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Optimization of Long Short Term Memory Model for Gold Price Prediction Using Adaptive Moment Estimation

Optimasi Model *Long Short Term Memory* Untuk Memprediksi Harga Emas Menggunakan *Adaptive Moment Estimation*

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Abstract

The era of globalization and rapidly evolving economic dynamics place the financial sector at the center of attention for market participants and investors. Financial instruments such as gold play a crucial role as hedging tools and portfolio diversification, yet face significant challenges due to complex and unpredictable price fluctuations. Artificial intelligence technology, particularly Long Short Term Memory (LSTM) models and Adaptive Moment Estimation (ADAM), offers relevant solutions for predicting financial asset prices with strong temporal fluctuations, such as gold prices. This research aims to optimize the LSTM model using the ADAM technique to enhance the accuracy of gold price predictions. The research findings indicate that the LSTM model optimized with ADAM can provide highly accurate gold price predictions with low error rates. The LSTM model used has 3 layers with 128, 64, and 32 units, and uses 100 epochs in the model training process. At the 100th epoch, the final loss obtained was 0,000336. Model evaluation results showed a MAPE of around 0,0108 or 1,08% an accuracy rate of about 98,92%, and a low loss value of 0,00025.

Keywords: Gold Price Prediction, Artificial Intelligence, Long Short Term Memory, Adaptive Moment Estimation.

Abstrak

Era globalisasi dan dinamika ekonomi yang berkembang pesat menempatkan sektor keuangan sebagai pusat perhatian bagi para pelaku pasar dan investor. Instrumen keuangan seperti emas memiliki peran penting sebagai alat lindung nilai dan diversifikasi portofolio, namun menghadapi tantangan signifikan akibat fluktuasi harga yang kompleks dan tidak terduga. Teknologi kecerdasan buatan, khususnya model *Long Short Term Memory* (LSTM) dan *Adaptive Moment Estimation* (ADAM), menawarkan solusi yang relevan untuk memprediksi harga aset keuangan yang memiliki fluktuasi temporal yang kuat, seperti harga emas. Penelitian ini bertujuan untuk mengoptimalkan model LSTM menggunakan teknik ADAM untuk meningkatkan akurasi prediksi harga emas. Hasil penelitian menunjukkan bahwa model LSTM yang dioptimalkan dengan ADAM dapat memberikan prediksi harga emas dengan akurasi tinggi dan tingkat kesalahan yang rendah. Model LSTM yang digunakan memiliki 3 lapisan dengan unit 128, 64, dan 32, serta menggunakan 100 *epoch* pada proses pelatihan model. Pada *epoch* ke-100, didapatkan *loss* terakhir sebesar 0,000336. Hasil evaluasi model didapatkan MAPE sekitar 0,0108 atau 1,08% dan tingkat akurasi sekitar 98,92% serta nilai *loss* yang rendah, yaitu 0,00025.

Kata kunci: Prediksi Harga Emas, Kecerdasan Buatan, Long Short Term Memory, Adaptive Moment Estimation.

1. INTRODUCTION AND PRELIMINARIES

1.1 Research Background

The era of globalization and rapidly evolving economic dynamics has shifted the main focus to the financial sector, which has become the center of attention for market players and investors. Financial instruments such as gold are playing an increasingly important role as hedging tools and portfolio diversifiers, but they face significant challenges due to complex and unpredictable price fluctuations. The world economy is experiencing significant uncertainty, driven by factors such as geopolitics, monetary policy, and global events, making gold price predictions a critical element in investment decision-making [14]. This attracts investors to plan more effective investment strategies, manage risks better, and capitalize on emerging market opportunities.

Machine Learning, a fusion of statistical concepts and computer science, was first introduced by Arthur Samuel in 1959. Today, it is considered a part of Artificial Intelligence (AI) and is associated with algorithms that enable computers to automatically process and classify new data based on previous data and information [1]. As efforts to enhance understanding and readiness in responding to rapid market changes continue, AI technology has become a primary focus in the development of predictive models, particularly for gold price prediction. Leveraging advanced data analysis capabilities and machine learning algorithms, AI can identify patterns and trends [9]. The Long Short-Term Memory (LSTM) model has proven effective in addressing time patterns and non-linear dynamics [19]. The characteristic that distinguishes LSTM from other artificial neural network methods is its feature known as "long-term memory." This long-term memory refers to LSTM's ability to utilize information from the past over an extended period, provided that it enhances prediction accuracy [10]. As artificial neural network architectures continue to evolve, various deep learning models are now extensively implemented across multiple domains [7]. This model provides relevant solutions for predicting the prices of financial assets that exhibit strong temporal fluctuations, such as gold prices.

With the advancement of artificial intelligence technology, questions arise about the effectiveness and performance improvement of the model [8]. In this framework, the application of Adaptive Moment Estimation (ADAM) optimization emerges as a promising approach to improving model accuracy. ADAM addresses the issue of parameter sensitivity by adaptively adjusting the learning rate, correcting bias, and using parameters based on gradient history [13]. The adaptive features in ADAM also prevent the occurrence of vanishing gradient or exploding gradient phenomena [18]. The ADAM process calculates the first moment (gradient mean) and the second moment (gradient variance) using a corrected exponential method to avoid initial bias [3]. This process ensures stable and effective parameter adjustments during model training, optimizing the learning process and improving the prediction accuracy of LSTM in dealing with complex fluctuations in gold prices [21]. Thus, the ADAM algorithm can unlock the potential to enhance the predictive power of LSTM in forecasting gold prices.

