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Improving the Quality of Islamic Stock Prediction in the Indonesian Islamic Stock Index Using Deep Learning with Long Short-Term Memory Modeling

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ABSTRACT
Accurate forecasting of Islamic stock prices is essential for supporting investment decisions in increasingly dynamic capital markets. However, traditional statistical approaches often face limitations in capturing the non-linear and temporal characteristics of stock market data. This study aims to improve the quality of Islamic stock price prediction within the Indonesian Islamic capital market using a Long Short-Term Memory (LSTM)-based deep learning model. Bank Syariah Indonesia (BRIS.JK), one of the largest Shariah-compliant banking stocks in Indonesia, was selected as the research object. The study employed a quantitative experimental approach using 1,504 daily stock observations collected from Yahoo Finance over the period 2018-2024. Data preprocessing included cleaning, Min-Max Scaling, and an 80:20 chronological train-test split. The forecasting model was developed using an optimized stacked LSTM architecture and evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). To assess model robustness, the training and evaluation process was repeated ten times under identical experimental settings. The results show that the proposed model achieved an average MAE of 1.04%, RMSE of 1.54%, and MAPE of 1.97%, indicating highly accurate forecasting performance and stable results across repeated experiments. The findings demonstrate that LSTM effectively captures complex temporal patterns in Islamic stock price movements and provides reliable forecasting outcomes. This study contributes to the literature by providing empirical evidence from BRIS.JK, incorporating systematic hyperparameter optimization, and evaluating model consistency through repeated experimental procedures. The proposed model offers a practical decision-support tool for investors and market participants in the Indonesian Islamic capital market.

Keywords: Deep Learning, Long Short-Term Memory, Islamic Stock Forecasting, BRIS.JK, Islamic Capital Market.

I. Introduction

Economic growth is strongly associated with investment activities that contribute to capital accumulation, productivity enhancement, and ultimately Gross Domestic Product (GDP) growth. Within the framework of Islamic economics, the Islamic capital market has become an increasingly important investment

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vehicle, providing opportunities for investors to achieve financial returns while adhering to Shariah principles. Islamic stocks are screened based on compliance with Islamic law, excluding companies engaged in interest-based transactions (riba), gambling (maysir), excessive uncertainty (gharar), and businesses related to prohibited products and services(Wahyudi et al., 2024). Beyond their religious and ethical foundations, Shariah-compliant firms tend to demonstrate stronger financial discipline, lower debt exposure, and more sustainable long-term performance compared to conventional firms(Pepis & De Jong, 2019). These characteristics make Islamic equities an attractive alternative not only for Muslim investors seeking faith-based compliance, but also for conventional investors who value prudent leverage management and transparent governance practices.

The development of the Islamic capital market in Indonesia has shown significant progress over the last decade. The Indonesia Stock Exchange (IDX) currently manages several Islamic stock indices, including the Indonesian Sharia Stock Index (ISSI), Jakarta Islamic Index (JII), Jakarta Islamic Index 70 (JII70), IDX-MES BUMN 17, and IDX Sharia Growth (IDXSHAGROW). According to the Financial Services Authority (OJK), the number of Sharia-compliant stocks listed on the Indonesian capital market has continued to increase, reflecting the growing demand for ethical and faith-based investment products. The Indonesian Islamic Stock Index (ISSI) serves as the broadest benchmark of Sharia-compliant equities and plays a strategic role in facilitating investment decisions for Muslim and non-Muslim investors alike(Saputra et al., 2021) This expanding ecosystem of indices and instruments underscores the growing maturity of Islamic finance in Indonesia, yet it also raises the stakes for accurate, evidence-based analytical tools that can help investors navigate an increasingly complex and diversified market. Among Islamic equities listed on the IDX, PT Bank Syariah Indonesia Tbk (BRIS) occupies a strategic position as the largest Islamic banking institution in Indonesia following the merger of three state-owned Islamic banks in 2021. The bank's significant market capitalization, high trading volume, and inclusion in major Islamic stock indices make BRIS a representative case for examining stock price forecasting in the Islamic financial sector. Nevertheless, fluctuations in BRIS stock prices remain highly sensitive to macroeconomic conditions, market sentiment, monetary policy, and firm-specific performance indicators. Consequently, accurate forecasting of stock price movements is essential to support investment decision-making and risk management. For an institution of this scale, even modest improvements in forecasting accuracy translate into meaningful practical benefits for portfolio managers, retail investors, and regulators who monitor the stability of the Islamic banking sector.

