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Predicting ANTAM Stock Price with Deep Learning: A Tool for Strategic Investment Decisions

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Abstract. In the dynamic and often unpredictable financial markets, accurate stock price predictions are crucial for making informed investment decisions. This study explores the application of deep learning techniques to predict the stock prices of PT Aneka Tambang (ANTAM), a prominent Indonesian mining company, with the aim of enhancing investment strategies. By utilizing historical stock price data, technical indicators, and relevant economic factors, we develop a comprehensive deep learning model to forecast future stock prices. The study employs deep learning architectures: Long Short-Term Memory (LSTM) networks capture both temporal dependencies and intricate patterns within the financial data. The findings indicate that deep learning models, particularly those leveraging complex feature sets, provide more accurate and timely predictions. The result of forecasting ANTAM stock price using an LSTM model, trained over 250 epochs, resulted in a Root Mean Square Error (RMSE) of 26,212, indicating a reasonable level of prediction accuracy. Furthermore, the research examines the practical implications of integrating deep learning predictions into investment decision-making processes. Based on the forecast model, the investment decision suggestion is to buy ANTAM stock.

BACKGROUND

ANTAM is a mining company which processes several minerals as well as operating other businesses including trade and industry, transportation and other services related with the mining sector. ANTAM operating segments are distinguished according to three cores businesses which comprised on nickel, gold and refinery. ANTAM stock price went public on 27 November 1997 and nowadays 65% of ANTAM stock is owned by the government and the rest by the public. ANTAM shares are traded on the Indonesia Stock Exchange (IDX), moreover ANTAM's shares remains part of LQ45 Index, IDX30, IDX80 Index, IDX Small Mid Cap (SMC) Composite Index, IDX SMC Liquid Index, PEFINDO Investment Grade (I-Grade) Index, Jakarta Islamic Index, Jakarta Islamic Index 70, Kompas100 Index, IDX BUMN20 Index, MNC36 Index and Bisnis-27 Index which is the list companies with the highest liquidity at the IDX.

Stock price prediction plays a pivotal role in modern investment strategies due to its direct impact on risk management, decision-making, and portfolio optimization. Accurate forecasting of stock prices allows investors to anticipate market movements, thereby enabling timely buy or sell decisions that align with their financial goals and risk appetite (Fischer & Krauss, 2018). By identifying potential uptrends or downturns in advance, investors can mitigate losses and capitalize on profit opportunities, especially in volatile markets.

Furthermore, effective stock price prediction supports portfolio management by informing asset allocation and rebalancing strategies. Integrating predictive models into investment workflows enhances the ability to diversify risk and maintain optimal portfolio performance under changing market conditions (Chong et al., 2017). With the increasing complexity of financial markets, traditional forecasting methods are often insufficient for capturing nonlinear and chaotic patterns in stock data.

In response to these challenges, the adoption of machine learning and deep learning techniques such as Long Short-Term Memory (LSTM) networks and hybrid models like CNN-LSTM has significantly improved forecasting accuracy (Chen et al., 2019; Zhang et al., 2020). These models are capable of learning hidden patterns and long-term dependencies in financial time series, which traditional statistical methods often fail to capture.

Moreover, the integration of artificial intelligence in finance reflects a broader trend of digital transformation, where data-driven technologies enable faster, smarter, and more adaptive decision-making (Kim & Won, 2018). As a result, stock price prediction not only enhances individual investment strategies but also contributes to more efficient and informed financial systems.

In summary, stock price prediction is essential for investors seeking to reduce uncertainty, make proactive decisions, and harness the power of modern technology for competitive advantage. The continuous advancement in predictive modeling, especially through deep learning, offers promising pathways for achieving higher returns and robust investment outcomes (Nelson et al., 2017; Sari et al., 2021).

This study focuses on applying deep learning to predict the stock price of PT Aneka Tambang Tbk (ANTAM), one of Indonesia's leading mining companies. ANTAM's stock is significantly influenced by fluctuations in global commodity prices, particularly gold and nickel, making it a valuable case for predictive modeling. By utilizing historical stock data and deep learning architectures, the aim is to build a robust forecasting model that can assist investors in making strategic decisions based on data-driven insights.

