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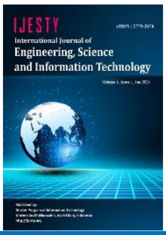

Gold Price Prediction Using Long-Short Term Memory Algorithm Based on Web Application

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Abstract

Gold is a significant investment asset, particularly in times of economic instability. Various factors, including decisions by financial authorities, inflation, and global economic dynamics, influence the fluctuations in gold prices. Accurately predicting gold prices is valuable for investors when making investment decisions. This study aims to utilize the Long Short-Term Memory (LSTM) algorithm for predicting gold prices and develop a web-based application connected to Yahoo Finance to acquire real-time gold price data. The LSTM algorithm was chosen because it handles time series data with long-term dependencies. LSTM has an architecture that allows the model to retain relevant information over long periods and forget irrelevant data. In this study, the developed LSTM model produced a Mean Absolute Error (MAE) of 19.81, indicating that the average prediction deviates by approximately 19.81 units from the actual value. Furthermore, an average Mean Absolute Percentage Error (MAPE) of 0.83% demonstrates the high prediction accuracy. The results of this study show that LSTM is an effective method for predicting gold prices. The resulting web application allows users to access gold price projections interactively, thereby assisting investors in making more accurate and data-driven decisions with easy access. Additionally, the web application offers customizable features such as adjusting prediction parameters and visualizing results in real time. These features not only enhance user engagement but also improve decision-making processes. This research provides a practical tool for optimizing investment strategies in a dynamic economic environment by leveraging machine learning and seamless web integration.

Keywords: *Gold, Long-Short Term Memory Prediction, Website, Yahoo Finance*

1. Introduction

Gold is one of the most critical investment assets in the financial world, particularly as a stable store of value during economic uncertainty. In economic instability, gold is often considered a haven, an asset that can retain its value even when financial markets experience turbulence. The fluctuations in gold prices are influenced by various economic factors, such as decisions made by monetary authorities, inflation, interest rates, and global economic dynamics [1]. Therefore, accurately predicting gold prices is highly valuable for investors in making informed investment decisions.

Gold prices generally align with inflation, making it an effective hedge against value loss. In times of high inflation, investors prefer gold as a safer investment instrument than the more volatile stock market [2]. Additionally, gold has high liquidity, making it relatively easy to sell when needed. However, like any other investment, gold also carries risks, particularly the risk of sharp price fluctuations that can occur within a short period [3]. Therefore, investors must predict gold price movements accurately.

Advancements in information technology, particularly in big data analytics and machine learning, have transformed how predictions are made. By leveraging these technologies, complex data analysis can be conducted more effectively, resulting in more accurate and reliable predictions. In this context, computer science plays a key role by providing tools and methods to process, analyze, and interpret data, including gold price prediction, which heavily relies on historical data and other economic factors [4].

One algorithm that can predict gold prices is Long Short-Term Memory (LSTM), an artificial neural network that handles time series data with long-term dependencies. LSTM excels at identifying long-term patterns and dependencies, making it highly suitable for predicting commodity prices like gold, whose price movements are influenced by historical patterns that may recur [5]. The advantage of LSTM lies in its complex memory cell architecture, which enables the model to retain relevant information over the long term and forget irrelevant data, resulting in more accurate predictions.

Previous studies, such as those conducted by [6], demonstrate the effectiveness of LSTM in predicting bitcoin prices. However, the model experienced overfitting on the test data and showed higher prediction errors on unseen data. This study develops a web-based application connected to Yahoo Finance to automatically and in real-time acquire gold price data, enabling users to access gold price projections interactively. Unlike the previous study, which focused solely on predicting bitcoin prices, this research aims to develop a gold price prediction system using LSTM, expecting to provide investors with more accurate and valuable information when deciding future gold prices. The web-based application is expected to assist governments, companies, and other related institutions in planning more efficient and sustainable policies and strategies regarding gold prices.

2. Literature Review

2.1. Previous Research

The research conducted by Sahrina Hasibuan & Novialdi in 2022, titled " Bulk and Packaged Cooking Oil Price Prediction Using the Long Short-Term Memory (LSTM) Algorithm," This study develops a model to predict the price of cooking oil, both sold in bulk and packages, using a deep learning variant specifically designed to process time series data, namely short-long term memory (LSTM). Based on NRMSE measurements, the developed model can identify price patterns for the two types of cooking oil. The NRMSE results from the LSTM model at the training stage reached 0.019 for bulk and cooking oil data and 0.037 for packaged cooking oil data [7].

