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Comparison of Long Short-Term Memory and Recurrent Neural Network For Stock Market Price Movement Classification in Islamic Bank Finance

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ABSTRACT

This study addresses the importance of accurate stock price prediction in the Islamic finance sector, where reliable forecasting supports better investment decisions and market stability. Despite the growing use of deep learning methods, comparative studies on sequential models in this domain remain limited. Therefore, this research compares the performance of Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) models for classifying stock price movement direction of Islamic banks in Indonesia. The dataset was sourced from two Islamic banks in Indonesia, covering the period from 2022 to mid-2024, with features such as Open, High, Low, Close, Adjusted Close, and Volume. The CRISP-DM method was applied for data processing, and testing was performed with data splits of 60:40, 70:30, and 80:20, as well as epoch variations (30, 50, 80). Results indicate that RNN outperforms LSTM, with the highest accuracy of 58% for RNN and 53% for LSTM. Evaluation metrics also included precision, recall, and F1-score. In conclusion, RNN performs better for stock movement classification direction, while LSTM is more effective for minimizing prediction error.

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1. INTRODUCTION

Stocks represent ownership in a company and provide investors with opportunities to obtain profits through dividends and capital gains. Stock prices fluctuate due to various factors such as economic conditions, company performance, and investor behavior. In the Indonesian capital market, Islamic financial institutions have become an important investment sector that operates based on Islamic principles which prohibit *riba* and emphasize fairness, transparency, and profit-sharing mechanisms in financial transactions[1], [2]. Therefore, predicting stock price movements, especially in Islamic financial institutions, is important to support better investment decision-making.

Stock price prediction is challenging because market movements are influenced by technical patterns, company fundamentals, and investor sentiment, which often produce nonlinear and complex time-series behavior [3]. With the development of artificial intelligence, deep learning models have been widely used to analyze financial time-series data. One commonly used model is *Recurrent Neural Network* (RNN), which processes sequential data by maintaining information from previous time steps [4]. However, RNN often suffers from the *vanishing gradient* problem when capturing long-term dependencies. To address this limitation, *Long Short-Term Memory* (LSTM) was developed as an improved architecture capable of retaining long-term information more effectively for time-series prediction tasks [5] .

Several previous studies have demonstrated the effectiveness of deep learning approaches for prediction tasks. Research using LSTM-based models shows high accuracy in stock price prediction and financial data analysis[6], [7]. Other studies have applied hybrid deep learning architectures such as DBN-RNN to improve prediction performance [8], while combinations of RNN and probabilistic models have been used to analyze stock market trends effectively [9]. Additional research also shows that LSTM performs well in time-series prediction tasks due to its ability to capture sequential patterns and long-term dependencies[10]. Furthermore, several studies applied LSTM and RNN in various forecasting domains such as time-series prediction, financial analysis, and environmental data modeling, showing promising results in handling sequential datasets [11], [12], [13], [14], [15].

Despite the growing number of studies on deep learning-based prediction, most research focuses on using a single model or hybrid architectures without directly comparing the performance of fundamental recurrent models. In addition, studies focusing specifically on Islamic financial sector stocks remain limited. Therefore, this research aims to implement and compare the performance of LSTM and RNN algorithms in classifying Islamic banking stock prices movement. The results of this study are expected to provide a clearer understanding of the effectiveness of both algorithms in modeling financial time-series data and supporting investment decision-making.

2. METHOD

The stages carried out in this study follow the CRISP-DM methodology, which begins with data collection, data understanding, data preparation, data modeling, and model evaluation [16][17]. The explanation of each of these stages is presented in the following subsections.

