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Original Research

Website-Based Gold Price Movement Prediction System Using the Long Short-Term Memory (LSTM) Method

Farlin Nurjananti

Departement of Computer Science, University of Jember

Abstract

Gold price prediction is an important aspect in supporting investment decision making amid dynamic market fluctuations. This research aims to find the best hyperparameter combination in building a gold price prediction model using the Long Short-Term Memory (LSTM) method through the Grid Search and Bayesian Optimization tuning approaches. The data used is historical gold price data from Yahoo Finance for the last 10 years (2015-2025) which includes date attributes, opening price, closing price, highest price, lowest price, and trading volume. This study was conducted with two data divisions, namely the 70%:30% and 80:20 ratios, to evaluate the performance of the model to find optimal results. The hyperparameter tuning process includes finding optimal values for epoch, batch size, learning rate, number of neurons, dropout, and optimizer parameters. Model evaluation was conducted using MAE, RMSE, and MAPE metrics and the best results were obtained from tuning using Grid Search at a split ratio of 70%:30% with MAE values of 19.5470, RMSE of 26.5331, and MAPE of 0.93%. The system automatically updates the daily model by using web scraping technique and utilizing Python scheduler. The system was developed based on a website using the Flask framework and has an interactive display consisting of dashboard, historical, and prediction pages. The test results show that the system runs according to its function and the LSTM model is able to predict gold prices with good accuracy. This research shows that proper hyperparameter tuning can significantly improve the performance of the prediction model.

Keywords

Gold Price Prediction, Long Short-Term Memory (LSTM), Hyperparameter Tuning, Web-based Prediction System, Time Series Forecasting.

*Corresponding author: **Farlin Nurjananti**

Email addresses:
212410102041@unej.ac.id (M. Fathony Ramdhan)

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1. Introduction

Fluctuations in gold prices are one aspect that reflects the volatility of the commodity market in an unstable global eco- nomic situation. Based on data from the World Gold Council, in the last 10 years, gold price data has experienced quite high fluctuations [1]. Gold is considered a "safe haven" asset, where its value tends to be stable or even increase when the financial market increases [2]. The demand for gold is increasing every year because many people know that gold can be used as a safe haven asset. The increasing demand not only shows that gold is a safe asset, but also raises investor concerns about market volatility because it spreads globally. In gold trading, prices often change based on historical patterns that include closing prices (close), opening prices (open), highest prices (high), lowest prices (low), and volume. With these various factors, gold price movements become complex and difficult to predict conventionally, so that a prediction method based on historical data is needed to help investors understand gold price movement patterns in the future.

Many people are interested in investing in gold, not only because the price is quite affordable but also because investing in gold is very easy to do and flexible [3]. Therefore, gold price predictions are important to help investors understand price movement patterns and make more appropriate investment decisions in the future. Without predictions, investors only rely on historical data without considering current trends which leads to less-than-optimal investment decisions.

The field of artificial intelligence and machine learning methods has begun to be applied to solve problems in market analysis. Research by Hu et al. (2021) shows that the deep learning approach has been shown to provide higher accuracy in predicting financial conditions, including gold prices. One

type of deep learning that is classified is Long Short-Term Memory (LSTM). LSTM is part of an artificial neural network that has the ability to process long-term information, lear complex patterns, handle sequential data and multivariate data [4]. This makes LSTM suitable for predicting gold prices that are influenced by historical factors and current conditions. Research conducted by Nurhambali et al. (2024) compared the LSTM and ARIMA methods in gold price prediction and re-search by Yurtsever (2021) focused on the comparison between the LSTM, Bi-LSTM, and GRU methods in gold price prediction where the results of the study showed that LSTM has better prediction performance than other methods based on an evaluation of prediction accuracy. Based on this back-ground, a study entitled "Website-Based Gold Price Movement Prediction System Using the Long Short-Term Memory (LSTM) Method" is proposed to design a gold price movement prediction system using the LSTM method. In this study, the hyperparameter tuning process was carried out using the grid search and Bayesian optimizer methods to find the best combination of hyperparameter values that can produce the most accurate model performance. The evaluation model we carried out using the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics to analyze errors in assessing the performance of the prediction model. This system was created to meet market needs as a tool that can provide accurate prediction results in dealing with unstated gold price changes, help investors understand market trends, and make better investment decisions.