Traditional forecasting methods such as Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Support Vector Regression (SVR) have been widely employed in stock market prediction. However, financial time-series data exhibit complex nonlinear, dynamic, and non-stationary characteristics that are difficult to model using conventional statistical approaches. Previous studies have reported that the predictive performance of traditional methods often deteriorates when confronted with abrupt market fluctuations and long-term dependencies embedded in stock price movements(Budiprasetyo et al., 2022). These limitations are particularly pronounced during periods of structural change, such as mergers, regulatory shifts, or macroeconomic shocks, precisely the type of events that have shaped BRIS's trading history since its formation in 2021. Recent advances in Artificial Intelligence (AI), particularly Deep Learning, have created new opportunities for financial forecasting. Deep learning models possess the capability to automatically learn complex representations from large datasets without requiring extensive manual feature engineering. Among these models, Long Short-Term Memory (LSTM), a specialized variant of Recurrent Neural Networks (RNN), has demonstrated remarkable performance in modeling sequential and time-series data. LSTM addresses the vanishing gradient problem through memory cells and gating mechanisms, enabling the model to capture both short-term and long-term dependencies in financial datasets. Empirical evidence suggests that LSTM consistently outperforms traditional machine learning models such as Decision Tree, k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Linear Regression in stock market forecasting tasks(Bansal et al., 2022). The ability of LSTM networks to selectively retain and discard information over long sequences makes them particularly well suited to financial markets,

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where price behavior is shaped by both recent momentum and structural patterns that unfold over weeks or months.

Several studies in Indonesia have also demonstrated the effectiveness of LSTM for stock price prediction. Budiprasetyo et al.(2022) reported that LSTM achieved superior forecasting performance compared to conventional statistical models in predicting Islamic stock prices. Likewise, research by Hidayat, (2025)(Hidayat, 2025) found that deep learning-based approaches significantly improved prediction accuracy when applied to Indonesian financial market data. However, most previous studies focused primarily on model implementation without providing systematic hyperparameter optimization, repeated experimental evaluation, or specific attention to Islamic banking stocks. Furthermore, studies examining BRIS as a representative Islamic stock remain relatively limited despite its strategic importance within Indonesia's Islamic financial ecosystem. This gap is notable given that BRIS, as a post-merger institution, presents a distinctive time-series profile that combines the trading history of its predecessor banks with a new phase of consolidated performance, an aspect that has not been thoroughly examined using deep learning techniques. Therefore, this study proposes an LSTM-based forecasting model for Islamic stock price prediction using historical BRIS.JK data from 2018-2024. The proposed model incorporates systematic hyperparameter optimization involving the number of neurons, hidden layers, epochs, learning rate, and dropout regularization. The model is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), with repeated experiments conducted to assess model consistency and reliability. The experimental results demonstrate that the proposed model achieves a MAPE value of 1.97%, indicating a high level of predictive accuracy. This study contributes to the growing literature on Islamic financial analytics by providing empirical evidence regarding the effectiveness of deep learning techniques for forecasting Islamic stock prices and offering a practical analytical tool for investors and practitioners in the Indonesian Islamic capital market.

The growing intersection between artificial intelligence and Islamic finance also reflects a broader global trend toward financial technology (fintech) adoption within Shariah-compliant institutions. Islamic banks and asset managers increasingly rely on data-driven analytics to enhance operational efficiency, strengthen risk management, and improve customer-facing services, while remaining bound by Shariah governance requirements that emphasize transparency and the avoidance of excessive speculation. Within this context, a well-validated, reproducible forecasting model such as the one proposed in this study can be viewed not merely as a technical exercise, but as a contribution toward the responsible integration of AI-based decision-support tools into an industry that places high value on prudence and accountability. The remainder of this article is organized as follows. Section II reviews the relevant literature on Islamic stocks, time-series forecasting, and LSTM-based deep learning, and presents the conceptual framework underlying this study. Section III describes the research method, including data collection, preprocessing, model architecture, and evaluation procedures. Section IV presents the empirical results and discusses their implications in light of prior research. Section V concludes the study, summarizes its theoretical and managerial contributions, and outlines directions for future research.

II. Literature Review and Hypothesis Development

2.1. Islamic Stocks and the Indonesian Capital Market

Islamic stocks represent equity securities issued by companies whose business activities and financial structures comply with Islamic principles. In Indonesia, the screening process for Shariah-compliant securities is conducted by the Financial Services Authority (OJK) in collaboration with the National Sharia Board-Indonesian Council of Ulama (DSN-MUI). Screening criteria encompass both qualitative and quantitative dimensions, including restrictions on interest-based transactions, gambling, speculative activities, and financial ratio requirements related to debt and non-halal income (Rini et al., 2020). These dual screening layers, business-activity screening and financial-ratio screening, are periodically reviewed to ensure that listed

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companies remain compliant as their capital structures and revenue streams evolve over time. The Indonesian Islamic capital market has experienced substantial growth over the past decade. The Indonesian Sharia Stock Index (ISSI) serves as the broadest benchmark of Shariah-compliant equities listed on the Indonesia Stock Exchange (IDX), encompassing hundreds of eligible companies from various sectors. Previous studies indicate that ISSI performance is significantly influenced by macroeconomic variables such as inflation, exchange rates, and benchmark interest rates (Saputra et al., 2021). Furthermore, Shariah-compliant firms generally demonstrate lower leverage ratios and more prudent risk management practices, contributing to stronger long-term financial stability(Pepis & De Jong, 2019). This lower reliance on interest-bearing debt tends to make Islamic stocks comparatively more resilient during periods of monetary tightening, although they remain exposed to broader market sentiment and sector-specific risks.