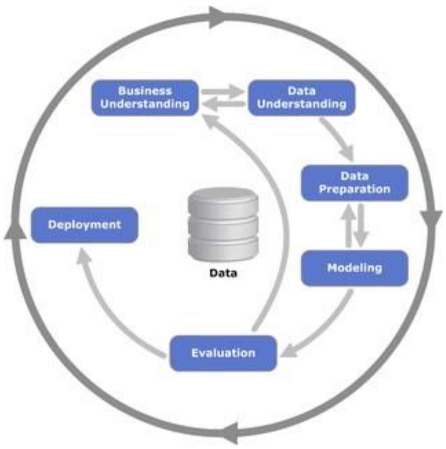

Figure 1. CRISP-DM Methodology[18]

2.1 Collecting Data

The dataset used in this study was obtained from Yahoo Finance, which provides historical stock market data. The research focuses on two Islamic financial companies listed on the Indonesian stock market: Asuransi Jiwa Syariah Jasa Mitra Abadi Tbk (JMAS) and Bank Panin Syariah Tbk (PNBS). The data used in this study cover the period from 2022 to 2024 and consist of daily stock price records. Each dataset includes several attributes such as Date, Open, High, Low, Close, Adjusted Close, and Volume. These attributes represent the historical trading information required for classification models.

Table 1. The Data Attributes for Stock Market Price Movement Classification

Data Attributes	Description
Date	Trading date
Open	Opening stock price
High	Highest price in the trading day
Low	Lowest price in the trading day
Close	Closing stock price

Data Attributes	Description
Adj Close	Adjusted closing price
Volume	Total trading volume

2.2 Data Preparation

The data preparation stage is an important step to ensure that the dataset is suitable for the modeling process. In this stage, the raw stock price data obtained from Yahoo Finance are processed and transformed to improve data quality and model performance. The data preparation process consists of several steps, including data cleaning, feature selection, and data normalization. The overall process of data preparation is illustrated in Figure 2.

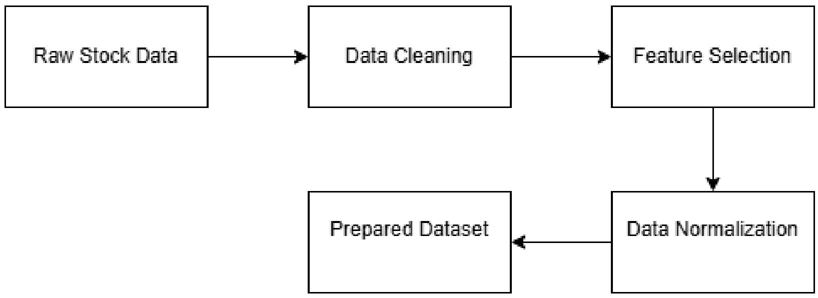

Figure 2. Data Preparation Process

2.2.1 Data Cleaning

Data cleaning is performed to ensure that the dataset does not contain missing values or inconsistent data. In this step, the dataset is checked for duplicated records and missing values. If missing values are found in the dataset, they are replaced using the previous valid value in the same column. This technique helps maintain the continuity of time-series data and prevents disruptions in the modeling process.

2.2 2 Feature Selection

Feature selection is conducted to identify the most relevant variable for predicting stock price movements. From the available attributes in the Yahoo Finance dataset, only the closing price (Close) is selected as the primary feature used in the prediction model. The closing price is considered the most representative indicator of stock market movements because it reflects the final trading value of a stock within a trading day. Other attributes such as timestamp and trading volume are not included in the model since this research focuses on analyzing price movement patterns in time-series data. To analyze the relationship between features, a correlation matrix is generated and visualized using a heatmap. The correlation analysis helps identify the relevance of each feature with the target variable.

2.2.3 Data Normalization

After selecting the relevant feature, the next step is data normalization. Normalization is applied to scale the data into a uniform range so that the deep learning model can process the data more efficiently. In this study, the Min-Max Normalization technique is used to transform the values of the selected feature into a range between 0 and 1 This normalization process helps prevent features with large numerical values from dominating the learning process and improves the convergence of deep learning models during training.

2.3 Model Development

Model development is the stage where predictive models are constructed to analyze sequential patterns in stock price data. In this research, two deep learning architectures are implemented, namely Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). These models are widely used in time-series forecasting because they can capture temporal dependencies and sequential relationships within historical data [19] . By learning from past stock price movements, the models aim to identify patterns that can be used to predict future price trends.