Previous research is used as a reference and comparison. Based on previous research that has been conducted, the LSTM method is effective in predicting gold price movements because of its ability to capture complex patterns in time series data so that it can produce accurate predictions for the short to medium term. LSTM can also adapt to dynamic price change patterns so that it can provide accurate predictions even though there are significant market fluctuations.

The accuracy of the LSTM model prediction is influenced by the selection of the right hyperparameters. With the righ combination of hyperparameters such as epoch, optimizer, batch size, learning rate, neurons, and dropout, the LSTM model can produce optimal accuracy and increase the accuracy of model predictions in the short to medium term wit out overfitting or underfitting. Model evaluation uses the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics to ensure that the model can predict gold price movements with a lower error rate than other methods.

2. Research Method

The research begins with the data collection stage taken from Yahoo Finance sources. The data taken are the closing price (close), opening price (open), highest price (high), lowest price (low), date (date), and volume. The next stage is data preprocessing which is data cleaning to check for null data and data normalization using the MinMax scaler technique. After that, the data is divided into two parts, namely training data and test data with a variation of the division ratio of 70%: 30% and 80%: 20%. The next stage is the construction and training of the model where LSTM is designed and implemented using a variation of hyperparameters, namely epoch, neuron, learning rate, optimizer, batch size, and dropout. After the model is built, a model evaluation is carried out using the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics to assess the performance of the model in predicting gold prices based on test data. The next stage is storage, where the model that has been drilled and evaluated is stored for

*Corresponding author: **Farlin Nurjananti**

Email addresses:
212410102041@unej.ac.id (M. Fathony Ramdhan)

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reuse. The next stage of system development is integrated into a website-based system that displays the results of predictions and analysis of the latest gold price data. Then a system evaluation is carried out to determine whether the system is running well.

2. 1 Data Collection

The data used in this study is secondary data in the form of time series. The dataset test consists of historical gold price data for the last 10 years from 2015 to 2025, with a focus on predicting gold price movements for the next two months using daily intervals. Based on previous research by Beryl Na-gata et al. (2024) that monthly predictions are better than others because predictions with a time span that is too short such as weekly have high volatility so that predictions are less accurate and annual predictions have a long-time span so that the accuracy model can decrease. Gold price data is taken from the Yahoo Finance financial API (finance.yahoo.com/) with the data collected in the form of historical price information, namely closing price (close), opening price (open), highest price (high), lowest price (low), date (date), and volume.

2. 2 Data Preprocessing

The data preprocessing stage involves data cleansing and normalization. Data cleansing aims to improve data quality by removing duplication, handling missing data, handling outliers, and ensuring data format consistency. Furthermore, data normalization is carried out using the MinMax scaler method, which functions to equalize the scale of all features in the dataset by changing the data values into a smaller range, namely between 0 and 1. The main purpose of data normalization is to eliminate scale differences between various features in the dataset and determine the minimum and maximum values of each feature or variable in the dataset to be normalized. This value is used as a reference for changing data values into the specified range.

2. 3 Data Division

The processed data is then separated into training data and testing data. Training data is used to train the LSTM model in recognizing patterns and trends in gold price move- ments based on historical data. Meanwhile, the test data serves to evaluate the performance of the model after the training stage. Data division is carried out in various ways to explore the effect of the proportion of training data on model accuracy. The variations in data division used are shown in Table 3.1 [5].