Among Shariah-compliant companies listed on the IDX, PT Bank Syariah Indonesia Tbk (BRIS) occupies a strategic position as the largest Islamic banking institution in Indonesia. Following the merger of three state-owned Islamic banks in 2021, BRIS has become a major player in the national Islamic financial industry, attracting considerable attention from investors and market analysts. Its substantial market capitalization, high trading volume, and inclusion in major Islamic stock indices make BRIS a representative case for examining stock price forecasting within the Islamic banking sector. Consequently, understanding the dynamics of BRIS stock movements is not only relevant for investors but also contributes to broader discussions on the development of the Islamic capital market in Indonesia. As the flagship entity of Indonesia's Islamic banking consolidation strategy, BRIS also serves as a bellwether for investor confidence in state-supported Shariah financial institutions more broadly.

2.2. Time Series Forecasting in Financial Markets

Stock price forecasting belongs to the broader domain of time-series analysis, where observations are recorded sequentially over time. Financial time-series data exhibit several unique characteristics, including non-linearity, volatility clustering, seasonality, trend shifts, and temporal dependency. These characteristics make stock price prediction particularly challenging because future values are often influenced by both recent and historical market conditions.(Vuong et al., 2024). Forecasting methods generally fall into two categories: statistical approaches and machine learning approaches. Traditional statistical models assume that historical patterns can be mathematically represented through linear relationships and stationary processes. However, stock market data frequently violate these assumptions due to abrupt market changes, investor sentiment, and macroeconomic shocks. Therefore, advanced computational methods capable of learning complex temporal relationships have gained increasing attention in financial forecasting research(Soni et al., 2022). The concept of temporal dependency is particularly important in stock prediction because price movements observed today are often influenced by patterns that occurred days, weeks, or even months earlier. Consequently, forecasting models must be capable of capturing both short-term fluctuations and long-term dependencies embedded within historical price sequences. Volatility clustering, in which large price changes tend to be followed by further large changes of either sign, adds another layer of complexity, since it implies that the variance of returns is itself time-varying rather than constant, a property that classical linear models generally struggle to represent without additional extensions(Wei et al., 2020).

2.3. Traditional Methods for Stock Price Prediction

Conventional stock forecasting approaches typically rely on fundamental analysis and technical analysis. Fundamental analysis focuses on evaluating a company's intrinsic value through financial statements, profitability indicators, and macroeconomic variables. In contrast, technical analysis utilizes historical price movements and trading volume patterns to predict future market behaviour. Common technical indicators include Moving Average (MA), Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD)(Hayati & Ulama, 2016). Several statistical models have been developed to support stock forecasting. Autoregressive Integrated Moving Average (ARIMA) remains one of the most widely used approaches for modelling time-series data. Putra & Kurniawati (2021) compared ARIMA and Support Vector Regression (SVR) for stock prediction and found that SVR slightly outperformed ARIMA under certain conditions. Similarly, Putra & Kurniawati, (2021) proposed an improved multiple linear regression approach but reported limitations in handling highly non-linear stock market dynamics. Although these methods have demonstrated acceptable performance in relatively stable environments, their predictive capability tends to decline when confronted with highly volatile and non-stationary financial data. ARIMA-type models, in particular, rely on the assumption of a linear relationship between past and future values after differencing, which limits their ability to capture regime shifts such as the sharp appreciation experienced by BRIS during 2020-2021. This limitation has motivated researchers to explore machine learning and deep learning approaches that can automatically learn complex patterns without relying on strict statistical assumptions.

2.4. Deep Learning and Long Short-Term Memory (LSTM)

Deep learning is a branch of artificial intelligence that employs multi-layer neural networks to learn hierarchical representations from large datasets. Unlike traditional statistical models, deep learning algorithms can capture highly complex and non-linear relationships without requiring extensive manual feature engineering (Gupta et al., 2022). This automatic representation learning is particularly advantageous for financial data, which is characterised by complex non-linear interactions and evolving temporal dependencies. Among deep learning architectures, Long Short-Term Memory (LSTM) has emerged as one of the most effective methods for financial time-series forecasting. Introduced by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997), LSTM was specifically designed to address the vanishing gradient problem commonly encountered in conventional Recurrent Neural Networks (RNNs). Through its memory-cell architecture and gating mechanisms, including input, forget, and output gates, LSTM can selectively retain relevant information while discarding irrelevant patterns over extended periods. The forget gate regulates how much of the previous cell state is carried forward, the input gate determines how much new information is written into the cell state, and the output gate controls how much of the internal memory is exposed to the next layer, together allowing the network to maintain a stable gradient flow across long input sequences.

This capability makes LSTM particularly suitable for stock market forecasting, where long-term historical information often influences future price movements. Previous studies consistently report superior predictive performance of LSTM compared to conventional statistical and machine learning approaches. Budiprasetyo et al., (2022) applied LSTM to Islamic stock forecasting and demonstrated promising predictive accuracy. Similarly, Bansal et al., (2022) reported that LSTM outperformed Decision Tree, Support Vector Machine, Linear Regression, and k-Nearest Neighbours in stock market prediction tasks. The ability of LSTM to model sequential dependencies and non-linear interactions makes it particularly relevant for forecasting BRIS stock prices, which exhibit dynamic fluctuations influenced by both firm-level and market-wide factors. Beyond single-layer implementations, stacked LSTM architectures, in which the output sequence of one LSTM layer is fed as input into a subsequent LSTM layer, have been shown to improve representational capacity by allowing the network to learn hierarchical temporal features, from short-horizon fluctuations captured in earlier layers to longer-horizon trends captured in deeper layers.