The research conducted by David et al. in 2023, titled " Chili Price Prediction using the Long-Short Term Memory Method (Case Study: Malang City)," The experiment was carried out using daily data on fluctuations in the price of cayenne pepper in the Malang area during the period January 1 2021 to July 31 2022. Implementation of the LSTM method produced the lowest MSE value of 0,0155. This analysis divides the data into 70% for training and 30% for testing. The parameters used include a data sequence of 21, the number of units hidden as many as 128, and training iterations (epoch) as many as 150 times [8].

The research conducted by Budiprasetyo et al. in 2023, titled " Syariah Stock Price Prediction Using the Long Short-Term Memory (LSTM) Algorithm," Experiments show that the LSTM method is effective in projecting stock prices accurately, with the number of layers having a significant effect on the error rate measured using MAPE. The configuration with eight layers shows better performance. For PT Aneka Tambang Tbk, the best model produces a MAPE of 2.64. Erajaya Swasembada Tbk achieves a MAPE of 2.24 MAPE 1.83. Meanwhile, Wijaya Karya recorded a MAPE of 2.66 [1].

The research conducted by Husaini et al. in 2024, titled " Application of the Long Short-Term Memory Algorithm for Predicting Palm Oil Production," implements the LSTM algorithm by testing various parameters to find the optimal model for predicting palm oil production results. Based on a series of experiments, it was found that the best configuration uses the RMSprop optimizer, a learning rate of 0.001, and batch size 8. This model produces RMSE values of 0.1725, MAPE 0.5087, and R2 0.0578. Using this model, the prediction results show a tendency to decrease palm oil production in the future [9].

The research conducted by Julian & Pribadi in 2021, titled " Forecasting Mining Stock Prices on the Indonesian Stock Exchange (BEI) Using Long Short-Term Memory (LSTM)," The implementation of LSTM in this study shows promising performance, with increasing accuracy as the number of learning iterations increases. Experiments show that the optimal configuration is achieved in 200 learning cycles. Evaluation using the Root Mean Square Error (RMSE) metric shows the best results for TINS shares, with an RMSE value of 31.71. This finding indicates the potential of LSTM as an effective tool in predicting price trends in the market capital [10].

The research conducted by Khaira et al., 2020, titled " Predicting the Occurrence of Hotspots in Peatlands of Riau Province Using Long Short Term Memory," An innovative approach has been developed using long short-term memory (LSTM)-based machine learning techniques to estimate the potential emergence of fire-prone spots in wetlands. A recent study applied this method to predict the emergence of high-temperature areas in the Riau region over six months, from August 2019 to January 2020. The implementation of LSTM in time series analysis produced a promising level of accuracy, with a root mean square standard deviation value reaching 363.38. These results show the significant potential of using artificial intelligence technology to prevent forest fires. [11].

In the study by Aprian et al., 2020, titled " Cargo Revenue Prediction Using Long Short Term Memory Architecture, "LSTM selection was based on its ability to analyze time series data. Model accuracy was evaluated using the root mean squared error (RMSE) metric. The data source came from daily transaction records in one of the goods delivery services units in the Tangerang urban area. Before further processing, the data goes through four preprocessing stages: subtotal calculation, extreme value identification, differentiation, and scale normalization. The remaining 10% is for testing. This configuration produces an RMSE value of 641,375.70 for training data and 594,197.70 for testing data. This finding indicates the significant potential of applying deep learning techniques in predicting revenue trends in the logistics sector [12].

The research conducted by Dwika & Avianto, 2024, titled " Implementation of the LSTM Algorithm for Predicting Prices of Curly Red Chilies in Yogyakarta," This study implements long-short term-memory (LSTM) based machine learning techniques to analyze price data for curly red chilies in the Yogyakarta region over six years, from October 2017 to October 2023. A series of experiments were carried out to optimize the predictive model. The best configuration was obtained by dividing the dataset into 70% for training and 30% for testing learning, with a data batch size of 48 and a learning rate of 0.001. The 30 computing units chosen were ReLU, with Adam as the optimization algorithm. The final results show promising performance, with a MAPE of 3.6995%, equivalent to an accuracy rate of 96.3005%. These findings indicate significant potential for using machine learning techniques in predicting agricultural commodity price trends.[13].