***Table 1.* Data Distribution variations**

Training Data	Testing Data
70%	30%
80%	20%

2. 4 Model Development and Training

The next stage after the data has been successfully separated into training data and testing data is the development and training of the LSTM model to predict gold price movements. This training data is used to train the model to recognize pat- terns and trends in gold price movements. Furthermore, a model is formed with a combination of hyperparameters where to optimize model performance with the hyperparameters used are epoch, batch size, learning rate, neurons, dropout, and optimizer. Determining the right hyperparameters is very important because it affects the model's ability to understand complex data patterns. The model is then trained using previously processed training data to predict gold prices based on historical patterns. To get the best performance, hyperparameter tuning is carried out using two approaches, namely grid search and Bayesian optimization. After the optimal combina- tion is found, the final model is tested using test data to con- duct a comprehensive performance evaluation. Model evalua- tion is carried out by calculating the MAE, RMSE, and MAPE metrics. The results of this evaluation are used to ensure that the model has good and reliable predictive capabilities before being implemented further.

2. 5 Model Evaluation

The model is evaluated using previously separated test data. Model evaluation is done by calculating the Mean Abso- lute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) values to determine how accurate the model is in making predictions.

2. 6 Model Evaluation

The next stage is to save the trained model. After the LSTM model has been trained and evaluated, the model with the best performance based on the evaluation metrics will be stored for use in the next prediction process. This model storage is done so that the model does not need to be retrained from the beginning every time it is used, saving time and computing resources.

2. 7 Prediction

The gold price prediction process for the next 2 months is carried out using the LSTM model that has been trained with the best hyperparameters that have been obtained previously. The prediction process is carried out using the latest data that has gone through the previous preprocessing and normalization stages. The model utilizes the latest data that has gone through a preprocessing stage, such as eliminating missing values, converting date formats, and normalizing values to be on a uniform scale. Predictions are made using a time series approach so that the model can identify historical patterns and continue them to predict future prices sequentially.

2. 8 System Development and Testing

The system development stage is the implementation of the LSTM model into a web-based application or system that will be used to predict gold prices. The system will visualize the results of the gold price prediction for the next 2 months using the previously built model.

2. 9 Daily Model Updates and Retraining

The last stage is daily model updates and retraining, where in order for the model to remain relevant to the latest market trends, model updates are carried out through daily re- training. The system will take the latest gold price data from Yahoo Finance sources and add it to the existing dataset.

3. Results and Analysis

3. 1 Data Collection

The data used is time series data of gold prices taken from Yahoo Finance sources. The data consists of historical gold price data for the last 10 years from 2015 - 2025 with daily intervals. Yahoo Finance is a company that contains in- formation on the global economy and finance that presents the latest gold price data so that the data obtained is valid data. Gold price data includes closing price (close), opening price (open), highest price (high), lowest price (low), date (date), and volume. The gold price data attribute table is shown in Table 2.

Table 2. Gold Price Data

Date	Open	High	Low	Close	Volume
29/05/15	1189.04.00	193.03.00	1185.06.00	1187.08.00	4748
01/06/15	1188.03.00	204.00.00	1184.03.0	1190.05.00	1236
02/06/15	1194.00.00	194.03.00	1186.00.0	1189.00.00	1003
03/06/15	1184.06.00	193.09.00	1179.00.0	1193.09.00	630
04/06/15	1174.09.00	185.03.00	1173.00.0	1184.09.00	447
…	…	…	…	…	…
21/05/25	3309.03.00	317.05.00	3290.01.0	3293.03.00	979
22/05/25	3292.03.00	328.00.00	3282.06.0	3327.03.00	1210
23/05/25	3363.06.00	363.06.00	3323.05.0	3328.00.00	1210

Table 2 shows several rows of data from gold prices. The table consists of columns for date, opening price, highest price, lowest price, closing price, and volume. The four values, namely opening price, highest price, lowest price, and closing price, have small differences in value, while volume is the number of gold units traded in market activity. The amount of data from that period is 2511 rows of gold price data.

3. 2 Data Preprocessing

The collected gold price data will go through a data preprocessing stage which includes the data cleaning and data normalization process. This aims to clean the data and adjust it so that the data matches the desired format in building the LSTM model.

3.2. 1 Data Cleaning

The data preprocessing stage includes the process of checking for missing values where the data is checked to find missing or null values. This process is important because incomplete data can affect the performance of the prediction model and produce inaccurate results. The data is checked to identify attributes that do not have complete values and if there are missing or null values, they are resolved by the data deletion method. Furthermore, the date format is standardized so that all data rows have a consistent and sequential time format because the LSTM model is sensitive to the order of data in the time series. This process ensures that the dataset used in the model is clean. The cleaned gold price data is shown in Table 3.