Compared with other deep learning architectures commonly used in sequence modeling, such as plain Recurrent Neural Networks (RNNs) or one-dimensional Convolutional Neural Networks (CNNs), LSTM offers a particular advantage for financial time-series because of its explicit, learnable mechanism for controlling information flow across time steps. Plain RNNs are theoretically capable of modeling long sequences but suffer in practice from vanishing or exploding gradients during backpropagation through time, which limits their effective memory to only a few time steps. CNN-based sequence models, on the other hand, are efficient at extracting local patterns through convolutional filters but are less naturally suited to capturing dependencies that span the entire length of a long historical sequence unless combined with additional

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architectural elements such as dilated convolutions or attention mechanisms. LSTM occupies a middle ground that has proven particularly effective for financial applications: it retains the sequential processing structure needed to respect the temporal ordering of stock price observations, while its gating mechanisms give it the flexibility to learn, directly from the data, which historical information is worth remembering and which can safely be forgotten.

2.5. Model Evaluation in Stock Price Forecasting

The performance of forecasting models is commonly evaluated using quantitative error metrics. Mean Absolute Error (MAE) measures the average magnitude of prediction errors regardless of direction. Root Mean Square Error (RMSE) evaluates prediction accuracy while assigning greater penalties to larger errors. Mean Absolute Percentage Error (MAPE) expresses prediction errors as percentages, enabling comparison across datasets with different scales(Beniwal et al., 2023). Among these metrics, MAPE is widely used in financial forecasting because of its intuitive interpretation. According to Lewis (Lewis, 1982), a MAPE value below 10% indicates highly accurate forecasting performance, values between 10% and 20% indicate good forecasting performance, values between 20% and 50% indicate reasonable forecasting performance, and values above 50% indicate poor forecasting performance. Therefore, the simultaneous use of MAE, RMSE, and MAPE provides a comprehensive assessment of forecasting accuracy and model reliability. Relying on a single metric can be misleading: MAE treats all errors proportionally, RMSE is more sensitive to occasional large deviations, and MAPE facilitates comparison with studies conducted on stocks with different price scales, so reporting all three jointly offers a more balanced picture of model performance.

2.6. Research Gap and Conceptual Framework

Existing studies have demonstrated the potential of LSTM for stock-price forecasting; however, several methodological limitations remain evident in the existing literature. First, many previous studies have focused on conventional stocks, while empirical research specifically examining Shariah-compliant banking stocks remains relatively limited. Second, model performance is frequently reported based on a single training session, which provides limited evidence regarding the consistency of forecasting results under stochastic neural-network training conditions. Third, studies focusing specifically on BRIS.JK remain relatively scarce despite the strategic position of Bank Syariah Indonesia within Indonesia's Islamic financial system. Another limitation concerns the treatment of LSTM hyperparameters. Forecasting performance is influenced not only by the selection of the LSTM architecture but also by parameters such as the number of neurons, number of layers, learning rate, dropout rate, and number of training epochs. However, several previous studies provide limited explanation of how these parameters were selected or optimized. Consequently, a model that produces favorable results in one experimental configuration may not necessarily provide equally stable results under repeated training. Addressing this issue is important for predictive modeling because model reliability should be assessed not only from its average forecasting error but also from the consistency of its performance across repeated experiments.

To address these gaps, the present study adopts a predictive-modeling analytical framework rather than a hypothesis-testing framework. The analysis begins with the collection of historical BRIS.JK daily stock data, followed by data cleaning, normalization, and chronological partitioning into training and testing datasets. The processed time-series data are subsequently transformed into sequential inputs for a stacked LSTM architecture. Hyperparameter configurations involving the number of neurons, hidden layers, learning rate, dropout rate, and training epochs are evaluated to identify an appropriate model configuration. The selected configuration is then subjected to repeated training and testing procedures to examine the stability of forecasting performance. Model performance is assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics provide complementary information regarding the magnitude, sensitivity to larger errors, and relative percentage error of the

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forecasts. The repeated experimental procedure further allows the study to examine whether the obtained forecasting performance remains relatively stable across different training sessions (Huiyong & Wang, 2025). Thus, the analytical framework of this research consists of five sequential stages: data acquisition, data preprocessing, LSTM model development, hyperparameter optimization, and repeated model evaluation. This analytical framework is consistent with the objective of the study, which is to develop and empirically evaluate an LSTM-based forecasting model for BRIS.JK stock prices. The study therefore does not formulate statistical hypotheses regarding causal relationships among independent and dependent variables (Nelson et al., 2017). Instead, the research evaluates model performance through predefined forecasting metrics and repeated experimental observations. The resulting evidence is used to assess predictive accuracy, consistency, and the potential applicability of the LSTM approach to Islamic stock-price forecasting.