The research conducted by Sujjada & Sembiring, 2024, titled " Bitcoin Price Prediction Using the Long Short Term Memory Algorithm," implements deep learning techniques, specifically LSTM, to project the trend in the asset's value. The analysis used historical data over 40 months, from late 2020 to mid 2024. Evaluation of model performance using two main metrics, RMSE and MAPE. Test results show that the RMSE value reaches 17,318.40 for training data, while the MAPE value is 3.24%. The Square Root Standard Deviation was recorded as 27,921.84 with an Average Absolute Percentage Error of 5.36%. The relatively small difference between the metric values in the training and testing data, especially considering the high price volatility, indicates the model's ability to capture value movement patterns. These digital assets are entirely accurate [14].

2.2. Prediction

Prediction or forecasting refers to the effort to anticipate and predict events that will occur in the future, especially over a long period. In this context, forecasting includes the conditions expected to emerge in the future, and to project these events, structured steps are required to calculate the likelihood of an event occurring, utilizing available historical and current data [15]. Forecasting aims to minimize the error between the predicted results and the actual outcomes. Quantitative data is often used in predictions, although future predictions do not guarantee certainty about future events [16]. This effort aims to provide the most logical and reasonable answers based on accurate and precise information from previous periods, which can serve as a foundation for understanding the possible events that may occur in the future [17].

2.3. Gold

Gold is a stable investment asset and an effective hedge against inflation, with significant symbolic and practical value as a safeguard against economic instability[18]. Their purity and usage distinguish various types of gold. Pure gold, or 24-carat, with a purity of 99.9%, is commonly used in jewelry and luxury items, although it is often alloyed with other metals to enhance its strength. Additionally, there are lower-carat gold types, such as 22, 18, 14, and 10-carat, with the lower the carat, the higher the proportion of alloyed metals such as silver or copper. In addition to yellow gold, variations include white gold and rose gold. White gold is alloyed with metals like palladium or nickel to give it a white color, while rose gold is mixed with copper to impart a pink hue. Gold is used in various industries, including jewelry, electronics, and the financial sector. The price of gold is influenced by global economic factors, monetary policies, and market sentiment [19].

2.4. Time Series Analysis

Forecasting analysis is a systematic approach to estimating future events based on relevant historical data. The selection of the forecasting period depends on the current conditions and the objectives to be achieved, with typical choices including daily, weekly, monthly, semi-annual, and annual intervals [20]. The accuracy of the forecast tends to decrease as the forecast horizon lengthens. Quantitative time series forecasting models use time within a data sequence with consistent intervals, whereas time series analysis aims to understand specific mechanisms, predict future values, and optimize system control. Time series analysis is used to model the behavior of historical data to understand patterns and relationships among data, estimate future trends, and determine the optimal control approach to ensure the system operates efficiently.

2.5. Long-Short-Term Memory Algorithm

Long Short-Term Memory (LSTM) is an advancement of the RNN structure, which was first introduced by Hochreiter and Schmidhuber in 1997 [21]. Since then, many researchers have continued to expand the development of LSTM architectures in areas such as speech recognition and prediction, showing significant progress in its application [22]. The structure of the LSTM algorithm consists of a neural network and several memory units called cells. Data from the cell and hidden states will be conveyed to the next cell. As shown in the following image.

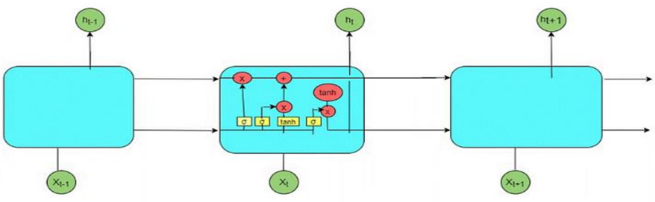

Fig 1. Workflow of LSTM

In building an LSTM model, several steps need to be considered. These stages include the construction of the LSTM unit, determining initial values for weights and biases, gate calculations, and integrating the LSTM unit with other layers in the neural network. Following are the calculations.

1. Initialization weights and bias
   Initialization is done by determining the weights' initial values and bias. Weights and biases will be calculated during the training phase using historical data, which minimizes the possibility of prediction errors.
2. Forget Gate
   In LSTM, forget gates are essential in determining how much information will be retained or discarded from network memory. This helps the network overcome the challenge of vanishing gradients, which often arise in other deep learning models and allows LSTMs to store and utilize significant information over extended periods. This way, the forget gate increases the LSTM's ability to make predictions based on existing data. The following is the formula for calculating the forget gate value.