Research discussing gold price prediction using Long Short Term Memory, namely Owen et al., [11], explains decision-support materials for investors by presenting information related to gold buying and selling price movements. The development of a gold price movement prediction model using LSTM, which is capable of providing more accurate predictions. Then, the research conducted by Jamaluddin & Toto [5] contributes to exploring the potential use of LSTM to predict gold prices as an investment strategy in facing global economic uncertainty, especially in anticipating the global recession predicted to occur in 2023. Therefore, the LSTM model can provide accurate predictions in forecasting gold prices as an investment tool. Thus, the authors intend to conduct this study to fill the existing knowledge gap. Additionally, this research explores the extent of the potential of the LSTM model in the context of gold price prediction by utilizing the ADAM optimization technique.

1.2 Theoretical Foundations

1.2.1 Forecasting

Forecasting is a branch of science that aims to predict events that may occur in the future through the analysis of historical data [12]. This technique helps in predicting potential changes or outcomes in various fields, such as economics, finance, and science, by utilising available information from the past [17].

1.2.2 Autocorrelation Function (ACF)

Autocorrelation Function (ACF) is a key instrument in time series analysis for different time intervals (lags), which is useful for identifying potential correlation patterns in the dataset. Autocorrelation is also useful in determining whether the data is stationary or not. The stationary process of a time series data (X_t) where the mean $E(X_t) = \mu$ and $Var(X_t) = \sigma^2$are constant, and the covariance $Cov\left(X_{t,}X_{t+k}\right)$ is a function of the time difference $|t-(t+k)|$.
Therefore, the covariance between X_t and X_{t+k},namely

$$\gamma_k = Cov\left(X_{t,}X_{t+k}\right) = E(X_t-\mu)(X_{t+k}-\mu). \tag{1}$$

The value ρ_k is the autocorrelation function at $k = 1,2,3$ .... [22]

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Cov\left(X_{t,}X_{t+k}\right)}{\sqrt{Var(X_t)}\sqrt{Var(X_{t+k})}}. \tag{2}$$

1.2.3 Long Short Term Memory (LSTM)

The Long Short Term Memory (LSTM) model is a variant of the Recurrent Neural Network (RNN) that has been modified with the aim of accurately predicting variables. The first discovery of Long Short Term Memory (LSTM) was proposed by Sepp Hochreiter and Jurgen Schmidhuber in 1997. LSTM is specifically designed to address long-term dependency issues and is suitable for analyzing and predicting time series. The LSTM architecture consists of an input layer, hidden layer, and output layer, where a series of unique memory cells replace the neurons in the RNN's hidden layer [15]. A key component of LSTM is the presence of memory cells, which are updated and maintained through gate structures [6]. These gate structures consist of the input gate, forget gate, and output gate. In LSTM, the activation function is used to activate or not activate how the neurons produce output [16]. The LSTM architecture can be seen in the following **figure 1**.

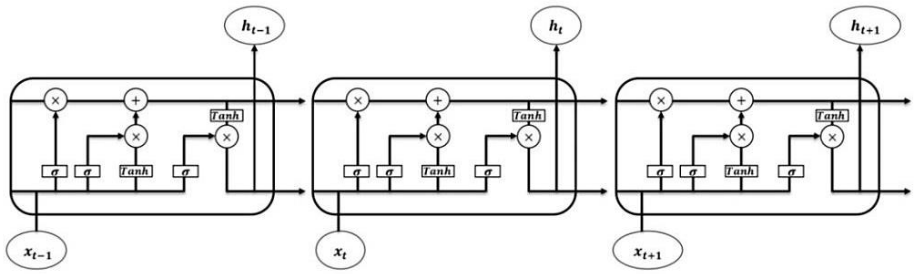

Figure 1. LSTM Architecture

Here are the gates present in LSTM.

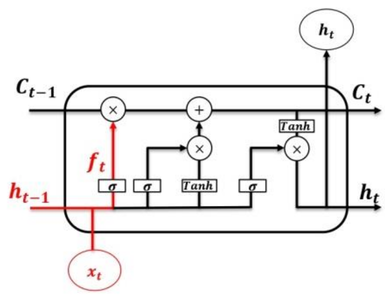

Figure 2. Forget Gate

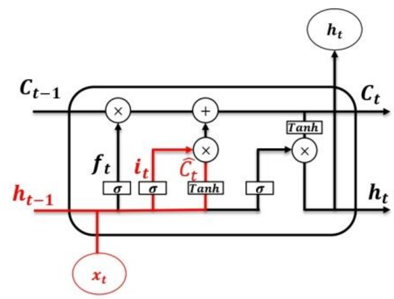

Figure 3. Input Gate

Forget Gate $\rightarrow$ $f_t = \sigma(W_f \,.\, x_t + U_f \,.\, h_{t-1} + b_f).$ (3)