2.3.1 Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is a neural network architecture specifically designed to process sequential data. Unlike traditional feed-forward neural networks, RNN introduces recurrent connections that allow information from previous time steps to influence the current prediction. This mechanism enables the network to retain contextual information through hidden states, making it suitable for modeling temporal relationships in time-series data such as financial market prediction for time[20].

At each time step, the hidden state of the RNN is updated based on the current input and the hidden state from the previous step. Through this recursive process, the model can capture patterns that evolve over time. Because of this capability, RNN has been widely applied in various sequence modeling tasks including speech recognition, language modeling, and time-series forecasting. However, traditional RNN models often suffer from the vanishing gradient problem, which limits their ability to capture long-term dependencies in long sequences[21].

2.3.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an advanced variant of Recurrent Neural Network designed to overcome the limitations of conventional RNN models. LSTM introduces a memory cell mechanism that allows the network to retain information over longer time periods. This architecture was developed to address the vanishing gradient problem that often occurs when training traditional RNN models on long sequential data. The key component of LSTM is the gating mechanism that regulates the flow of information within the network. LSTM consists of three main gates: input gate, forget gate, and output gate. The forget gate determines which information from the previous cell state should be removed, while the input gate decides which new information should be stored in the memory cell. The output gate then controls which information will be passed to the next hidden state as output [22].

Through this mechanism, LSTM can capture long-term dependencies and complex temporal patterns in sequential data. Because of its effectiveness in modeling time-series data, LSTM has been widely applied in various prediction tasks such as financial forecasting, energy demand prediction, and weather forecasting [23]. In this study, LSTM is used to model historical stock price data, and its performance is compared with the standard RNN model.

2.4 Model Evaluation

Model evaluation is conducted using several performance metrics to assess the effectiveness of the predictive model. Accuracy measures the proportion of correctly predicted instances among the total number of observations. In the context of stock market prediction, models such as Long Short-Term Memory (LSTM) tend to achieve higher accuracy than standard Recurrent Neural Networks (RNNs) due to their capability to capture complex temporal dependencies in sequential data[24]. Precision represents the ratio of true positive predictions to the total number of predicted positive instances. This metric is particularly important in stock prediction, as high precision reduces the occurrence of false positives, which could otherwise lead to unfavorable investment decisions [25]. Recall, on the other hand, measures the model's ability to correctly identify all relevant instances. In financial forecasting, high recall ensures that most actual stock price movements are detected, enabling timely and informed trading actions [26]. Finally, the F1-Score is the harmonic mean of precision and recall, providing a balanced evaluation of both metrics. This is especially useful when dealing with imbalanced datasets, a common characteristic of stock market data, where certain classes may dominate others [27].

3. RESULTS AND DISCUSSION

This study compares the performance of Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) algorithms in predicting stock prices in the Islamic finance sector. The dataset was sourced from two Islamic banks in Indonesia, covering the period from 2022 to mid-2024, with features such as Open, High, Low, Close, Adjusted Close, and Volume. The CRISP-DM method was applied for data processing, and testing was performed with data splits of 60:40, 70:30, and 80:20, as well as epoch variations (30, 50, 80). Results indicate that RNN outperforms LSTM, with the highest accuracy of 58% for RNN and 53% for LSTM.

Evaluation metrics included accuracy, precision, recall, and F1-score. In conclusion, RNN proves to be superior for predicting stock prices in the Islamic finance sector.

3.1. Model Comparation

Table 1. Comparison LSTM and RNN Models

Model	Accuracy	Precision	Recall	F1-score
LSTM	53%	52%	52%	52%
RNN	58%	57%	58%	56%

Based on the comparison that shows on Table 1, the LSTM model achieved an accuracy of 53%, precision of 52%, recall of 52%, and an F1-score of 52%. These results were obtained under the best testing configuration, namely an 80:20 data split with 50 epochs. Although the LSTM architecture is theoretically designed to capture long-term dependencies in sequential data through its gating mechanism, the results indicate that the model struggles to generalize well on the Islamic banking stock price dataset. This may be attributed to the relatively limited size of the dataset or the complexity of stock price movements that are influenced by external factors beyond historical price patterns. The RNN model demonstrated superior performance compared to LSTM, achieving the highest accuracy of 58%, precision of 57%, recall of 58%, and an F1-score of 56%. The best results were obtained with a 70:30 data split and epoch variations of 30 and 80. Despite being a simpler architecture than LSTM, RNN proved more effective in capturing the sequential patterns present in the stock price data of Islamic financial institutions. This finding suggests that for relatively short time-series data, the simpler recurrent structure of RNN may generalize better than the more complex LSTM architecture.