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

Description:
f_t is the forget gate vector at time (t)
σ is the sigmoid function
W_f is the weight for forget gate

h_{t-1} is the output of the cell at the previous time
x_t is the input at time t
b_f is bias

3. Input Gate
The input gate regulates and controls the information entered into the cell state (memory) at each time stage. Its primary function is to determine which new data from the current input is worth storing in the cell state. The following is the input gate formula.

$$i_t=\sigma(W_i.[h_{t-1}, x_t]+b_i) \quad (2)$$

Description:
i_t is the input gate vector at time (t)
σ is the sigmoid function
tanh is the hyperbolic tangent function
W_i is the weight for the gate input
b_i is biased

After calculating the gate input (i_t), the next stage is to estimate the candidate cell state (C_t'). *Cell candidate* (C_t') describes new information submitted to be entered into the LSTM cell memory. Candidate cell state calculation is performed after input gate calculation (i_t) to update the cell memory efficiently. The input gate determines the amount of new information to be received, while the candidate cell states provide new values based on the weights and inputs that have been integrated.

4. Cell State
The cell state serves as the main memory path in the LSTM, streaming information through time with minimal change. This component is a relatively stable store of essential data from one stage to the next. The following is the cell state calculation formula.

$$C_t= f_t.C_{t-1}+i_t.C_t' \quad (3)$$

Description:
C_t is *cell state*
f_t is *forget gate*
i_t is *input gate*
C_t' is *cell candidate*

5. Output gate
The output gate controls the information from the cell state that will be passed on as the hidden state (ht) to the next time stage or the next layer in the network. In other words, this gate controls how much of the LSTM's internal process results will be expressed.

$$O_t=\sigma(W_o.[h_{t-1}, x_t]+b_o) \quad (4)$$

Description:
O_t is the output gate vector at time t
h_t is the output of the LSTM cell at time t
σ is a sigmoid function
tanh is hyperbolic tangent function
W_o is the weight for the output gate
b_o is the bias
C_t is the cell state at time t

2.6. MAE and MAPE Parameters

The evaluation method of Mean Absolute Error (MAE) is a statistical technique used to measure the accuracy of a prediction model by calculating the average absolute difference between the actual data and the predicted results. MAE provides a transparent assessment of prediction performance without considering the direction of the error, whether positive or negative, and offers an objective overview of the model's error rate. The lower the MAE value, the more accurate the prediction model is. Conversely, Mean Absolute Percentage Error (MAPE) is an evaluation method that uses a percentage-based approach to calculate the average percentage of the absolute difference between the actual data and the predictions compared to the exact value. A low MAPE value indicates a good prediction model. However, MAPE should be used cautiously on datasets with very small or near-zero values, as in such conditions, MAPE may yield unstable or biased interpretations [15].

3. Research Methods

3.1. Research Workflow

One of the steps undertaken in this research process is using the waterfall method. The waterfall method consists of several steps, and the sequence of these steps can be seen in the figure below.

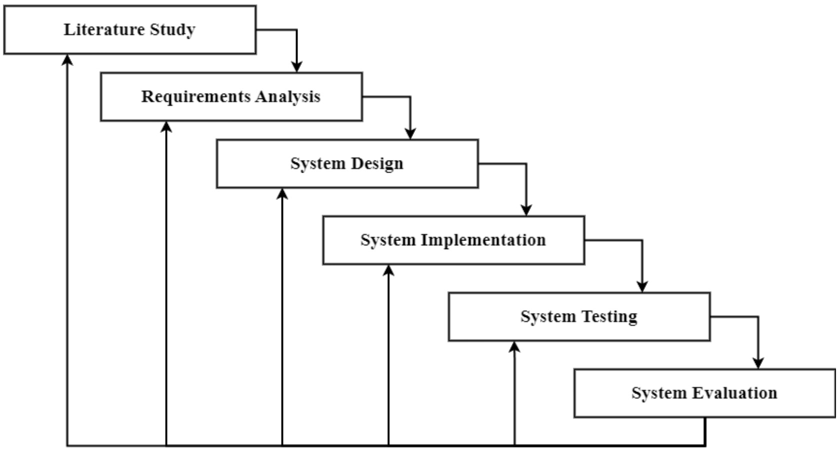

Fig 2. Research Workflow

3.2. Literature Study

Before conducting research, it is essential to carry out a literature review related to previous studies. The literature review significantly contributes to identifying trends and patterns that emerge in predicting fluctuations in gold commodity prices.

3.3. Requirement Analysis

The requirements analysis in this research includes identifying the necessary hardware and software. Data for gold price prediction is collected from Yahoo Finance, while the hardware used is an Acer Aspire 5 laptop. For software, Streamlit is used for web application development, Google Colab is used for data processing and model implementation, and Visual Studio Code is the development environment to support code writing and testing.