Input Gate $\rightarrow$ $i_t = \sigma(W_i \,.\, x_t + U_i \,.\, h_{t-1} + b_i)$ (4)

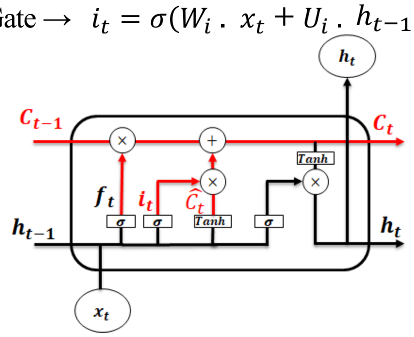

Figure 4. Cell State

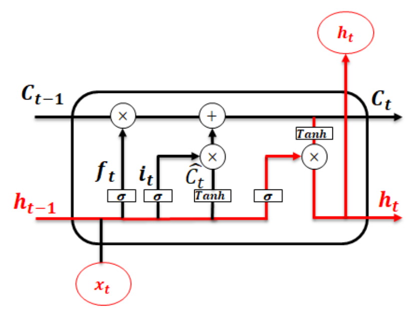

Figure 5. OutputGate

Cell State $\rightarrow$ $\widehat{C_t} = tanh(W_c \,.\, x_t + U_c \,.\, h_{t-1} + b_c)$ (4)

$$C_t = f_t . C_{t-1} + i_t . \widehat{C}_t \quad (5)$$

Output Gate $\rightarrow$ $O_t = \sigma\,(W_o \,.\, x_t + U_o \,.\, h_{t-1} + b_o)$ (6)

1.2.4 Adaptive Moment Estimation (ADAM)

Adaptive Moment Estimation (ADAM) is one of the optimization algorithms aimed at minimizing the loss function (x) on various parameters such as weights and biases. ADAM is used to optimize gradient descent. ADAM can calculate an adaptive learning rate for each weight in the neural network and can estimate the first and second moments of the gradient to update the weights and biases [20].

$$g_t = \nabla_\theta f_t(\theta_t - 1) \quad (7)$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (8)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \quad (9)$$
$$\widehat{m}_t = \frac{m_t}{(1-\beta_1^t)} \quad (10)$$
$$\widehat{v}_t = \frac{v_t}{(1-\beta_2^t)} \quad (11)$$
$$\theta_t = \frac{\theta_{t-1} - (\alpha\, \widehat{m}_t)}{(\sqrt{\widehat{v}_t} + \epsilon)} \quad (12)$$

1.2.5 Normalization and Denormalization of Data

Normalization is a technique used in data processing to change the range of values into a range between 0 and 1. Normalization can help improve model performance by ensuring that all features have a similar scale. The general equation for data normalization is,

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (13)$$

Denormalization is a necessary step to revert the normalized data back to its original values after the prediction process. The goal of denormalization is to retrieve the actual values from the previously normalized prediction results [2]. The general equation for data denormalization is

$$Xi = (X(\max(X) - \min(X)) + \min(X)) \quad (14)$$

1.2.6 Mean absolute percentage error (MAPE)

MAPE stands for Mean Absolute Percentage Error, which is the average of the absolute differences between predicted values and actual values, expressed as a percentage of the actual values.

$$PE = \left(\frac{X_t - f_t}{X_t}\right) \times 100\% \quad (15)$$

MAPE can be calculated using Equation 16.

$$MAPE = \frac{\sum |PE|}{n} \quad (16)$$

1.3 Research methodology

This research is an applied study that implements the Long Short-Term Memory (LSTM) model and the Adaptive Moment Estimation (ADAM) method to predict gold prices. The data consists of daily gold closing prices, which serve as variable X, from January 2, 2014, to June 25, 2024, totaling 2,641 data points obtained from id.investing.com, and variable Y represents the predicted gold prices. The research procedure begins with data input that goes through the preprocessing stage, including handling missing values and normalization using min-max. The dataset is divided into 80% training data and 20% testing data, where the training data is used to train the LSTM model and the testing data is used to evaluate its performance. The LSTM model is built using the TensorFlow or Keras framework with an architecture that includes setting the number of LSTM layers and adjusting hyperparameters such as the number of units, batch size, epochs, and verbosity. Model training uses ADAM optimization, which adjusts the model's weights and biases through parameters such as learning rate (α), first moment exponential decay rate (β_1), and second moment (β_2), to minimize prediction error adaptively based on the gradient. After the predictions are generated, the predicted values are normalized back to their original scale to be correctly interpreted. Model evaluation is conducted using Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) loss function, where a MAPE below 10% indicates that the model has good prediction accuracy. The results of the gold price predictions are visualized with a graph comparing actual data and model predictions, to assess the extent to which the model can accurately represent the gold price pattern.