III. Research Method

This section explains, in sequence, the research design, data sources, preprocessing procedures, model architecture, training configuration, and evaluation strategy used to develop and validate the proposed forecasting model (Bao et al., 2017). This study employed a quantitative experimental approach to develop and evaluate a deep learning model for forecasting Islamic stock prices. The research focused on PT Bank Syariah Indonesia Tbk (BRIS.JK), which was selected because it represents the largest Islamic banking institution in Indonesia and is among the most actively traded Sharia-compliant stocks listed on the Indonesia Stock Exchange (IDX). In addition, BRIS plays a strategic role in Indonesia's Islamic financial ecosystem and serves as one of the key constituents of the Indonesian Sharia Stock Index (ISSI). Therefore, forecasting BRIS stock prices provides valuable insights into the behavior of Islamic banking stocks within the Indonesian capital market. The experimental design applied in this study follows the predictive-modeling framework outlined in Section II.F, moving sequentially from data acquisition through repeated model evaluation(Sun et al., 2025).

Historical stock market data were collected from Yahoo Finance covering the period from January 2018 to December 2024. The dataset consisted of daily trading observations, including opening price (Open), highest price (High), lowest price (Low), closing price (Close), adjusted closing price (Adj Close), and trading volume (Volume). These variables were selected because they provide comprehensive information regarding daily market movements and are commonly used in stock forecasting studies. The seven-year observation window was chosen to capture BRIS's trading behavior both prior to and after the 2021 merger, allowing the model to learn from a sufficiently long and heterogeneous price history rather than a single market regime.

Table 1. Dataset Description

Variable	Description
Open	Opening stock price
High	Highest stock price during trading
Low	Lowest stock price during trading
Close	Closing stock price
Adj Close	Adjusted closing price
Volume	Daily trading volume

Prior to model development, the collected data underwent several preprocessing procedures. Missing values and inconsistent observations were examined to ensure data quality and completeness. Subsequently, all numerical variables were normalized using the Min-Max Scaling technique, transforming values into a range between 0 and 1. This normalization process is essential for deep learning models because it prevents variables with larger numerical scales, such as trading volume, from dominating the learning process relative to price-based variables, and it facilitates faster and more stable model convergence during training by keeping the gradients within a comparable range across input features. Following preprocessing, the dataset was divided chronologically into training and testing subsets using an 80:20 ratio. The

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chronological split was applied to preserve the temporal structure of the time-series data and prevent information leakage from future observations into the training process. The training subset was utilized to learn historical stock price patterns, whereas the testing subset was reserved exclusively for evaluating forecasting performance on unseen data. Unlike random train-test splitting, which is common in cross-sectional data, a chronological split ensures that the model is always evaluated on observations that occur after the period it was trained on, thereby providing a more realistic simulation of how the model would be used in practice to forecast future, as yet unobserved, prices.

The forecasting model was developed using a Long Short-Term Memory (LSTM) network, a specialized variant of Recurrent Neural Networks (RNN) designed to capture sequential dependencies in time-series data. LSTM was selected because of its capability to address the vanishing gradient problem through memory-cell mechanisms that retain relevant information over long periods. Such characteristics make LSTM particularly suitable for financial forecasting, where current stock prices are often influenced by both recent and historical market conditions(Song et al., 2020). The proposed forecasting model employed a stacked LSTM architecture consisting of two LSTM layers, two dropout layers, one hidden dense layer, and one output layer. The first LSTM layer was designed to extract temporal patterns from the input sequence and pass the learned representations to the subsequent layer. Dropout regularization was applied after each LSTM layer to reduce overfitting by randomly deactivating a proportion of neurons during training. The second LSTM layer condensed the extracted information into a more compact representation, while the dense hidden layer introduced additional non-linearity before the final output layer generated continuous-valued stock price predictions. The complete architecture, together with the number of units, activation functions, output shapes, and trainable parameters for each layer, is summarized in Table 2.

Table 2. Proposed LSTM Model Architecture

Layer	Type	Units	Activation	Output Shape	Parameters
1	LSTM	128	Tanh	(None, 1, 128)	66,560
2	Dropout	0.2	-	(None, 1, 128)	0
3	LSTM	64	Tanh	(None, 64)	49,408
4	Dropout	0.2	-	(None, 64)	0
5	Dense	32	ReLU	(None, 32)	2,080
6	Dense	1	Linear	(None, 1)	33
Total Trainable Parameters					**118,081**

The architecture was determined through iterative hyperparameter optimization. Several configurations were evaluated by varying the number of neurons, hidden layers, learning rates, dropout rates, and training epochs. Configurations with a substantially larger number of neurons per layer were found to increase training time without a proportional improvement in validation accuracy, while configurations with too few neurons underfit the temporal patterns present in the data. The final architecture, summarized in Table 2, was selected based on its ability to provide stable forecasting performance while maintaining computational efficiency. Model training was conducted using the Adaptive Moment Estimation (Adam) optimizer, which combines adaptive learning rates and momentum-based optimization. Adam was chosen over standard Stochastic Gradient Descent because it adjusts the learning rate for each parameter individually based on estimates of the first and second moments of the gradients, which generally leads to faster and more stable convergence for recurrent architectures such as LSTM. The selected training configuration is presented in Table 3.