3.4. System Design

System design involves structuring the hardware and software required to run the gold price prediction model. At this stage, the system components are designed to integrate seamlessly, from data processing and the LSTM algorithm's implementation to the presentation of results through a web application based on Streamlit.

3.5. System Implementation

System implementation transforms the designed framework into a fully functional program. In this context, gold price data is retrieved from Yahoo Finance and processed using the LSTM model for prediction. The prediction results are then displayed in a web application developed with Streamlit, enabling users to access real-time predictions.

3.6. System Testing

System testing is conducted to ensure that all components function as expected. This testing involves verifying whether the web application can correctly display gold price predictions and whether the LSTM model produces accurate results. Additionally, the testing includes performance evaluation to ensure the system operates smoothly without any technical issues.

3.7. System Evaluation

System evaluation measures whether the developed system aligns with the initial specifications and research objectives. If shortcomings are identified, such as low prediction accuracy or issues with the usability of the web application, improvements will be made. This evaluation is essential to ensure the system operates optimally and meets user requirements.

3.8. System Diagram

The following is the system schematic for Gold Price Prediction depicted using the Long Short-Term Memory (LSTM) algorithm.

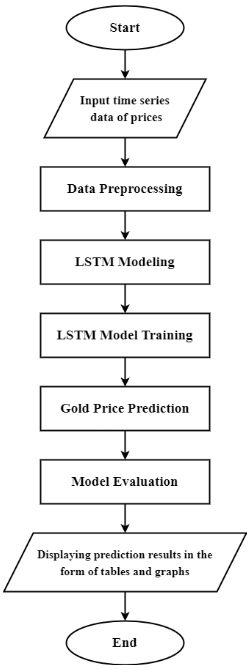

Fig 3. System Diagram

The system schema used to predict 24-karat gold prices with the Long Short-Term Memory (LSTM) algorithm begins with inputting historical gold price data into the application via the user interface. This historical data includes gold prices from 2022 to 2024. Next, a preprocessing process is carried out on the webserver to prepare the data before it is fed into the LSTM model. The data obtained from the initial collection is raw and contains incomplete entries or missing dates, requiring preprocessing to clean the data. Afterward, LSTM modeling is employed to understand and recognize temporal patterns in the historical gold price data.

In the LSTM model training phase, the model parameters are initialized randomly, and the model uses optimization algorithms such as Adam, SGD, or RMSprop to adjust the weights and biases in the network, minimizing the loss function. This iterative process uses training data to improve the model's prediction accuracy. After the training, the LSTM model can predict future gold prices based on the learned patterns. The model is evaluated using metrics such as Mean Absolute Error (MAE) or Mean Absolute Percentage Error (MAPE), which measure the accuracy of the predictions by comparing the predicted results with historical data. Finally, the prediction results are visualized in graphs or tables to help users understand the comparison between actual gold prices and the predictions generated by the LSTM model.

4. Research and Discussion

4.1. Prediction Results

Based on the research findings, the Long Short-Term Memory (LSTM) model used to predict 24-carat gold prices demonstrated a good ability to identify temporal patterns in the historical gold price data. After training with gold price data from 2022 to 2024, the LSTM model successfully learned the existing patterns and was able to predict future gold prices. The model evaluation was conducted using metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), which showed that the model achieved a relatively high level of accuracy in predicting gold prices. However, there were minor errors in a few predictions due to sharp price fluctuations.

Additionally, the prediction results from the LSTM model were visualized in the form of graphs and tables to help users better understand the comparison between actual gold prices and the predictions generated by the model. This visualization lets users see how well the gold price predictions align with market conditions. Overall, this study demonstrates that the LSTM algorithm is reliable for predicting gold prices and can serve as a valuable tool for investors in making more informed decisions in the gold market.

4.2. Yahoo Finance Gold Data

The data used in this study was obtained from Yahoo Finance, which provides historical data and other financial information. The data collected includes daily gold prices with several variables, namely the opening price (open), highest price (high), lowest price (low), and closing price (close), which will be used in the analysis and prediction modeling of gold prices using the Long Short-Term Memory (LSTM) algorithm. The data was sourced from Yahoo Finance covering the last three years, from January 1, 2022, to September 30, 2024, to ensure that the model could learn from various market conditions, such as periods of high and low volatility, as well as long-term trends in gold prices. The key variables used include the date, which represents the daily trading date and serves as the basis for sorting the data and dividing it into training, validation, and testing sets. At the same time, the opening price (open), highest price (high), lowest price (low), and closing price (close) reflect the price movements of gold on each trading day. Table 1 below contains gold price data from Yahoo Finance.