Table 3. Gold Price Data After Data Cleaning

Date	Close	High	Low	Open	Volume
29/05/15	1,189.4	1,193.3	1,185.6	1,187.8	4,748
01/06/15	1,188.3	1,204.0	1,184.3	1,190.5	1,236
02/06/15	1,194.0	1,194.3	1,186.0	1,189.0	1,003
03/06/15	1,184.6	1,193.9	1,179.0	1,193.9	630
…	…	…	…	…	…
21/05/25	3,309.3	3,317.5	3,290.1	3,293.3	979
22/05/25	3,292.3	3,328.0	3,282.6	3,327.3	1,21
23/05/25	3,363.6	3,363.6	3,323.5	3,328.0	1,21

3.2. 2 Normalization

The next process in the data preprocessing stage is data normalization using the MinMax scaler so that the values are in the range of 0 and 1. This aims to improve the performance of the prediction model that is sensitive to differences in data scale. The purpose of this process is that with a uniform data scale, the model can optimally utilize attributes to produce more accurate predictions and help speed up the training process by keeping values within a limited range. The gold price data normalization table is shown in Table 4.

Table 4. Gold Price Data Normalization

Date	Open	High	Low	Close	Volume
9/05/15	0,54791667	0,57083333	0,5548611	0,5493056	6,20625
1/06/15	0,54166667	0,53194444	0,5611111	0,5722222	5,036111
2/06/15	0,56111111	0,52986111	0,5333333	0,5347222	3,163194
3/06/15	0,525	0,49513889	0,5090278	0,4958333	2,244444
…	…	…	…	…	…

1/05/25	6,55694444	6,63680556	6,6076389	6,6402778	4,669444
2/05/25	6,73819444	6,79375	6,7465278	6,7673611	6,095833
3/05/25	6,83888889	6,83611111	6,7951389	6,7402778	4,940278

3. 3 Data Division

At this stage, the normalized data is divided into training data and test data. The goal is to ensure that the model has enough data to train the model and its performance can be evaluated. Training data is used to train the model while test data is used to evaluate model performance using variations in data division, namely the ratio of 70%:30% and 80%:20% to find the best configuration that provides balance for model accuracy.

3. 4 Data Transformation

The data is then converted into time series sequences with time_step = 30. The model uses the previous 30 days of data to predict the price of gold on the 31st day. Data transformation isdone by dividing the dataset into small pieces with a length of 30 days as input (x) and the price of gold on the 31st day as output (y). With that, a set of sequence data is produced which is used in training the LSTM model which aims to allow the model to recognize gold price movement patterns sequentially and learn short-term relationships between times more effectively.

3. 5 Model Development and Training

The model is built using the TensorFlow and Keras libraries. The model is trained using training data to predict future gold prices. To optimize model performance, the hyperparameters used in this model are variations of epoch, batch size, learning rate, neurons, dropout, and optimizer. Hyperparameter tuning is done using the grid search and Bayesian optimization methods to find the combination of hyperparameters that produce the best model performance.

Hyperparameter tuning grid search performs a system- attic search by trying combinations of all specified hyperpa- rameter values, while Bayesian optimization finds the optimal hyperparameter combination with fewer trials. Then, iterations are performed over all parameter combinations using Parameter Grid. At each iteration, an LSTM model is built based on the hyperparameters being tested, then trained using the training data. After training is complete, the model is used to make predictions on the test data.

The tuning process using Bayesian optimization begins by determining the objective function that represents the LSTM model training process based on the tested hyper parameter combinations. Furthermore, a hyperparameter search space is determined that covers the range of values of each hyperparameter. Bayesian optimization works iteratively by utilizing a probabilistic approach to predict the best hyper parameter combination based on previous evaluation results. After the optimization process is complete, the best model from Bayesian optimization is compared with the grid search results to select the model with the best performance.