Table 3. Training Configuration

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Epochs	200

Batch Size	32
Loss Function	Mean Squared Error (MSE)
Dropout Rate	0.2
Number of Experimental Runs	10

A relatively small learning rate of 0.0001 was selected after preliminary experimentation indicated that larger learning rates caused unstable convergence, characterized by oscillating training loss across epochs, whereas smaller learning rates produced smoother, more gradual convergence at the cost of requiring a larger number of training epochs. The number of training epochs was set to 200, with dropout regularization of 0.2 applied to mitigate overfitting given the relatively long training horizon. Forecasting performance was evaluated using three widely accepted regression metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE measures the average magnitude of prediction errors, RMSE emphasizes larger prediction deviations through quadratic penalization, and MAPE expresses forecasting errors as percentages, thereby facilitating comparisons with previous studies. Employing these three metrics simultaneously enables a comprehensive assessment of forecasting accuracy and model reliability. The formal definitions of each metric are presented in Table 4.

Table 4. Evaluation Metrics

Metric	**Formula**	**Description**
MAE	$MAE = (1/n)\ \Sigma\ \lvert Yi - \hat{Y}i \rvert$	Average absolute prediction error
RMSE	$RMSE = \sqrt{[(1/n)\ \Sigma(Yi - \hat{Y}i)^2]}$	Root mean squared prediction error
MAPE	$MAPE = (100/n)\ \Sigma\ \lvert (Yi - \hat{Y}i)/Yi \rvert$	Average percentage prediction error

Where: Yi = Actual value; $\hat{Y}i$ = Predicted value; n = Number of observations.

To ensure model robustness and reliability, the entire training and evaluation procedure was repeated ten times under identical experimental settings. The average values of MAE, RMSE, and MAPE were subsequently calculated and reported. This repeated evaluation approach minimizes the influence of random weight initialization and stochastic training processes, thereby providing a more reliable assessment of model performance. Reporting the variability across the ten sessions, rather than the result of a single training run, also allows the study to distinguish between a model that is accurate on average and a model that is both accurate and consistently reliable, an important distinction for any tool intended to support real investment decisions. The resulting forecasting outputs were then analyzed to evaluate the effectiveness of the proposed LSTM model in predicting Islamic stock prices and to assess its practical implications for investment decision-making in the Indonesian Islamic capital market.

IV. Results and Discussion

This section presents the empirical findings of the study, beginning with a description of the observed dataset and preprocessing outcomes, followed by the model training results, the repeated-evaluation results, a comparison with prior studies, and a discussion of the theoretical, practical, and Islamic finance implications of the findings.

4.1. Result

The historical dataset of BRIS.JK stock consisted of 1,505 daily observations covering the period from May 2018 to June 2024. Initial data screening identified six missing observations recorded on 10 May 2018, which were subsequently removed during the preprocessing stage, resulting in a final dataset of 1,504 observations. Visual examination of the stock price series revealed substantial fluctuations throughout the observation period. The stock experienced relatively stable growth during 2018-2019, followed by a

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significant upward trend between 2020 and 2021, coinciding with heightened investor expectations surrounding the merger of state-owned Islamic banks into Bank Syariah Indonesia. During this period, the stock price reached its highest level of approximately IDR 3,500 before entering a consolidation phase characterized by moderate volatility from 2022 to 2024. The presence of multiple market regimes and changing volatility patterns indicates the complexity of BRIS stock dynamics and justifies the use of a deep learning approach capable of capturing non-linear temporal relationships. This regime-switching behaviour, in particular the transition from a merger-driven rally to a comparatively calmer consolidation phase, is exactly the kind of pattern that linear statistical models struggle to represent without manual structural-break adjustments. Following data cleaning, all variables were normalized using the Min-Max Scaling technique to ensure numerical consistency and facilitate efficient model learning. The dataset was then divided chronologically into training and testing subsets using an 80:20 ratio, resulting in 1,203 observations for model training and 301 observations for testing. The chronological partition preserved the temporal structure of the data and prevented information leakage from future observations into the training process.

The chronological organization of the dataset was particularly important because stock-price forecasting involves temporal dependencies between preceding and subsequent observations. Rather than randomly shuffling the observations, the study retained their original time order so that the model was trained only on information available before the forecasting period. Following normalization, the observations were organized into sequential input patterns for the LSTM model, enabling the network to learn temporal relationships between historical price movements and subsequent observations. This procedure was designed to maintain the temporal structure of the financial time series and to minimize the risk of information leakage from future observations into the training process. Consequently, the experimental setting more closely reflects the conditions of actual financial forecasting, in which future market information is not available when predictions are generated.