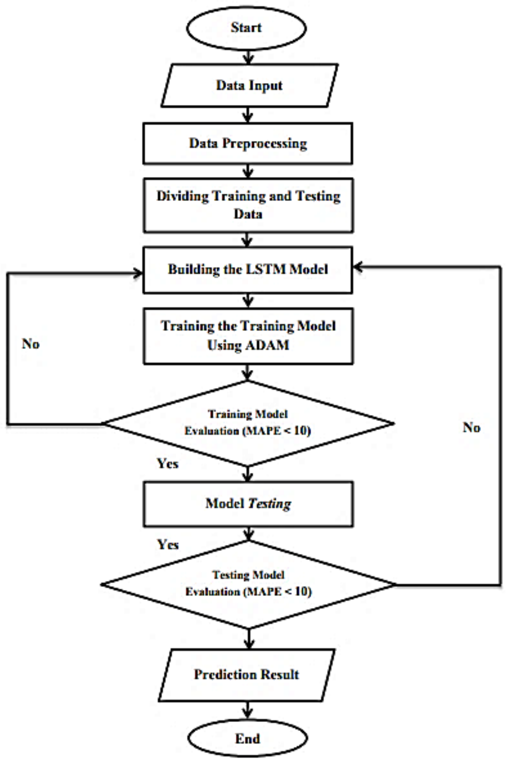

Figure 6. *Flowchart* LSTM dan ADAM

2. MAIN RESULTS

This research begins with data collection and then transforms it into a dataset. Below is the gold price data used in the study.

Table 1. Gold Price Data

No	Date	Gold Price (USD)
1	02/01/2014	1.225,20
2	03/01/2014	1.238,60
3	06/01/2014	1.238,00
4	07/01/2014	1.229,60
5	08/01/2014	1.225,50
.	.	.
.	.	.
2641	25/06/2024	2.344,50

Graphical visualization depicting the movement of gold prices. This graph provides a visual representation of the fluctuations in gold prices over time.

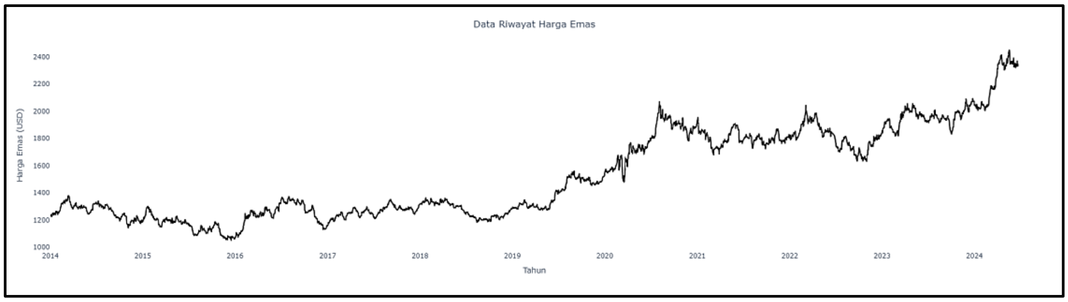

Figure 7. Gold Price graph

Based on the graph in **Figure 7**, it shows the trend of gold prices in USD from 2014 to 2024, indicating several periods of decline and increase. The overall trend in the last 10 years has been an increase. After the dataset is prepared, the next step is data preprocessing using Google Colaboratory. At this stage, a check is also performed to see if there are any duplicate data and missing values.

```
# Menghitung jumlah baris data duplikat
df.duplicated().sum()

0

# Menghitung jumlah total nilai data yang hilang (missing value)
df.isnull().sum().sum()

0
```

Figure 8. Output of Checking Duplicate Data and Missing values

Based on **Figure 8**, the data in this study does not have duplicate data and missing values so that the process can proceed to the data normalisation stage. The following are the results of normalising gold price data.

Table 2. Data Normalisation Results

Date	Gold Price	Normalisation Result
02/01/2014	1.225,20	0,12543753
03/01/2014	1.238,60	0,13500964
06/01/2014	1.238,00	0,13458104
.	.	.
.	.	.
.	.	.
25/06/2024	2.340,50	0,922137296

The next step is the formation of the LSTM model with ADAM optimization, starting with the initial stage, which is dividing the data into training data and testing data. This research uses a scenario of 80% for training data and 20% for testing data. Based on a total of 2,641 data points, 2,112 data points were used to train the model (training data) and 529 data points were used to test the model. (data testing). The visualization of the division between training data and testing data is shown in **Figure 9**.

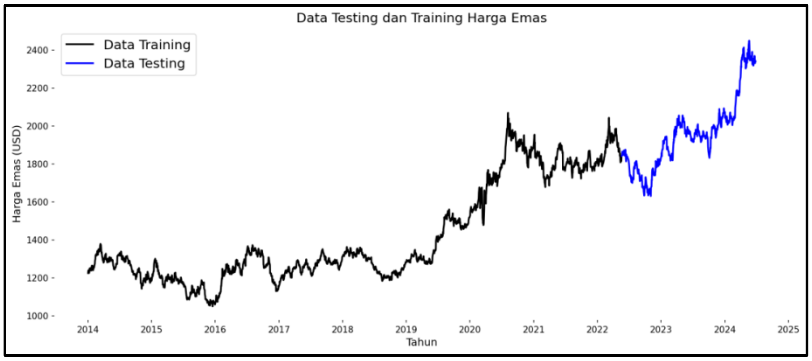

Figure 9. Training and Testing Data Graph

Based on the graph in **Figure 9**, it shows how the data is divided over time. The training data, depicted in black, includes gold price data from 2014 to the end of 2022. Meanwhile, the testing data, depicted in blue, represents data from the end of 2022 to 2024. Next, in creating the model, the determination of the input layer was carried out using the autocorrelation function or Autocorrelation Function (ACF). ACF is used to identify patterns and determine the relationship between values in the data series at different times. The ACF obtained had 96 lags, indicating a significant correlation between the current value and the 96 previous time periods. Thus, the LSTM model can be designed to include information from the 96 previous time periods as input to predict the gold price in the next period. Here are the input and output layers for the training and testing data.

