term dependencies [34].

Several studies have demonstrated the superiority of LSTM models in stock price prediction. For instance, Nelson et al. [35] compared LSTM with ARIMA and found that LSTM outperformed in predicting the stock prices of Brazilian companies. Similarly, Selvin et al. [36] showed that LSTM models achieved higher accuracy compared to CNN and RNN in short-term stock price forecasting.

2.3. Bidirectional LSTM in Financial

Bidirectional Long Short-Term Memory (Bi-LSTM) networks represent an advancement over traditional LSTM by processing input sequences in both forward and backward directions [37]. This bidirectional processing allows the model to capture context from both past and future states, potentially uncovering more complex temporal relationships in the data [38]. Figure 1 ilustrate general bi-LSTM architecture.

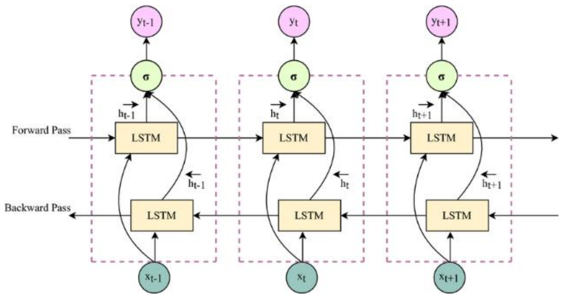

Figure 1.bi-LSTM Architecture

In the context of financial forecasting, Bi-LSTM has shown promising results. Chen et al. [39] applied Bi-LSTM to predict stock returns and demonstrated its superiority over unidirectional LSTM and other machine learning models. Liang et al. [40] proposed a hybrid model combining Bi-LSTM with Attention mechanisms for stock price prediction, achieving improved accuracy and interpretability.

2.4. Islamic Banking and Stock Price Prediction

Islamic banking operates under principles derived from Islamic law (Sharia), which introduces unique characteristics that may influence stock price dynamics [41]. These principles include the prohibition of interest (riba), profit-and-loss sharing mechanisms, and restrictions on certain types of investments [42]. Consequently, Islamic bank stocks may exhibit different behavior compared to conventional bank stocks, necessitating tailored approaches to price prediction [43].

Several studies have explored the performance and predictability of Islamic bank stocks. Alqahtani and Mayes [44] investigated the financial stability of Islamic banks during the global financial crisis, finding that they demonstrated greater resilience compared to conventional banks. Azmat et al. [45] examined the challenges of Shariah compliance in Islamic bond markets, highlighting the unique factors influencing Islamic financial instruments.

However, research specifically focusing on the application of advanced machine learning techniques, such as Bi-LSTM, to Islamic bank stock prediction remains limited. This gap in the literature presents an opportunity for exploring how these sophisticated models can be adapted to capture the unique characteristics of Islamic banking stocks.

3. METHOD

This study employs a Bidirectional Long Short-Term Memory (BiLSTM) model to predict the closing price of Bank Syariah Indonesia stock (BRIS.JK). The dataset comprises daily closing prices from January 2022 to June 2024, obtained from reliable financial data sources. The BiLSTM architecture is chosen for its ability to capture long-term dependencies and process information in both forward and backward directions, potentially enhancing prediction accuracy for time series data.

The model's hyperparameters will be optimized through a systematic grid search approach. The key hyperparameters under consideration include the number of BiLSTM layers (ranging from 1 to 3), the number of neurons in each layer (32, 64 or 128), dropout rate (0.2, or 0.3) to prevent overfitting, batch size (16 or 32), and the number of epochs (50, 100, or 200). Additionally, we will experiment with different optimizer algorithms (Adam or SGD) and learning rates (0.001, 0.01, and 0.1) to find the optimal combination for our specific dataset.

The input sequence length, representing the number of previous days' data used for prediction, will be varied (5, 10, and 20 days) to determine the most effective historical context for accurate forecasting. The model will be trained on 70% of the dataset, validated on 15%, and tested on the remaining 15% to ensure robust performance evaluation.