Table 1. Gold price data

Date	Open Price	High Price	Low Price	Close Price
01/01/2022	1.830.10	1.830.10	1.784.40	1.797.00
03/01/2022	1.830.10	1.830.10	1.789.80	1.799.40
04/01/2022	1.800.50	1.815.30	1.800.00	1.814.00
05/01/2022	1.813.10	1.824.50	1.813.10	1.824.00
06/01/2022	1.787.10	1.791.30	1.787.10	1.788.70
....	....	....	....	....
25/09/2024	2.656.30	2.664.20	2.649.30	2.659.20
26/09/2024	2.662.30	2.669.30	2.660.80	2.669.90
27/09/2024	2.670.00	2.672.10	2.641.70	2.644.30
28/09/2024	2.660.90	2.670.90	2.623.20	2.647.10
30/09/2024	2.660.90	2.662.10	2.623.20	2.636.10

4.3. Normalization Data

In this research, before the data is used in training the model, it is necessary to normalize the data using MinMaxScaler so that the data scale has a range of values between 0 and 1. The normalization process needs to be done on the data to ensure that all features have the same scale so that the system can produce optimal predictions without the possibility of producing biased values. The MinMaxScaler formula that can be used is as follows.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (5)$$

Description:

X_{norm}: Normalized value

X: Original data value

X_{min}: Minimum value in the data

X_{max}: Maximum value in the data

Based on the above equation, an example of calculating the normalization process can be obtained using January 03, 2022 data in Table 2.

Table 2. Normalization Data

Date	Open Price	High Price	Low Price	Close Price
03/01/2022	1.830.10	1.830.10	1.798.90	1.799.40

The results of the normalization calculation are as follows.

1. Open Price

$X_{norm}=\frac{1.830.10-1.623.30}{}=0.198$

2. High Price

$X_{norm}=\frac{1.830.10-1.623.30}{}=0.197$

3. Low Price

$X_{norm}=\frac{1.798.90-1.623.30}{}=0.169$

4. Close Price

$X_{norm}=\frac{1.799.40-1.623.30}{}=0.164$

Based on the results above, the results of normalizing gold data on January 03, 2022, can be obtained as follows.

Table 3. Result of Normalization

Date	Open Price	High Price	Low Price	Close Price
03/01/2022	0.198	0.197	0.169	0.164

Then, the overall results for normalization calculations on gold data are as follows **Table 4**.

Table 4. Normalization

Date	Open Price	High Price	Low Price	Close Price
03/01/2022	0,198	0.197	0,169	0,164
19/01/2022	0,185	0.21	0,187	0,204
07/02/2022	0,18	0.189	0,179	0,183
22/02/2022	0,272	0.275	0,258	0,263
11/03/2022	0,346	0.355	0,324	0,334
....	....	....	....	....
22/07/2024	0,744	0.743	0,741	0,714
05/08/2024	0,782	0.788	0,717	0,723
30/08/2024	0,856	0.86	0,839	0,809
03/09/2024	0,839	0.838	0,822	0,805
18/09/2024	0,905	0.903	0,892	0,88

4.4. Analysis of LSTM Prediction Results

In building an LSTM model, several steps need to be considered. These steps include constructing the LSTM unit, determining initial values for weights and biases, calculating gates, and integrating the LSTM unit with other layers in the neural network.

1. LSTM Calculation (Forget Gate, Input Gate, Cell Gate, candidate layer, and Output Gate)

Through the calculations carried out at the forget gate, input gate, cell gate, and output gate stages, the LSTM calculation results are obtained in Table 5 below.