Tabel 3. *Input* dan *Output Layer* Data *Training*

x_1	x_2	x_3	. . .	x_{96}	*Output*
0,125438	0,13501	0,134581	. . .	0,175013	0,170369
0,13501	0,134581	0,128581	. . .	0,170369	0,175298
.	.	.	. . .	.	.
.	.	.	. . .	.	.
0,54611	0,556468	0,53611	. . .	0,549539	0,547396
0,556468	0,53611	0,546468	. . .	0,547396	0,565469

Tabel 4. *Input* dan *Output Layer* Data *Testing*

x_1	x_2	x_3	. . .	x_{96}	*Output*
0,53611	0,546468	0,5539681	· · ·	0,565469	0,566112
0,546468	0,553968	0,5283235	· · ·	0,566112	0,570184
.	.	.	. . .	.	.
.	.	.	. . .	.	.
0,713122	0,70655	0,7024787	· · ·	0,915565	0,924923
0,70655	0,702479	0,6840489	· · ·	0,924923	0,922137

Based on **Tables 3** and **4**, the input and output layer data for the testing and training data are arranged in vector form. Next, we build an LSTM model with a multilayer structure, which means it has more than one hidden layer. This study uses three LSTM layers with a different number of units in each layer. The first layer has 128 units, the second layer has 64 units, and the third layer has 32 units. After determining the number of layers and units in the model, the next step is to initialize the weights and biases for the model optimization process using ADAM in each layer with random initialization. Here is one of the initial weights Wi of layer 1 before the ADAM optimization is performed.

```
Input Gate Weights (W_i) before optimization for LSTM Layer 1:
[[-1.15779713e-02 -7.82695264e-02  8.95451233e-02 -3.50880027e-02
   3.53599340e-03  1.80740654e-03 -8.45416859e-02  9.73156616e-02
   1.03844605e-01  2.34070197e-02 -5.37642911e-02  5.10971472e-02
  -1.01976633e-01  5.25374487e-02  2.32916400e-02  8.60603675e-02
  -1.97996870e-02 -1.01506196e-01  6.95674941e-02 -5.02969846e-02
  -3.57011035e-02 -9.36128199e-03  6.26458600e-02  6.71159998e-02
  -1.88985765e-02 -5.72279096e-02 -1.07976563e-01 -5.41062690e-02
  -1.70988217e-02 -9.83081833e-02  2.25550607e-02 -5.39943650e-02
   6.92948028e-02  1.04070760e-01  9.65333208e-02 -4.57136035e-02
   5.09569868e-02  7.82204345e-02 -9.89351794e-02  1.06806152e-01
  -4.13039550e-02 -6.63382113e-02 -1.67768300e-02 -1.46157295e-02
   3.33165899e-02  1.05261303e-01  9.56373885e-02 -6.85180202e-02
  -1.00194812e-02 -7.83969536e-02  8.25180486e-02 -2.42687911e-02
   7.72895589e-02 -5.23132496e-02  7.28958845e-03  4.15912941e-02
  -2.33921781e-02  2.86018923e-02  9.23837051e-02 -7.23246187e-02
  -1.03157379e-01 -8.05001333e-02  7.73541257e-02  2.35670730e-02
  -6.71888366e-02 -3.85387838e-02 -1.05409101e-01  6.11535087e-02
  -3.67044583e-02  3.31577137e-02 -2.00958177e-02 -6.61935583e-02
   3.17075849e-03  3.13559994e-02  1.07493870e-01  2.70374939e-02
   5.78102544e-02  2.24877670e-02 -3.58232483e-02  8.74903053e-03
   9.09130350e-02 -9.85505804e-02 -3.30921635e-02  4.16299179e-02
  -4.44095284e-02 -1.05356872e-02  8.11635926e-02 -1.01359844e-01
   7.77597204e-02  1.70090422e-02  5.82510903e-02 -1.04080461e-01
   7.85929933e-02  3.25048938e-02 -6.06526434e-02 -8.86652023e-02
   6.12880960e-02  4.94465232e-03 -6.29510134e-02  3.86315361e-02
  -1.40243769e-03  1.04850404e-01 -1.23668462e-02 -8.53395090e-02
  -6.78390265e-03  3.70331481e-02  6.38847053e-03 -6.32804334e-02
  -5.36702573e-04 -7.08436444e-02 -4.91614155e-02  1.05934463e-01
   9.96309444e-02 -2.60643438e-02 -5.03392443e-02 -8.56909230e-02
   5.65094277e-02  4.38776538e-02 -8.87420923e-02 -5.14686108e-05
  -7.48597234e-02  4.88130674e-02  6.30832091e-02  3.32012847e-02
   7.71498606e-02  5.50700948e-02 -1.53582469e-02  2.81153843e-02]]
```