For model evaluation, we will employ two widely recognized metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). MAPE will provide a percentage measure of prediction accuracy, while RMSE will offer an absolute measure of the difference between predicted and actual values. These metrics will allow for a comprehensive assessment of the model's performance and facilitate comparison with other forecasting methods in the literature.

4. RESULT AND DISCUSSION

The analysis of hyperparameter tuning for the Bi-LSTM model, focusing on optimizer selection, learning rates, batch sizes, and neuron configurations, provides insights into achieving optimal performance. This section discusses the implications of the results presented in the two tables, emphasizing their relevance in understanding the dynamics of model optimization.

Table 1. Evaluation of Model Error Based on Optimizer, Learning Rate, and Batch Size

Optimizer	Learning rate	Batch size	
		16	32
adam	0.001	0.0229	0.0229
	0.01	0.0307	0.0279
	0.1	0.1217	0.0984
sgd	0.001	0.0960	0.0985
	0.01	0.0740	0.0862
	0.1	0.0409	0.0462

Table 2. Evaluation of MAPE and RMSE Across number of Neuron

Metric	Neuron →	32	64
MAPE	Min	0.0179	0.0161
	Max	0.3975	0.4925
	Average	0.0615	0.0662
	Std	0.0430	0.0518
RMSE	Min	42.2460	37.3974
	Max	707.3808	1000.2850
	Average	158.5159	167.8723
	Std	94.4798	117.3340

Table 1 evaluates the performance of two optimizers, Adam and SGD, across varying learning rates (0.001, 0.01, and 0.1) and batch sizes (16 and 32). Results indicate that the Adam optimizer consistently outperforms SGD in terms of lower MAPE across most configurations, especially at lower learning rates. Specifically, with a learning rate of 0.001 and a batch size of 16, Adam achieves an impressive MAPE of 0.0229, while SGD exhibits significantly higher values at 0.0960. However, at higher learning rates (0.1), SGD demonstrates better robustness, achieving the lowest MAPE of 0.0409 at a batch size of 16, compared to Adam's 0.1217. This finding underscores the importance of fine-tuning learning rates for each optimizer to achieve optimal results. Furthermore, batch size variations (16 and 32) reveal marginal differences in performance for both optimizers, suggesting that batch size may have a lesser impact compared to learning rate and optimizer choice.

Table 2 examines the influence of the number of neurons (32 and 64) on the model's performance, evaluated through MAPE and RMSE metrics. For both configurations, the minimum MAPE values (0.0179 for 32 neurons and 0.0161 for 64 neurons) suggest that increasing the number of neurons slightly enhances the model’s best-case performance. However, the average MAPE (0.0615 for 32 neurons and 0.0662 for 64 neurons) and standard deviation (0.0430 for 32 neurons and 0.0518 for 64 neurons) indicate greater variability and slightly higher error margins with more neurons. A similar trend is observed in RMSE, where the minimum value improves with 64 neurons (37.3974) compared to 32 neurons (42.2460), but the maximum and average values increase substantially with the higher configuration, suggesting diminishing returns or overfitting risks when adding neurons. Notably, the standard deviation of RMSE also increases with 64 neurons (117.3340), highlighting greater instability in predictions.

The findings from these two tables highlight several key insights into Bi-LSTM hyperparameter tuning. First, optimizer selection is critical, with Adam demonstrating superior performance in most configurations, but SGD showing potential advantages at higher learning rates. Second, the learning rate significantly impacts performance, reinforcing the need for precise adjustments based on the optimizer used. Third, while increasing neurons can enhance minimum error metrics, the associated trade-offs in stability and risk of overfitting must be carefully managed. Finally, batch size variations appear to have limited impact within the tested range, suggesting that computational efficiency could guide its selection without substantial performance penalties.