Table 5. Result of LSTM Calculation

Date	Forget Gate	Input Gate	Candidate Layer	Cell State	Output Gate
03/01/2022	0,5883	0,6064	0,5466	0,6256	0,5883
19/01/2022	0,5894	0,6074	0,551	0,6294	0,5894
07/02/2022	0,18	0.189	0,179	0,183	0,5873
22/02/2022	0,272	0.275	0,258	0,263	0,602
11/03/2022	0,346	0.355	0,324	0,334	0,6143
....	....	....	....	....	....
22/07/2024	0,6775	0,6937	0,8227	0,9094	0,6775
05/08/2024	0,6816	0,6977	0,8305	0,9203	0,6816
30/08/2024	0,6939	0,7096	0,8549	0,9536	0,6939
03/09/2024	0,6915	0,7072	0,8502	0,947	0,6915
18/09/2024	0,7015	0,7169	0,8678	0,9729	0,7015

2. Hidden State Calculation

This hidden state calculation is a reflection of the system's understanding of the model at a certain point in time; it functions as a description of the collection of knowledge that has been accumulated by the model until a particular moment, reflecting the model's level of understanding of the data set that has been processed up to that time. The hidden state can be calculated using the equation.

$$h_t = O_t . \tanh(C_t) \quad (6)$$

Based on the calculation using the hidden state equation, the results of the hidden gate calculation on the test data are listed in **Table 6** below.

Table 6. Result of Hidden Gate Calculation

Date	Cell State	Output Gate	Hidden State
03/01/2022	0,6256	0,5883	0,2186
19/01/2022	0,6294	0,5894	0,2207
07/02/2022	0,6221	0,5873	0,2167
22/02/2022	0,6733	0,602	0,2452
11/03/2022	0,7153	0,6143	0,269
....	....	....	....
22/07/2024	0,9094	0,6775	0,382
05/08/2024	0,9203	0,6816	0,3886
30/08/2024	0,9536	0,6939	0,4087
03/09/2024	0,947	0,6915	0,4047
18/09/2024	0,9729	0,7015	0,4205

3. Calculation of LSTM Prediction Results

Based on the results of hidden state calculations obtained, the results of gold price predictions can be calculated using the Long-Short Term Memory algorithm equation.

$$y_t = \tanh(h_t) \tag{7}$$

The gold price prediction results using LSTM are calculated using this formula and obtained in **Table 7** below.

Table 7. Result of LSTM Prediction Calculation

Date	Hidden State	Prediction Price
03/01/2022	0,2186	0,2152
19/01/2022	0,2207	0,2172
07/02/2022	0,2167	0,2134
22/02/2022	0,2452	0,2404
11/03/2022	0,269	0,2627
....	....	....
22/07/2024	0,382	0,3644
05/08/2024	0,3886	0,3701
30/08/2024	0,4087	0,3874
03/09/2024	0,4047	0,384
18/09/2024	0,4205	0,3974

4. Evaluation of MAE and MAPE Metrics

After obtaining the prediction results, the MAE and MAPE evaluation metrics are calculated. For example, the calculation is based on the prediction result data dated January 03, 2022.

1. MAE Calculation

The formula or equation for calculating MAE evaluation on predicted data is as follows.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\text{Actual price} - \text{Prediction Price}| \tag{8}$$

MAE = 0.164-0.2152

MAE = 0.0512

2. MAPE Calculation

The formula or equation used for calculating the MAPE evaluation on the predicted data is as follows.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{\text{Actual Price} - \text{Prediction Price}}{\text{Actual Price}}\right) \times 100 \tag{9}$$

MAPE = (0.164-0.2152)/0.164×100

MAPE = 31.22%

The results of the calculation of MAE and MAPE on the whole data can be seen in **Table 8** below.

Table 8. Result of LSTM Prediction Calculation

Date	Actual Price	Prediction Result	MAE	MAPE
03/01/2022	1.799.40	0,2152	0,0512	31,222
19/01/2022	1.843.10	0,2172	0,0132	6,4807
07/02/2022	1.820.60	0,2134	0,0304	16,5967
22/02/2022	1.906.10	0,2404	0,0226	8,5758
11/03/2022	1.982.70	0,2627	0,0713	21,3526
....	....	....	....	....
22/07/2024	2.392.00	0,3644	0,3496	48,9587
05/08/2024	2.401.70	0,3701	0,3529	48,8083
30/08/2024	2.493.80	0,3874	0,4216	52,1179
03/09/2024	2.489.90	0,384	0,421	52,3029
18/09/2024	2.570.70	0,3974	0,4826	54,8448

5. Data Denormalization

This step is carried out after the machine learning model estimates the normalized data. The aim is for the prediction results to be interpreted in terms of their original size. In other words, it is restoring the data to its original format after it has been adjusted for analysis purposes. This step is essential post-modeling, allowing the analysis results to be translated back into a context that is easier to understand and apply in real situations.

The equation used in calculating data denormalization is as follows.

$$X\_denormalization = X\_normalization \times (max-min) + min \quad (10)$$

Then, the data denormalization calculation results are obtained in **Table 9** below.