Figure 10. Input Gate Weight Weight at Layer 1

The weight values in **Figure 10** are optimised using the ADAM method by considering the parameters used in ADAM optimisation, namely learning rate $(\alpha) = 0{,}001$, $(\beta_1) = 0{,}9$, $(\beta_2) = 0{,}999$, epsilon $(\epsilon) = 10^{-8}$ [4]. Here is one of the ADAM optimisation results on the weights Wi layer 1 in Figure 11.

```
Input Gate Weights (W_i) after optimization for LSTM Layer 1:
[[-0.01257797 -0.07926953  0.08854512 -0.034088    0.00253599  0.00080741
  -0.08354168  0.09631566  0.10484461  0.02240702 -0.05476429  0.05009715
  -0.10097663  0.05353745  0.02429164  0.08706037 -0.02079969 -0.10050619
   0.06856749 -0.05129698 -0.0367011  -0.01036128  0.06364586  0.066116
  -0.01789858 -0.05622791 -0.10697656 -0.05310627 -0.01809882 -0.09930819
   0.02155506 -0.05299437  0.0682948   0.10307076  0.09553332 -0.0467136
   0.05195699  0.07722043 -0.09793518  0.10780615 -0.04030396 -0.06733821
  -0.01577683 -0.01561573  0.03431659  0.10626131  0.09663739 -0.06751802
  -0.00901948 -0.07739695  0.08351805 -0.02326879  0.07828956 -0.05331325
   0.00628959  0.04259129 -0.02439218  0.02760189  0.09338371 -0.07132462
  -0.10415738 -0.07950013  0.07635412  0.02256707 -0.06818884 -0.03753879
  -0.1044091   0.06015351 -0.03570446  0.03415771 -0.02109582 -0.06519356
   0.00217076  0.030356    0.10649387  0.02803749  0.05881025  0.02148777
  -0.03682325  0.00774903  0.08991303 -0.09755058 -0.03209217  0.04062992
  -0.04540953 -0.01153569  0.08216359 -0.10035984  0.07675972  0.01800904
   0.05925109 -0.10308046  0.079593    0.0315049  -0.05965265 -0.0896652
   0.0602881   0.00394465 -0.06395102  0.03963153 -0.00040244  0.1038504
  -0.01136685 -0.08633951 -0.0057839   0.03803315  0.00538847 -0.06428044
   0.0004633  -0.07184365 -0.05016141  0.10693447  0.10063095 -0.02506434
  -0.05133924 -0.08469092  0.05750943  0.04487765 -0.08774209 -0.00105147
  -0.07385972  0.04781307  0.06408321  0.03420128  0.07614986  0.0540701
  -0.01635825  0.02911538]]
```

Figure 11. Gate Layer 1 Input Weight Update

The update of each weight and bias will continue throughout the training process. Before proceeding with the model training process, the next step is to design the LSTM model.

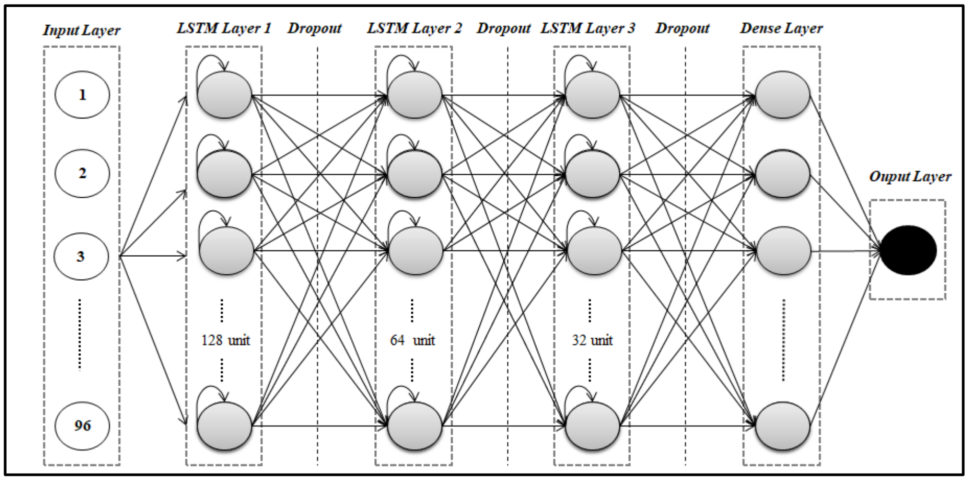

Figure 12. Model Structure

Figure 12 shows the structure of the LSTM network used to predict gold prices. The model has several layers that are interconnected and aim to capture patterns in the data. Starting from the input layer, the model receives 96 as input. After the input layer, the model enters the first of three LSTM layers. The first layer has 128 LSTM units capable of storing both long- and short-term information. Each unit in this layer is connected to units in the next and previous layers, creating a complex network capable of capturing temporal relationships in the data. After the first LSTM layer, a dropout layer is applied to prevent overfitting by randomly ignoring some units during training. The second and third layers of the LSTM have 64 units and 32 units, less than the first layer to capture important patterns in the data. As in the first layer, a dropout layer is applied. Next, the data then enters the dense or fully connected layer. This layer combines all the information that has been learned by the previous layers of the LSTM and prepares it to produce the final prediction. The output of the dense layer is then forwarded to the output layer which provides the final prediction of the gold price. The following details of the model structure are shown in Table 5.