Overall, the evaluation results indicate that RNN outperforms LSTM across all metrics in this study. While neither model achieved particularly high accuracy, RNN demonstrates a more consistent and balanced performance across different data split configurations. The relatively modest accuracy values of both models reflect the inherent difficulty of predicting stock prices, which are influenced by numerous unpredictable variables. Based on these findings, RNN is considered the more suitable model for stock price movement classification in the Islamic finance sector within the scope of this study.

3.2. Confusion Matrix Visualization

The LSTM model demonstrates moderate performance in distinguishing between rising (Naik) and falling (Turun) stock price movements. From the total test data, the model correctly classified 29 instances of falling prices (True Negative) and 16 instances of rising prices (True Positive). However, 16 rising price movements were incorrectly predicted as falling (False Negative), and 24 falling price movements were incorrectly predicted as rising (False Positive). This indicates that the model has a stronger tendency to predict falling prices, as reflected by the higher number of correct predictions in the Falling class compared to the rising class.

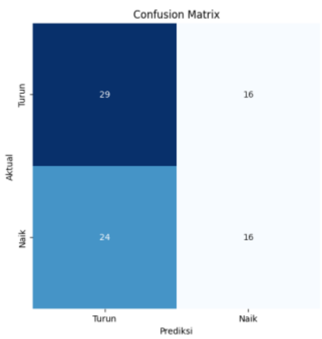

Figure 3. Confusion Matrix for LSTM Model

The RNN model demonstrates relatively better performance compared to LSTM in classifying stock price movements. From the total test data, the model correctly classified 71 instances of falling prices (True Negative) and 32 instances of rising prices (True Positive). However, 51 falling price movements were incorrectly predicted as rising (False Positive), and 25 rising price movements were incorrectly predicted as falling (False Negative). This indicates that while the RNN model achieves a higher overall accuracy than LSTM, it still shows a notable tendency to misclassify falling price movements as rising, as reflected by the relatively large number of false positives.

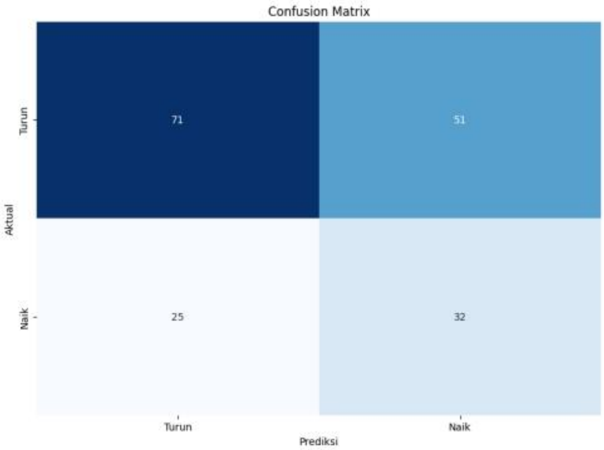

Figure 4. Confusion Matrix for RNN Model

3.3. Interpretation of Results and Model Implications

The evaluation results of the two deep learning models reveal fundamental differences in their architectural approaches, which directly affect stock price movement prediction patterns. In the context of financial time-series data that is highly volatile and influenced by numerous external factors, model effectiveness is strongly determined by how well the architecture captures temporal dependencies and sequential patterns. The varying performance across metrics such as recall and precision indicates that neither algorithm achieves optimal results across all aspects. In stock price prediction, where system effectiveness largely depends on the consistent identification of upward and downward price movements, the trade-off between false positives and false negatives becomes critical. Models that are overly biased toward one direction may fail to detect real price reversals, potentially leading to poor investment decisions.