3. 6 Model Development and Training

The LSTM model that has been built is evaluated. The model predicts the value of the testing data based on the input data that the model has learned. Evaluation of the performance of the LSTM model in predicting gold price movements using MAE, RMSE, and MAPE metrics. In addition, during the training process, the LSTM model uses the Mean Squared Error (MSE) loss function to measure how much error the model produces so that the model can learn better in predicting gold price patterns. To determine the performance of the model during training, a visualization of the loss function graph is carried out which shows changes in training loss and validation loss as shown in Figure 1. The graph provides an overview of how well the model adapts to the training data.

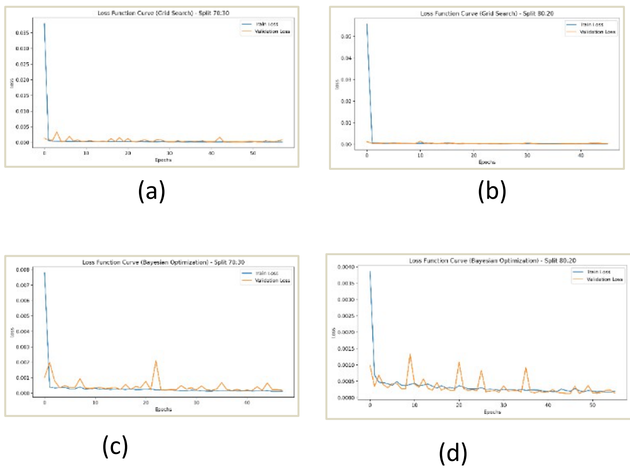


Figure 1. Loss Function Graph (a) Grid Search 70:30, (b) Grid Search 80:20, (c) Bayesian 70:30, (d) Bayesian 80:20

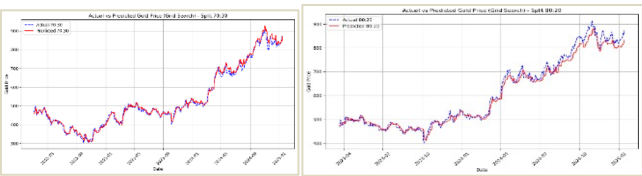
The best hyperparameter value was obtained with an MAE value of 19.5470, an RMSE value of 26.5331, and a MAPE value of 0.93% using grid search hyperparameter tuning with a data split of 70%:30%. Table 5 will show the results of the formation of the LSTM model for each hyperparameter from each tuning and data split. After obtaining the best hyperparameter, the values are stored for use in retraining the model in the future.

The LSTM model that was built showed quite good performance in predicting gold price movements. The relatively low MAE value indicates that the average absolute error between the actual value and the predicted value is relatively small, which means that the model is able to capture historical data patterns with sufficient precision. Meanwhile, the RMSE value which is still within reasonable limits indicates that the model is not too sensitive to large errors (outliers) and still provides accurate prediction results. The MAPE value obtained is 0.93% indicating that the prediction error against the actual value is below 1%, which reflects a very high level of model accuracy. The use and analysis of these metrics provide a different evaluation perspective so that a comprehensive picture of the accuracy, stability, and reliability of the model is obtained in various data conditions.

Figure 2 shows a comparison graph of actual and predicted prices from tuning hyperparameter grid search and Figure 3 shows a comparison graph of actual and predicted prices from tuning hyperparameter Bayesian optimization. The graph shows that the LSTM model is able to capture the gold price movement pattern quite well. Although there is a deviation or difference between the predicted results and the actual price in a certain period, the model can follow the overall trend of the actual value well. This shows that the model does not only rely on previous data, but also learns from sequence data to understand market dynamics. In addition, the graph also shows that the results of hyperparameter tuning have an impact on prediction accuracy. The tuning models with grid search and Bayesian optimization both show a tendency to follow the actual pattern, but have small differences in terms of the amplitude of price movements, namely how close the predicted value is to the actual value.