Table 5. Details of the LSTM Model Structure with 3 Layers

Layer (Type)	*Output* Shape	Parameter
Input Layer	[(None, 96, 1)]	0
lstm_1 (LSTM)	(None, 96, 128)	66560
Dropout	(None, 96, 128)	0
lstm_2 (LSTM)	(None, 96, 64)	49408
Dropout	(None, 96, 64)	0
lstm_3 (LSTM)	(None, 32)	12416
Dropout	(None, 32)	0
Dense	(None, 32)	1056
Output	(None, 1)	33
Total params :	129473 (505.75 KB)	
Trainable params :	129473 (505.75 KB)	
Non-Trainable params :	0 (0.00 Byte)	

The model summary in **Table 5** shows that this model has a total of 129,473 adjustable parameters. (trainable params). The next step is to train the model using the processed data. This training process is carried out by running 100 epochs, using a batch size of 64, and setting verbose to 1. At the 100th epoch, the final loss obtained was 0.000336. A small loss value indicates that the model has learned well from the training data and its prediction error is very small. Thus, the evaluation results obtained are a loss value of 0.00025 and a MAPE value of 0.0108. Here are the results comparing actual gold prices and predicted gold prices in **Table 6**.

Table 6. Comparison of Actual Results and Predicted Gold Prices

Actual Gold Price (USD)	Predicted Gold Price (USD)
1288,1	1300,868
1295	1299,213
1291,7	1300,090
1265,5	1301,243
.	.
.	.
.	.
2344,4	2352,976
2340,5	2350,238

The comparison results between the predicted gold prices and the actual gold prices indicate that the model is capable of providing gold price predictions with high accuracy. Additionally, the model's performance is approximately 98.92% in predicting gold prices. The model's performance is illustrated in **Figure 13**.

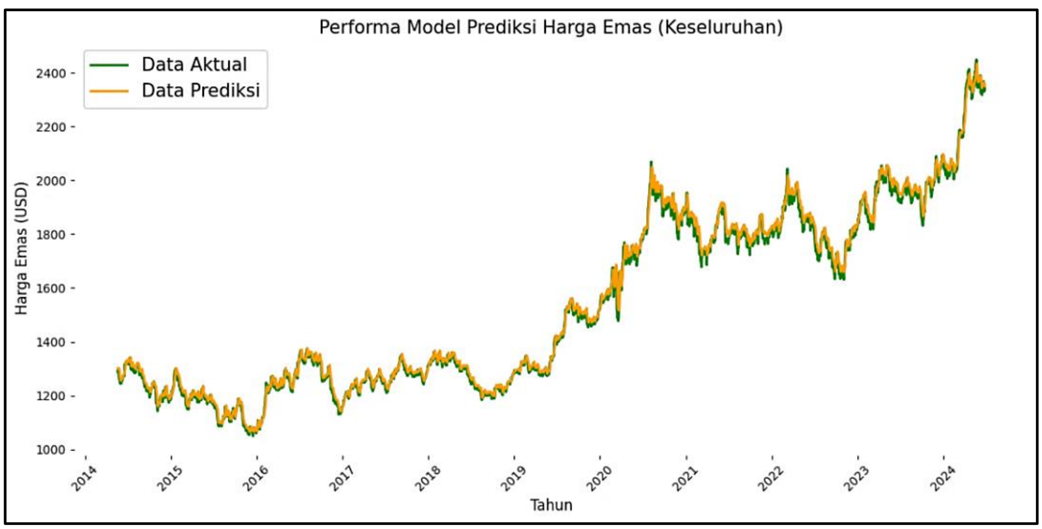

Figure 13. Gold Price Prediction Model Performance

Based on **Figure 13** displayed, the performance graph of the gold price prediction model shows that the predicted data (orange line) follows the trend of the actual data (green line) well. Overall, these results indicate that the approach used is very effective in predicting gold prices. This graph also reflects that the model successfully captures gold price fluctuations over time, with high accuracy in matching actual data, making it a reference for future gold price analysis. Next, predictions were made to evaluate the model's performance by forecasting the gold price for the next 30 days. Below are the predicted gold prices for the next 30 days using LSTM and ADAM.

Table 7. Predicted Gold Prices for the Next 30 Days

Date	Predicted Gold Price (USD)
26/06/2024	2352,473
27/06/2024	2359,121
28/06/2024	2366,18
.	.
.	.
.	.
05/08/2024	2443,27
06/08/2024	2445,621

Based on **Table 7**, it shows the predicted gold prices for the next 30 days, from June 26, 2024, to August 6, 2024. These values provide an overview of the trend in gold prices over the next 30 days. The visualization of the 30-day gold price prediction is shown in **Figure 14**.