The confusion matrix results further highlight this challenge. The LSTM model shows a stronger tendency to predict falling prices, correctly classifying 29 Falling instances but misclassifying 24 Rising instances as Falling. In contrast, the RNN model demonstrates a more distributed prediction pattern, correctly identifying 71 Falling and 32 Rising instances, although it still produces a notable number of false positives with 51 Falling instances incorrectly predicted as rising. These patterns suggest that RNN generalizes better across both classes, while LSTM tends to be biased toward the dominant class in the dataset.

From an architectural perspective, the superior performance of RNN over LSTM in this study may be attributed to the relatively short time-series length of the dataset. LSTM's gating mechanism, while theoretically advantageous for capturing long-term dependencies, may introduce unnecessary complexity when the sequential patterns in the data are not sufficiently long or complex to benefit from memory cell operations. This finding is consistent with observations in prior studies where simpler recurrent architectures outperform LSTM on smaller or less complex datasets.

Furthermore, these findings reinforce the view that data quality and quantity play a decisive role in deep learning model performance for financial forecasting. The relatively modest accuracy values of both models, 53% for LSTM and 58% for RNN, reflect the inherent difficulty of predicting stock prices, which are influenced by macroeconomic conditions, investor sentiment, and sector-specific factors beyond historical price data alone. To address this limitation, incorporating additional features such as trading volume, market indices, or sentiment analysis from financial news may serve as a promising direction for future development to improve model sensitivity to complex stock price dynamics.

From an implementation perspective, RNN shows stronger potential as a more stable and balanced model for stock price prediction in the Islamic finance sector, while LSTM may still be relevant in scenarios involving longer historical sequences or more complex multivariate data. The results of this study provide a foundation for selecting deep learning models for financial forecasting applications. System developers who prioritize simplicity and efficiency may rely on RNN, whereas systems that require modeling of longer temporal dependencies may consider LSTM with further hyperparameter optimization. Future exploration of hybrid architectures, attention mechanisms, or transformer-based models could provide broader insights into more advanced stock price prediction approaches. Additionally, evaluating model performance under different market conditions or incorporating external economic indicators remains an important area for further research.

4. CONCLUSION

This study compares two deep learning algorithms—Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN)—in classifying stock price movements in the Islamic finance sector using historical data from two Islamic banking companies listed on the Indonesian stock market. The evaluation results indicate that both models demonstrate moderate performance, with RNN consistently outperforming LSTM across all evaluation metrics. Based on the experimental results, RNN achieves the highest accuracy of 58%, precision of 57%, recall of 58%, and an F1-score of 56%, obtained under the best configuration of a 70:30 data split. The confusion matrix further confirms that RNN provides a more balanced classification between rising and falling price movements, correctly identifying 71 Falling and 32 rising instances. LSTM, on the other hand, achieves a maximum accuracy of 53% under an 80:20 data split with 50 epochs, and shows a stronger bias toward predicting falling prices, with 29 correct Falling predictions compared to only 16 correct rising predictions.

Considering the evaluation results and confusion matrix analysis, RNN can be concluded as the more suitable model for stock price movement classification in the Islamic finance sector within the scope of this study, as it demonstrates better generalization and more balanced performance across both price movement classes. The relatively modest accuracy values of both models reflect the inherent complexity of financial time-series data, which is influenced by numerous external and unpredictable variables beyond historical price patterns alone.

Future research may focus on incorporating additional features such as trading volume, macroeconomic indicators, and sentiment analysis from financial news to improve model generalization. Hybrid architectures combining RNN or LSTM with attention mechanisms or transformer-based models could be explored to enhance prediction accuracy. Additionally, expanding the dataset to cover a longer time period or a broader range of Islamic financial instruments is recommended to improve the robustness of the models. Evaluating model performance under different market conditions, such as during periods of high volatility or economic crisis, also remains an important direction for further research to develop more adaptive and reliable stock price prediction systems.

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