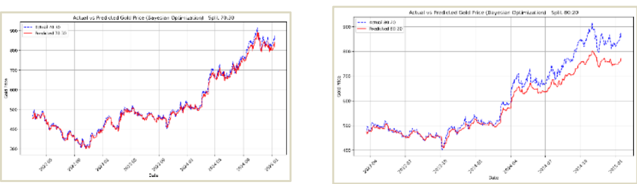
***Table 5.* Results of LSTM Model Formation**

Hyperparameter Tuning	***Grid Search***		***Bayesian Optimization***	
Split Data	70%:30%	80%:20%	70%:30%	80%:20%
Epoch	100	50	93	64
Batch Size	32	32	36	51
Neurons	100	100	85	72
Dropout	0,1	0,1	0,1	0,1
Learning Rate	0,01	0,01	0,006	0,004
Optimizer	Adam	Adam	Adam	Adam
MAE	195.470	262.328	220.284	614.271
RMSE	265.331	349.233	286.674	851.107
MAPE	0.93%	1.13%	1.03%	2.53%



(a) (b)

***Figure 2.* Comparison Graph of Actual Price and Grid Search Prediction (a) Split Data 70:30, (b) Split Data 80:20**



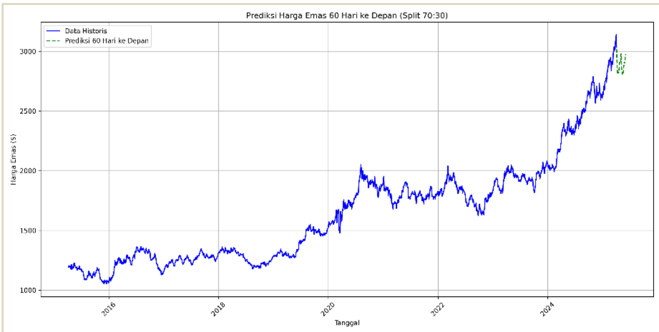
(a) (b)

***Figure 3.* Comparison Graph of Actual Price and Bayesian Optimization Prediction (a) Split Data 70:30, (b) Split Data 80:20**

3. 7 Prediction

The next stage is to forecast new data from gold prices. Figure 4 shows the prediction results for the gold price for the next 2 months shown in the form of a green line, while historical gold price data is shown in the blue line. From historical data, it can be seen that the gold price has experienced a significant upward trend since 2015, with an increasingly sharp spike in the period from 2019 to early 2025. The gold price prediction for the next 2 months shows fluctuations that are still in an upward trend. This shows that the gold price will most likely continue to increase, although it will continue to experience ups and downs in the short term.

***Figure 4.* 2-Month Forecast Graph**



3. 8 System Development and Testing

The completed model is implemented into a website- based system. The stages in system development are planning, implementing the model into the system, and developing and testing the system. The trained model is saved in the .h5 file format. This format is saved with the hyperparameters and weights that have been trained so that they can be reloaded without having to retrain from the beginning. Automatic reprocessing every day at 01.00 in the morning using a schedule on the server. Gold price data is obtained every day and added to the existing dataset and then the model is retrained using a combination of historical data and the latest data which includes processes including taking the latest gold price data from Yahoo Finance sources, merging new data with historical data, re-preprocessing to ensure the data is ready to use, retraining the model with the optimal hyperparameters that have been done previously, and saving the latest model for use in further predictions.

3. 9 Website Appearance Development

The website-based gold price prediction system is designed to provide an efficient user experience in monitoring gold price movements. System development uses Flask to integrate the backend and frontend. There are several pages on the website that was built, namely the dashboard page, historical gold price data, and gold price predictions. Figure 5 is a dashboard page display, Figure 6 is a historical page display, and Figure 7 is a prediction page display.

On the dashboard page, users can see an interactive graph of gold price movements over a fairly long historical period. The historical page displays a table of historical gold price data for the last 10 years. The prediction page displays the results of gold price predictions for the next 60 days using a previously trained LSTM model in graphical form.