The forecasting model was developed using a stacked Long Short-Term Memory (LSTM) architecture consisting of two LSTM layers, dropout regularization, and dense layers. During training, the model demonstrated stable convergence over 200 epochs. The final training loss reached 1.6099×10^{-4}, with a training MAE of 0.0098, while the validation loss reached 1.1425×10^{-4}, with a validation MAE of 0.0105. The relatively small difference between the training and validation errors suggests that the model did not exhibit an obvious indication of severe overfitting under the experimental configuration. The use of dropout regularization may have contributed to this behavior by reducing the model's dependence on particular training observations and encouraging more generalizable representations. Nevertheless, training and validation performance alone cannot establish generalization conclusively; the model's predictive capability should primarily be assessed using the held-out test set and the results of the repeated experimental runs. The stable convergence observed across the training process therefore provides supporting evidence that the selected LSTM configuration was able to learn the temporal patterns in the training data while maintaining relatively consistent performance on validation data.

The relationship between the training and validation errors provides additional evidence regarding the generalization behavior of the model. Although the validation error was not identical to the training error, the difference remained relatively small, suggesting that the model did not exhibit an obvious indication of severe overfitting under the experimental configuration. The use of dropout and a relatively conservative learning rate may have contributed to this behavior by limiting excessive dependence on particular training observations. Nevertheless, generalization should be interpreted primarily from the performance on the held-out test data and repeated experimental results rather than from training and validation loss alone. The forecasting outputs further demonstrated the capability of the LSTM model to follow actual stock price movements across different market conditions. The predicted values closely tracked observed price fluctuations, including upward trends, downward corrections, and periods of consolidation. Such performance reflects the ability of LSTM memory cells to retain relevant historical information over extended periods while simultaneously capturing short-term market movements. This finding is consistent with the theoretical advantages of LSTM proposed by Hochreiter & Schmidhuber (1997), who argued that gated

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memory mechanisms enable the model to overcome the vanishing gradient problem commonly encountered in conventional recurrent neural networks. To evaluate forecasting reliability, the training and testing procedures were repeated ten times under identical experimental settings. The results are presented in Table 1.

Table 1. LSTM Model Evaluation Results Across Ten Training Sessions

Training Session	MAE (%)	RMSE (%)	MAPE (%)
Session 1	1.02	1.52	1.93
Session 2	1.03	1.53	1.94
Session 3	1.06	1.57	2.00
Session 4	1.01	1.50	1.92
Session 5	1.06	1.57	1.99
Session 6	1.01	1.51	1.91
Session 7	1.02	1.50	1.94
Session 8	1.03	1.54	1.94
Session 9	1.10	1.61	2.08
Session 10	1.04	1.51	2.00
Average	**1.04**	**1.54**	**1.97**

The evaluation results indicate relatively consistent performance across the ten experimental runs.". The average MAE, RMSE, and MAPE values were 1.04%, 1.54%, and 1.97%, respectively. Moreover, the variation among repeated training sessions was minimal, with MAPE values ranging narrowly between 1.91% and 2.08% across the ten sessions, indicating that model performance was not significantly affected by random weight initialization or stochastic optimization processes. The average MAPE value of 1.97% falls within the category of highly accurate forecasting according to the classification proposed by Lewis (1982), Under the heuristic classification proposed by Lewis (1982), the average MAPE of 1.97% falls within the 'highly accurate' category."

4.2. Discussion

To provide a broader perspective on model performance, the results were compared with findings reported in previous forecasting studies. Table 2 presents a summary of selected studies employing conventional statistical methods and machine learning approaches.

Table 2. Comparative Performance of Prediction Methods

Study	Method	MAE	RMSE	MAPE
Putra & Kurniawati (2021)	ARIMA & SVR	-	0.053	-
Kushwaha et al. (2024)	Linear Regression / ARIMA	-	-	0.74%-6.96%
Budiprasetyo et al. (2022)	LSTM	-	<0.05	<3.0%
This Study	**Optimized LSTM**	**1.04%**	**1.54%**	**1.97%**

The comparison suggests that the proposed model achieves competitive forecasting performance relative to both conventional statistical approaches and previous deep learning applications(Singh et al., 2026). More importantly, the model demonstrates stable predictive accuracy across repeated experimental runs. This finding supports previous studies that emphasize the superiority of deep learning approaches in handling the non-linear and dynamic nature of financial time-series data. Unlike ARIMA and other traditional forecasting models that rely on linear assumptions, LSTM can learn complex temporal dependencies and adapt to changing market conditions, making it particularly suitable for stock price forecasting (Xiao & Su, 2022). Several factors may explain why the proposed model outperforms the benchmark studies summarized in Table 2. First, the systematic hyperparameter optimization process described in Section III allowed the model architecture, learning rate, and dropout configuration to be tailored specifically to the statistical

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properties of BRIS.JK price data, rather than relying on default or generic settings. Second, the use of a stacked two-layer LSTM architecture, rather than a single LSTM layer, likely enabled the model to capture both short-horizon fluctuations and longer-horizon structural patterns simultaneously. Third, the repeated ten-session evaluation procedure ensured that the reported performance reflects a stable average rather than a single favourable outcome, which increases confidence that the reported accuracy would be replicated under similar experimental conditions.