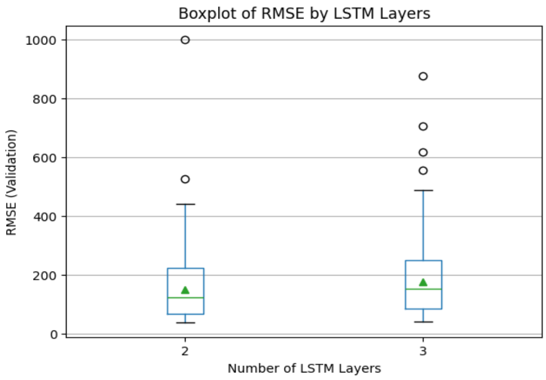

Figure 2. RMSE Distribution Across LSTM Layers

The RMSE values for different LSTM layers reveal notable variations in model performance. Models with 2 LSTM layers have a lower average RMSE (149.69) compared to those with 3 layers (176.70). The variability, represented by the standard deviation, is also slightly lower for 2 layers (100.43) than for 3 layers (110.84). Interestingly, while the minimum RMSE value (37.40) is observed in models with 2 layers, the maximum RMSE value is significantly higher in these models (1000.28 vs. 877.56 for 3 layers). This suggests that while increasing the number of layers might improve consistency in predictions, it does not necessarily lead to better performance. The interquartile range (IQR) further highlights this trend, with tighter clustering of RMSE values for 2 layers compared to 3 layers, emphasizing the trade-off between model complexity and stability.

The RMSE trends across different learning rates (0.001, 0.01, and 0.1) highlight the sensitivity of the model to this parameter. At a learning rate of 0.01, the model achieves the lowest average RMSE (147.80) and the smallest standard deviation (69.42), indicating both better performance and greater stability. Conversely, a learning rate of 0.1 leads to the highest average RMSE (182.96) and the widest variability (standard deviation: 135.74), suggesting overfitting or instability in the training process. The minimum RMSE values are relatively consistent across learning rates, ranging from 37.40 to 53.36, but the maximum RMSE for a learning rate of 0.1 (1000.28) is significantly higher than for the other rates. This finding underscores the importance of choosing an appropriate learning rate to balance model accuracy and stability.

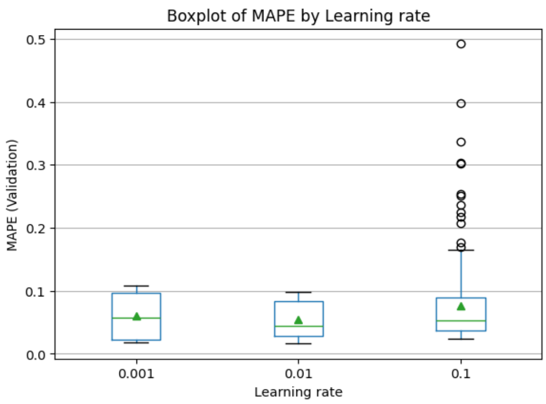

Figure 3. RMSE Distribution Across Learning Rates

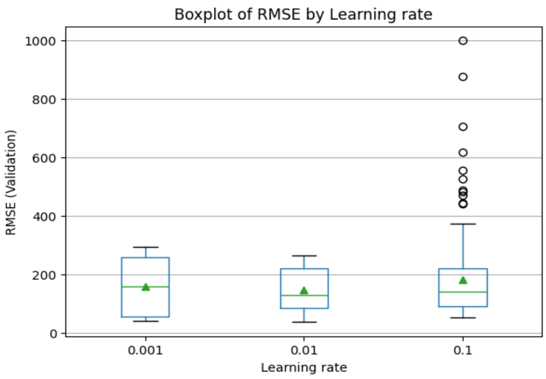

Figure 4. MAPE Distribution Across Learning Rates

The MAPE trends across learning rates provide complementary insights into model accuracy. A learning rate of 0.01 yields the lowest average MAPE (0.0547) and the smallest standard deviation (0.0273), reaffirming its effectiveness in minimizing errors. The highest average MAPE is observed at a learning rate of 0.1 (0.0768), accompanied by the largest variability (standard deviation: 0.0663). The interquartile range (IQR) for MAPE is also narrower at lower learning rates (0.001 and 0.01) compared to 0.1, reflecting more consistent performance. Notably, the maximum MAPE at a learning rate of 0.1 (0.4925) is substantially higher than for other rates, further highlighting the risks of using an overly high learning rate.