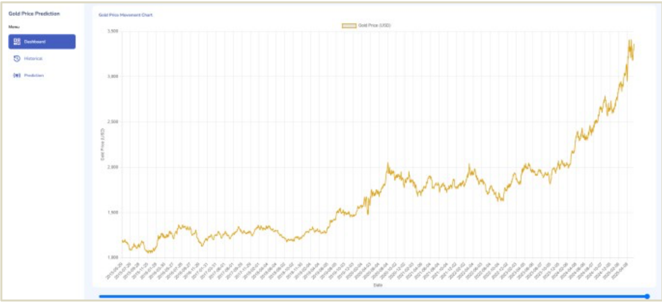


Figure 5. Dashboard Page Display

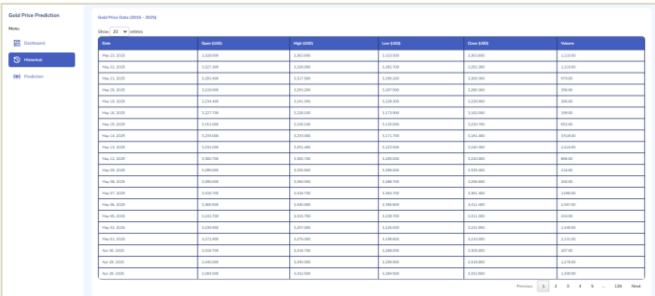


Figure 6. Historical Page Display

Figure 7. Prediction Page Display

System evaluation uses black box testing to ensure that all features run according to their functions without paying attention to the implementation of the code in it which focuses on testing the input and output of each system function. This testing is done by testing various scenarios (input and output) to see if the system provides the expected results.

The results of black box testing show that all features work correctly and as expected so that they meet user needs in predicting gold price movements. No errors were found in the system output during testing. This proves that the website- based gold price movement prediction system has met the functional requirements designed and can provide supporting information to users.

3. 10 Daily Model Updates and Retraining

The model update process is run automatically every day at 01.00 in the morning when the market closes and the latest data from the previous day is available. The model retraining process is carried out using the best combination of hyperparameters that have been previously obtained through the tuning process. The model is then retrained using the latest data to adjust the hyperparameter values to the latest patterns that appear in gold prices and the trained model is saved and used for predictions the next day.

The gold price prediction model update system is designed to run automatically every day using integrated scheduling using the python schedule module. The update process is scheduled to take place at 01.00 in the morning to ensure that the model always uses the latest data in making predictions. In each update cycle, the system will take the latest gold price data from the yahoo finance source, then retrain the model with the updated data. The system will update the prediction model independently every day without manual intervention so that it can capture the latest market trend changes and maintain optimal model accuracy.

4. Conclusion

The results of the development of a website-based gold price movement prediction system using the Long Short-Term Memory (LSTM) method show that the model has been successfully implemented into the system using the python programming language microframework, namely flask. This system can provide gold price predictions for the next 60 days and is visualized through an interactive web display consisting of dashboard, historical, and prediction pages. The LSTM model is built using daily automatic updates taking data from the yahoo finance financial API and python schedule. The model retraining process is carried out every 01.00 in the morning to ensure that the model remains adaptive to the latest gold price trends and can be used sustainably.

System testing using the black box testing method shows that all features function properly, display tables and graphs responsively and support gold price analysis effectively. The hyperparameter tuning process using grid search and Bayesian optimization is carried out to find the best combination of hyperparameters. The best hyperparameter combination was obtained from tuning grid search, namely epoch 100, batch size 32, dropout 0.1, neuron 100, learning rate 0.01, and adam optimizer with 70%:30% data split. From the tests carried out, the best hyperparameter values were obtained with an MAE value of 19.5470, an RMSE value of 26.5331, and a MAPE value of 0.93%. These values indicate that the model has a low error rate and high accuracy, so it can be used to predict gold price movements accurately.

Based on the results of the research that has been carried out, there are several suggestions that can be given for further development, including the system can be improved by adding external variables such as exchange rates, inflation, or world oil prices to see the influence of macroeconomic factors on gold price predictions so that the model becomes more com- plex. In addition, the prediction model can be developed using a hybrid or ensemble approach by combining the LSTM method with other algorithms such as GRU, ARIMA, or Random Forest to improve prediction accuracy and minimize errors.

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