Table 9. Denormalization Result

Date	Actual Data	Prediction Result	MAE	MAPE
03/01/2022	1.799.40	1.848.53	49.13	2.73
19/01/2022	1.843.10	1.816.23	26.864	1.457
07/02/2022	1.820.60	1.812.17	8.427	0.462
22/02/2022	1.906.10	1.898.84	7.258	0.3808
11/03/2022	1.982.70	1.984.34	1.642	0.0829
....	....	....	....	....
22/07/2024	2.392.00	2.389.33	2.661	0.1113
05/08/2024	2.401.70	2.416.46	14.768	0.6149
30/08/2024	2.493.80	2.506.48	12.688	0.5088
03/09/2024	2.489.90	2.475.58	14.318	0.5751
18/09/2024	2.570.70	2.541.26	29.435	1.145
	Average		19.809	0.83

4.5. LSTM Prediction Model Evaluation Results

From the prediction results table, for the date 03/01/2022, the MAE value of 49.13 and MAPE of 2.73% were recorded. This indicates that in this prediction, the predicted price deviates 49.13 USD from the actual gold price, with a percentage error of about 2.73% from the exact value. In the next prediction, dated 19/01/2022, the MAE value dropped to 26.864 and MAPE 1.457%, indicating an increase in model accuracy compared to the previous prediction. Overall, the manual calculation results of the average MAE of all predictions was 19.81, while the average MAPE reached 0.83%. These figures illustrate the fairly accurate performance of the prediction model, with an average absolute deviation of 19.81 USD from actual prices and a very low percentage error rate of 0.83%. These results indicate that the LSTM model used effectively predicts gold prices. However, there are variations in the error rate in specific periods, which fluctuations in gold prices may cause. The following is a comparison chart of the actual and predicted prices of gold using the LSTM algorithm.

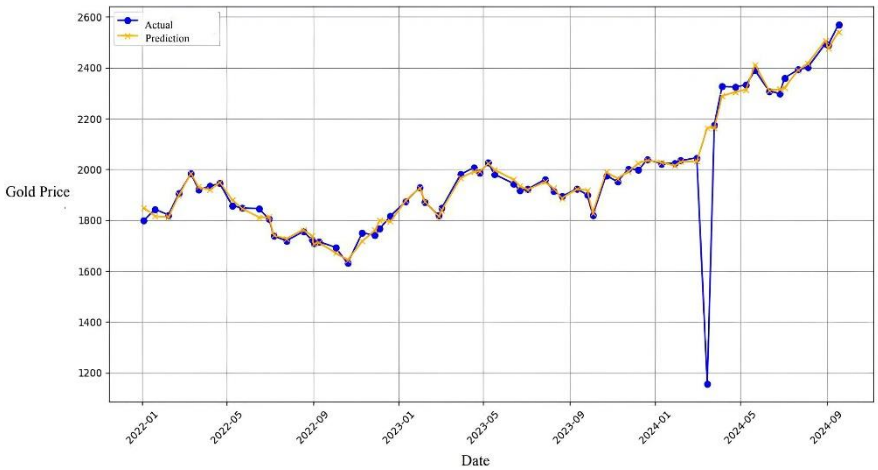

Fig 4 Comparison chart of actual price and predicted price of gold

This chart compares gold's actual and predicted price from 2022 to 2024. The blue line represents the actual data, while the yellow line with a cross shows the expected cost. These two lines run close together, indicating that the prediction model accurately follows the actual gold price trend. The following is a graph of the gold price prediction results for the next 60 days after making predictions in the web-based prediction application.

The graph above shows that the gold price prediction model using the Long Short-Term Memory (LSTM) algorithm accurately estimates future gold prices based on past data. From the graph and prediction table, this model predicts that there will be a considerable increase in gold prices in the next 60 days. This prediction can be seen from the sharp upward trend at the end of the forecast period, indicating that the gold price will likely rise rapidly.

5. Conclusion

The LSTM model used in this study showed a good ability to predict gold prices with a relatively small error rate. It was found that the Mean Absolute Error (MAE) of 19.81 indicates that the average model prediction deviates by about 19.81 units from the actual value. This means an absolute difference of 19.81 units in predicting the gold price, which likely refers to the cost of gold in USD per ounce. An average Mean Absolute Percentage Error (MAPE) value of 0.83% indicates that the model's prediction error, when calculated as a percentage of the actual value, is 0.83%. This shows a high level of prediction accuracy, given that MAPE values below 1% are generally considered indicators of highly accurate predictions relative to the actual data.

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