In addition to enhancing forecast accuracy, the use of deep learning models offers scalability and adaptability making them suitable for real-time applications in algorithmic trading, portfolio management, and risk assessment. This research not only contributes to the field of financial data science but also provides a practical tool for stakeholders seeking to navigate the uncertainties of the stock market with greater confidence.

RESEARCH METHOD

Long Short-Term Memory (LSTM) is a type of neural network in deep learning, especially for sequential data, such as time series, text, or video. Long Short-Term Memory (LSTM) is a special type of development of Recurrent Neural Network (RNN) to cope with information from very long sequences based on data, as well as handling problems such as vanishing gradient problem or loss of gradient that occurs in Artificial Neural Network (ANN) using back propagation in the training process (Sarkar et al., 2018). The vanishing gradient problem occurs when the gradient is very small relative to the initial layer weights, resulting in no information being updated during backpropagation and convergence becoming stagnant. The use of sigmoid activation function is one of the causes of vanishing gradients which makes it difficult for RNNs to learn long-term dependencies in data. LSTM has an advantage in its ability to remember important information from the past and ignore irrelevant information, making it very effective in predicting and analysing sequential data. The architecture of the LSTM is different from the RNN architecture, which has an addition as shown in Figure 1. The additional architecture in LSTM is used to overcome the vanishing gradient gradually (Sarkar et al., 2018).

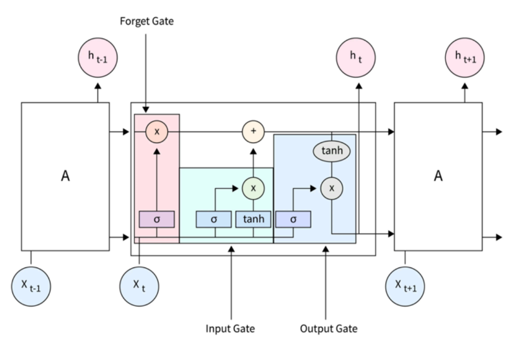

Figure 1. Architecture of LSTM

LSTM have specialised memory units that allow the network to remember information over a longer period of time. Each LSTM unit consists of three main gates:

1. Forget Gate

Forget gate in LSTM is responsible for determining what information needs to be removed in the cell state. The information in the cell state (c_{t-1}) is changed through the multiplication of elements from the forget gate output. The sigmoid activation function is used in the forget gate; it shows that the output value of the forget gate produces a continuous value in the range of 0 to 1. If the result of the multiplication between the sigmoid activation function and the matrix shows a value close to 1, it means that the information will be stored and if the resulting value is close to 0, it means that the information will be removed.

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

Where: f_t = forget gate output; σ = sigmoid activation function; W_f = the weight of the forget gate; h_{t-1} = the output of the cell state at time t-1; x_t = input at time t; and b_f = bias for forget gate.

2. Input Gate

The input gate in LSTM serves to regulate what new information is added to the memory cell or cell state. There are two functional units used in the input gate. The first functional unit is the use of a sigmoid activation function to determine the value to be updated. The second functional unit is the use of a tanh activation function that produces a value in the interval -1 to 1 and creates a change in the memory cell (c_t).

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right]\right) + b_i$$
$$C_t = \tanh tanh\left(W_c\left[h_{t-1}, x_t\right]\right) + b_c$$

Where: i_t = input gate output; W_i = the weight of the input gate; C_t = the new candidate value to be added to the memory cell; W_c = the weight of cell state; $tanh$ = tanh activation function; and b_i and b_c = bias for input gate and the new value in the cell state.

3. Output Gate

The output gate of the LSTM has the responsibility of retrieving key information from the current input to the previous output using the trained matrix W_o and bias B_o. The information is then combined with the new memory cell (c_t) to predict the next output (h_t). The output is reused for the next iteration of the process. If it has multiple layers, then the output can serve as an input in the next layer and if it does not have multiple layers then the output is the predicted result of the model.

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right]\right) + b_o$$
$$h_t = o_t * \tanh tanh\left(C_t\right)$$

Where: o_t = output of the gate output at time t; W_o = the weight of the output gate; h_t = the final output of the LSTM at time t; C_t = updated state cell value; and b_o = bias for output gate.