The findings also directly address the research gaps identified in the literature. First, the study provides empirical evidence on BRIS.JK, which remains underrepresented in Islamic stock forecasting research despite its significance as Indonesia's largest Islamic banking stock. Second, the implementation of repeated evaluation procedures demonstrates the consistency and robustness of the forecasting model beyond a single experimental run. Third, the incorporation of systematic hyperparameter optimization contributes to improved predictive performance and model stability. These contributions extend the existing literature on Islamic financial analytics and provide additional evidence regarding the practical applicability of deep learning techniques within Islamic capital markets (Salsabila et al., 2025). From an Islamic finance perspective, the findings offer important practical implications. Accurate forecasting tools can support investors in making more informed and evidence-based investment decisions while reducing reliance on speculation and excessive uncertainty(Sahroni et al., 2024). This aligns with the Islamic principles of prudence, transparency, and knowledge-based decision-making in financial transactions. Furthermore, the successful application of LSTM to BRIS.JK stock data suggests that similar approaches may be extended to other Shariah-compliant securities listed within the Indonesian Sharia Stock Index (ISSI) (Ledhem & Moussaoui, 2024). Consequently, the integration of artificial intelligence and Islamic finance presents promising opportunities for strengthening analytical capabilities, improving market efficiency, and supporting the sustainable development of the Islamic capital market in Indonesia. Despite these encouraging results, several limitations should be acknowledged. The proposed model was developed and validated using a single Islamic banking stock, BRIS.JK, which limits the extent to which the findings can be generalized to other Shariah-compliant securities without further validation. In addition, the model relies exclusively on historical price and volume data and does not incorporate external variables such as macroeconomic indicators, corporate actions, or investor sentiment, all of which may exert additional influence on price movements. These limitations do not diminish the contribution of the present study, but they do point toward concrete directions for extending and stress-testing.

V. Conclusion

This concluding section summarizes the key findings of the study, discusses their theoretical and managerial implications, acknowledges the boundaries of the present research design, and outlines directions for future research. This study developed and evaluated a Long Short-Term Memory (LSTM)-based deep learning model for forecasting the stock price of PT Bank Syariah Indonesia Tbk (BRIS.JK), one of the most prominent Shariah-compliant stocks listed on the Indonesia Stock Exchange. Using 1,504 daily observations collected between 2018 and 2024, the proposed model achieved an average MAE of 1.04%, RMSE of 1.54%, and MAPE of 1.97% across ten independent training sessions. These results indicate that the model provides highly accurate forecasting performance while maintaining consistent results under repeated experimental conditions. The findings demonstrate that LSTM is effective in capturing the complex and non-linear temporal dynamics of Islamic stock prices. The low variation in evaluation metrics across repeated training sessions further confirms the robustness and reliability of the proposed forecasting framework. In addition, the incorporation of systematic hyperparameter optimization contributed to stable model performance and enhanced predictive accuracy.

From a theoretical standpoint, this study reinforces and extends the growing body of evidence that gated recurrent architectures such as LSTM are better suited than classical linear time-series models to represent the non-stationary, regime-switching behaviour typical of emerging-market Islamic equities. By explicitly documenting model performance across ten independent training sessions rather than a single run, the study also contributes a methodological refinement to the Islamic finance forecasting literature, namely the practice of reporting consistency alongside accuracy, which allows future researchers to more meaningfully compare deep learning models not only on their best-case performance but also on their reliability under repeated estimation. From a practical standpoint, the proposed model may serve as a useful analytical tool for investors, portfolio managers, and market participants seeking data-driven support for decision-making in the Indonesian Islamic capital market. Because the model was shown to generalize well to unseen data and to produce stable results across repeated runs, it can plausibly be incorporated into routine monitoring workflows, for example as a supplementary input alongside fundamental and technical analysis when assessing short-term price movements in BRIS.JK. For Islamic financial institutions and Shariah-compliant fund managers in particular, the availability of a reliable, evidence-based forecasting tool supports the Islamic finance principles of prudence and informed decision-making, and may help reduce reliance on speculative trading behaviour that is discouraged under Shariah investment guidelines.

This study contributes to the growing literature on Islamic financial analytics in three ways. First, it provides empirical evidence on BRIS.JK, a strategically important Islamic banking stock that has received limited attention in forecasting research. Second, it demonstrates the practical value of hyperparameter optimization in improving forecasting performance. Third, the use of repeated evaluation procedures offers additional evidence regarding model consistency and reliability, extending beyond the single-run evaluation commonly employed in previous studies. Nevertheless, as noted in Section IV, the present findings are based on a single Islamic banking stock and rely solely on historical price and volume data, without incorporating external variables that may also influence price formation. Future research may incorporate external variables such as macroeconomic indicators, financial news sentiment, and social media sentiment to enrich model inputs and potentially improve forecasting accuracy further. Further studies may also explore hybrid forecasting architectures, including ARIMA-LSTM and CNN-LSTM models, as well as advanced hyperparameter optimization techniques such as Bayesian Optimization, which could reduce the manual effort involved in architecture selection. Expanding the analysis to multiple Shariah-compliant stocks within the Indonesian Sharia Stock Index (ISSI), and comparing forecasting performance across different sectors and firm sizes, would also provide broader validation of the proposed forecasting framework and a clearer picture of the conditions under which LSTM-based models.

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