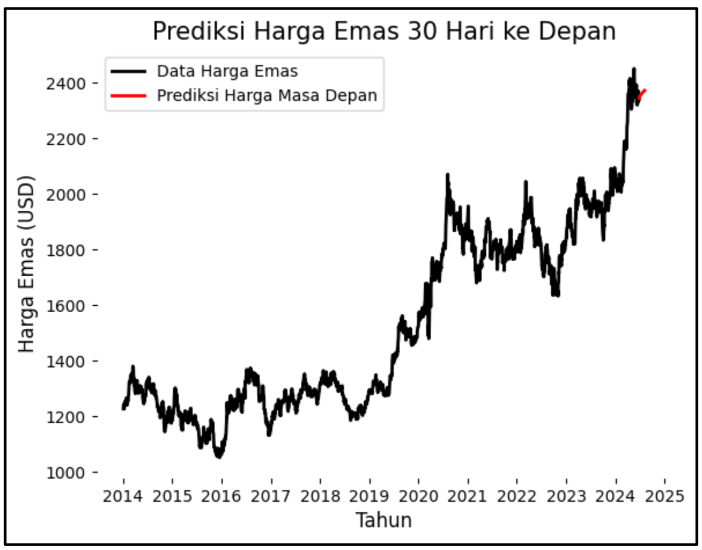

Figure 14. Gold Price Prediction Chart for the Next 30 Days

The visualization of the gold price prediction for the next 30 days is shown in **Figure 14**, which displays two main lines. The black line represents historical gold price data, while the red line shows the predicted gold price for the next 30 days. This graph shows that the model's predictions (red line) follow the upward trend observed in the historical data (black line), reflecting a consistent increase in gold prices. Based on the interpretation of the table and the gold price prediction graph for the next 30 days, it is evident that the predictions indicate a consistent upward trend in gold prices. The data in Table 7 displays the daily gold prices in USD from June 26, 2024, to August 6, 2024, with predictions peaking on August 6, 2024, at 2,445.621 USD or approximately Rp1,275,000, excluding taxes. The graph supports this prediction by showing a red line representing the expected upward trend in gold prices. The performance of the LSTM model used to forecast gold prices is able to capture the historical trends of gold prices well, as well as provide predictions with high accuracy. However, it is important to note that the price estimates in this forecast are still predictive in nature. Although the model has high accuracy, the actual prices in the future can be influenced by internal and external factors that the model cannot predict.

3. DISCUSSION

This study has several key differences compared to previous research, particularly in terms of data coverage, model architecture, variable selection, as well as evaluation and forecasting approaches for gold prices. Compared to the studies by Owen et al. [11] and Jamaludin and Toto [5], this study uses a larger and more recent dataset of gold prices, consisting of 2,641 data points from January 1 to June 25, 2024. Meanwhile, [11] used data from 2011 to 2018 with a total of 1,717 gold price data points, while [5] used data over five years, from November 16, 2017, to November 15, 2022, with a total of 1,259 data points.

There are also significant differences in terms of model architecture. [11] used only one layer in their model, while [5] used two layers without applying dropout. In contrast, this study developed a model with three layers and implemented dropout to prevent overfitting, thereby improving prediction accuracy. Other differences are evident in variable selection and input choice. The study [11] only considered the adjusted closing price, whereas this study uses the closing price. Additionally, both [11] and [5] did not use the autocorrelation function (ACF) in input selection, resulting in random input choices, while this study employs ACF to ensure a more systematic and structured input selection. In terms of model evaluation, [11] did not use metrics such as MAPE, RMSE, or MAE to compare prediction results with actual prices, while [5] used only RMSE as the primary accuracy measure. On the other hand, this study uses MAPE as the main metric, resulting in an error rate of 1.08% and an accuracy rate of 98.92%, providing a clearer representation of the difference between predicted and actual prices.

Furthermore, this study also forecasts gold prices for the next 30 days, from June 26 to August 6, 2024, to evaluate the model’s performance in predicting gold prices. This approach differs from [11], which did not include future price forecasting, and also differs from [5], which focused more on predicting gold prices as an investment strategy to anticipate a global recession. This study also emphasizes model optimization using the Adam algorithm to improve prediction accuracy, an approach not taken in previous studies. With these various advantages, this study provides a more comprehensive contribution to gold price prediction with a more accurate, structured, and optimal model compared to previous research.

4. CONCLUSION

Based on the analysis and discussion obtained, this study concludes that the Long Short Term Memory (LSTM) model optimized with the Adaptive Moment Estimation (ADAM) method can be an effective approach in predicting gold prices. The LSTM model used consists of three layers with a different number of units in each layer and uses 100 epochs. At the 100th epoch, the final loss value obtained is 0.000336. The performance of this model shows a low error rate, with a Mean Absolute Percentage Error (MAPE) value of around 0.0108 or 1.08% and a loss value of 0.00025. The model's performance accuracy reaches approximately 98.92%, indicating that this model is capable of providing gold price predictions with high accuracy. In addition, this model can be used to predict gold prices for the next 30 days in the form of estimates that have not yet been affected by internal or external factors that cannot be predicted by the model. The structure of the LSTM model used can be seen in Figure 7, while the details of the model structure are presented in Table 5.

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