The scatter plot analyzing RMSE versus MAPE across different optimizers provides valuable insights into their performance characteristics. Each data point represents a specific hyperparameter configuration, illustrating the trade-off between RMSE and MAPE. The Adam optimizer shows a tighter clustering of points toward lower RMSE and MAPE values, indicating consistent and robust performance across various configurations. This observation aligns with prior research highlighting Adam's efficiency in optimizing deep learning models due to its adaptive learning rate mechanism [46].

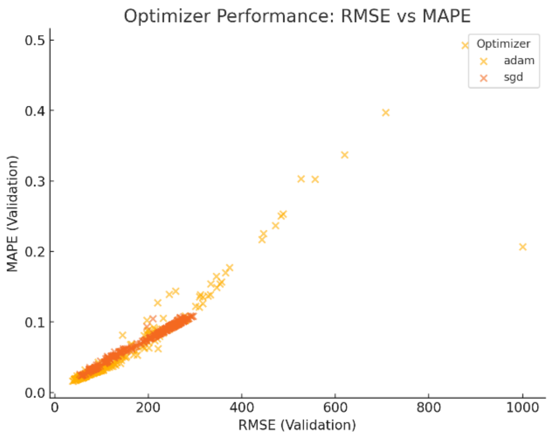

Figure 5. Optimizer Performance: RMSE vs. MAPE Scatter Plot

In contrast, the SGD optimizer displays a wider spread of points, with several configurations exhibiting higher RMSE and MAPE values. This variability suggests that SGD's performance is more sensitive to hyperparameter tuning and may struggle to achieve the same level of stability as Adam. However, some points for SGD approach the lower RMSE and MAPE range, implying that with careful tuning, it can perform competitively, particularly for simpler configurations or lower learning rates.

The scatter plot also reveals a general trend where configurations with lower RMSE tend to correspond to lower MAPE, emphasizing a correlation between these two metrics. However, certain outlier configurations exhibit a mismatch, with low RMSE but relatively high MAPE or vice versa. These outliers highlight the need to consider multiple metrics when evaluating model performance, as relying solely on one metric may lead to suboptimal conclusions.

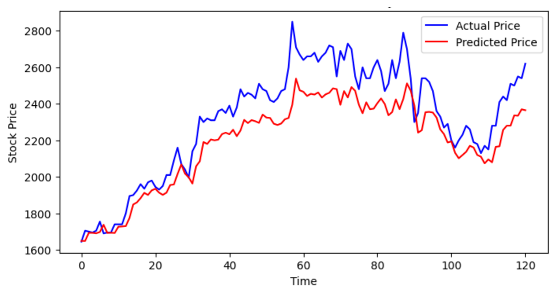

Figure 6. Stock Price Prediction for Bank Syariah Indonesia

5. CONCLUSION

This study demonstrates that the Bidirectional Long Short-Term Memory (Bi-LSTM) model is an effective method for predicting the stock prices of Bank Syariah Indonesia (BSI), addressing the inherent complexity and non-linear nature of financial market data. Hyperparameter optimization, including the number of layers, batch size, neurons, and learning rate, significantly affects the model's performance. Evaluation metrics, namely Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), reveal that the Adam optimizer with a low learning rate (0.001) achieves the highest accuracy. While increasing model complexity through additional neurons or layers can enhance minimum performance, it also introduces risks of overfitting and instability. This optimized approach strikes a balance between accuracy and stability. The findings contribute to the adaptation of deep learning techniques for modeling stock price dynamics in the Islamic banking sector, particularly within the context of emerging markets such as Indonesia.

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