The ANTAM stock price forecasting results obtained from deep learning LSTM will be used for investment decision making. In this research, we evaluated the performance of different investment decision, with are outline as follows:

(1) Buy, if $y_t > \hat{y}_{t+1}$

(2) Hold, if $y_t = \hat{y}_{t+1}$

(3) Sell, if $y_t < \hat{y}_{t+1}$

RESULT AND DISCUSSION

This study applied a deep learning model of LSTM for daily ANTAM stock prediction, then the results will be used for investment decision recommendations. The data used is taken from www.finance.yahoo.com which consists of the daily ANTAM closing stock price data from January 2nd 2023 to September 3rd 2024. The model was trained using a sliding window of 362 previous closing prices to predict the next day's price. The dataset was split into 90% training sets (in-sample) and 10% test sets (out-sample), and the model was trained for 250 epochs with a batch size of 32. The Adam optimizer was used to minimize the Mean Squared Error (MSE) loss function.

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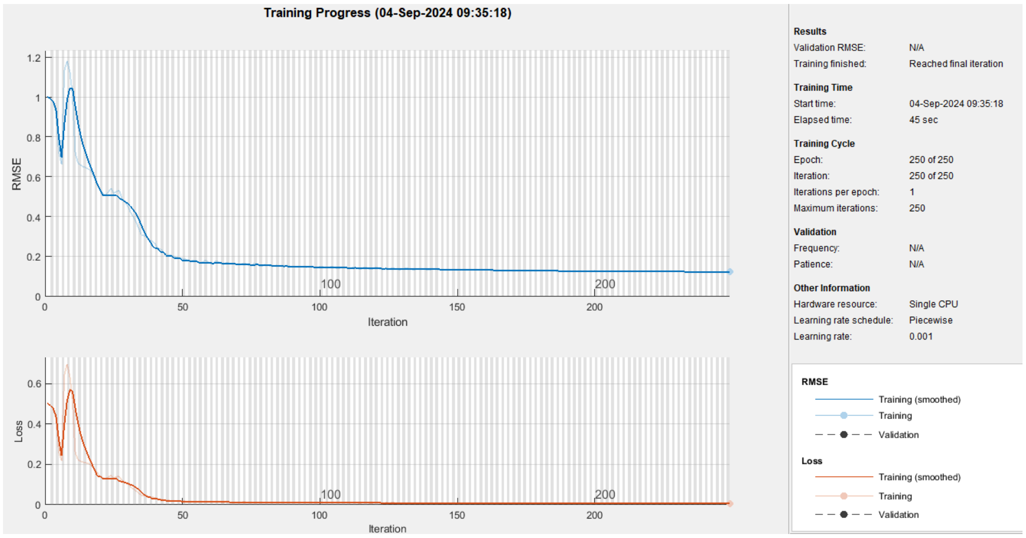

Figure 2. Training Progress of LSTM

After training, the model was evaluated on the 10% test data comprising previously unseen stock prices. The following performance were calculated and the RMSE 112.4711 values suggest that, on average, the model's prediction error was within a tolerable range for financial forecasting applications.

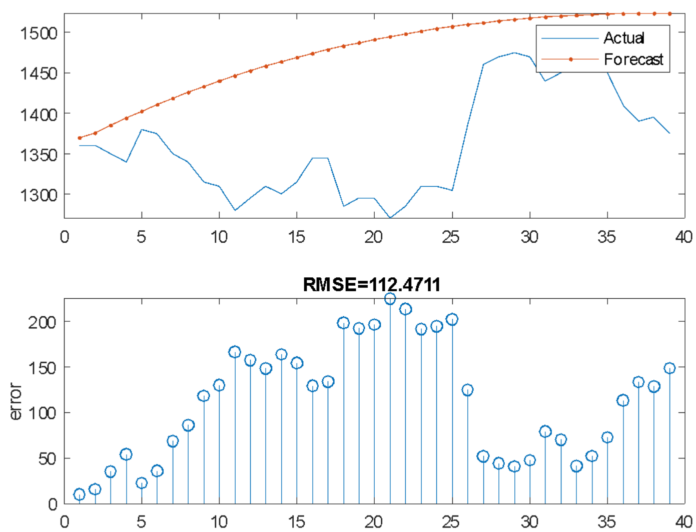

Figure 3. ANTAM Stock Forecast

Then the forecast results were improved resulting in the best RMSE of 26,212. A time-series plot comparing predicted and actual closing prices reveals the LSTM model's strong ability to track trends and levels.

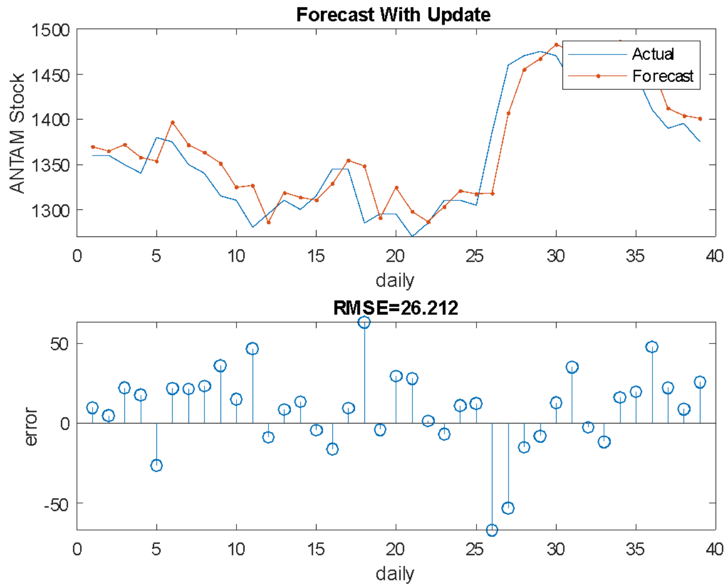

Figure 4. ANTAM Stock Update Forecast

The LSTM model's predictions indicate a consistently upward trend in ANTAM's stock price over the near future.

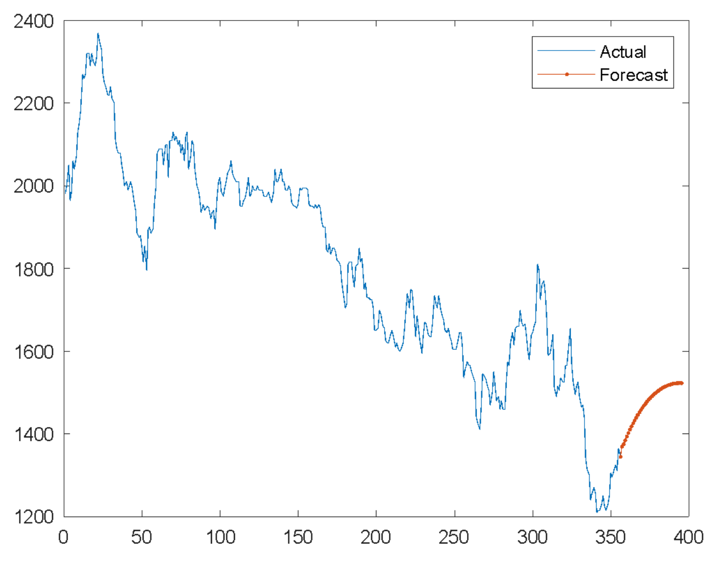

Figure 5. ANTAM Stock Prediction

TABLE 1. Investment Decision of ANTAM Stock Prediction

RMSE	Y_t	$\hat{Y}_{t+1}$	Decision
26.212	1375	1400.7	Buy

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The model predicts that the stock price will increase from Rp 1375 to Rp 1400.7 on the following trading day. This positive delta of Rp 25.7 represents an expected return of approximately +1.87% over one day. Given this upward forecast, a "**Buy**" recommendation is appropriate, suggesting that investors may benefit from entering a position in the stock before the price rises.

The LSTM model's strong performance indicates that deep learning, particularly memory-augmented architectures like LSTM, is suitable for modeling the inherently sequential and partially deterministic nature of stock price movements. Its ability to learn long-term dependencies provides a strategic advantage over traditional models like ARIMA or linear regression.

However, while LSTM performs well in capturing historical patterns, it does not inherently incorporate external events such as macroeconomic indicators, which could limit predictive accuracy during unpredictable market events.

CONCLUSION

The analysis of forecasting ANTAM stock price using an LSTM model, trained over 250 epochs, resulted in a Root Mean Square Error (RMSE) of 26,212, indicating a reasonable level of prediction accuracy. Despite this, it is important to consider the inherent volatility and other external factors influencing the stock market. Based on the model's forecast, the investment decision is to buy ANTAM stock, suggesting that the predicted price trend is favorable. However, it is advisable to complement this model-based decision with a broader analysis that includes market conditions and fundamental factors.

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