Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

Comparative Performance Analysis of Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) Algorithms in Gold Price Prediction

Siti Lailiyah[1,*], Yunita[2], Hanifah Ekawati[1]

[1] Program Studi Teknik Informatika, STMIK Widya Cipta Dharma, Samarinda, Indonesia
[2] Program Studidi Bisnis Digital, STMIK Widya Cipta Dharma, Samarinda, Indonesia
Email: [1,*]lail.59a@gmail.com, [2]yunita@wicida.ac.id, [3]hanifah@wicida.ac.id
Corresponding Author Email: lail.59a@gmail.com
Submitted: **27/10/2025**; Accepted: **31/12/2025**; Published**: 31/12/2025**

Abstract–Gold is one of the most important investment commodities in the global financial system, widely recognized for its role as a safe-haven asset and its ability to preserve value during periods of inflation, economic instability, and geopolitical uncertainty. Despite its relative stability compared to other financial instruments, gold prices exhibit significant volatility driven by various macroeconomic factors, including exchange rate movements, inflation dynamics, global monetary policy decisions, and market sentiment. As a result, accurate gold price prediction remains a critical challenge for investors, financial analysts, and policymakers. This study aims to conduct a comparative performance analysis of two machine learning algorithms, namely Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), in predicting gold prices represented by the XAU/USD currency pair. The research utilizes daily historical gold price data from 2004 to 2025 obtained from the Kaggle platform. The dataset includes key financial attributes such as Open, High, Low, Close prices, and trading Volume. Data preprocessing steps involve data cleaning, chronological sorting, handling missing values through linear interpolation, feature selection, and normalization using the Min-Max scaling technique. The dataset is then divided sequentially into training and testing sets with an 80:20 ratio to preserve temporal dependencies. The LSTM model is designed to capture long-term temporal patterns using the closing price as a time series input, while the SVR model leverages multiple input features to model non-linear relationships through kernel-based regression. Model performance is evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The experimental results demonstrate that the LSTM model outperforms the SVR model across all evaluation metrics. The LSTM achieved an RMSE of 0.0082, an MAE of 0.0060, and an R^2 value of 0.9969, indicating a very high level of predictive accuracy and strong generalization capability. In contrast, the SVR model recorded an RMSE of 0.0289, an MAE of 0.0143, and an R^2 of 0.9611, reflecting lower precision, particularly during periods of high price volatility. These findings confirm that LSTM is more effective in capturing complex temporal dependencies and non-linear dynamics inherent in gold price time series data. Consequently, LSTM is recommended as a superior approach for long-term gold price forecasting, while SVR may serve as a complementary or baseline predictive model in financial time series analysis.

Keywords: Comparison of Performance; Gold Price Prediction; Long Short-Term Memory (LSTM); Support Vector Regression (SVR); Time Series Data; Machine Learning

1. INTRODUCTION

Gold is an investment commodity that plays a significant role in the global financial system due to its stability against inflation and economic volatility. The price of gold is often regarded as an indicator of investor confidence in global economic conditions and serves as a safe-haven asset during periods of economic uncertainty [1]. The rapid advancement of information technology has driven the increasing use of data analysis and machine learning methods across various fields, including the financial sector. One of the most sought-after investment instruments is gold, due to its stability and resistance to inflation[2]. However, the price of gold is highly volatile and is influenced by various global economic factors such as exchange rates, inflation, and monetary policies[3]. Therefore, gold price prediction has become an important topic for investors, financial analysts, and policymakers in making informed and effective decisions [4].

The main challenge in gold price prediction lies in the complex, non-linear, and time-series nature of the data [5]. Traditional models such as linear regression often fail to capture long-term patterns and non-linear relationships among variables. This limitation results in less accurate and unstable predictions, particularly when significant changes occur in the global market [6]. Therefore, a more adaptive model is required one that can effectively learn and capture the dynamic relationships among variables [7].

As a solution, this study compares the performance of two popular machine learning algorithms, namely Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), in predicting gold prices. LSTM, as a variant of the Recurrent Neural Network (RNN), has the capability to learn long-term dependencies in time-series data, making it suitable for analyzing the temporal characteristics of gold price data [8]. Meanwhile, SVR is known for its strong generalization ability in handling non-linear data through the use of kernel functions [9]. By comparing these two algorithms, this study aims to determine the most effective and accurate method for predicting gold prices based on historical data [10].

A previous study conducted by Azaria Beryl Nagata et al. in 2024 employed the Long Short-Term Memory (LSTM) method to predict gold price movements based on daily, weekly, and monthly frequency data. The results showed RMSE values of 21.27 for daily data, 36.69 for weekly data, and 107.93 for monthly data. These findings indicate that the LSTM model is capable of capturing long-term temporal dependencies in gold price dynamics [11].

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

Subsequent research conducted by Fevrierdo Nathaniel Shanahan Putra Mawan Pradana and Frederik Samuel Papilaya in 2023 utilized the Support Vector Regression (SVR) method with a polynomial kernel to predict gold prices during a potential recession triggered by the Covid-19 pandemic and the Russia–Ukraine conflict. The model achieved a Mean Absolute Percentage Error (MAPE) of 4.8%, which is categorized as highly accurate in predicting gold prices for the year 2023 [12]. A subsequent study conducted by Yudha Randa Madhik et al. in 2023 compared the performance of the LSTM and ARIMA models in predicting gold prices. The results showed that the LSTM model outperformed ARIMA, achieving an RMSE of 8.124 and a MAPE of 0.023 using an 80% training and 20% testing data split. These findings demonstrate the superiority of the LSTM model in processing economic indicators that influence gold prices [13]. Another study conducted by Arya Bima Sena et al. in 2024 compared the use of SVR with a linear kernel in modeling gold prices. The results showed an error rate of 0.73% with parameters $C = 10^{-4}$ and $\varepsilon = 10^{-4}$, indicating that the SVR method possesses a high capability in accurately capturing and tracking gold price fluctuation patterns [14].

2. RESEARCH METHODOLOGY

2.1 Research Stages

This study was conducted through several systematic stages to ensure accurate and reproducible results. The research stages are described as follows:

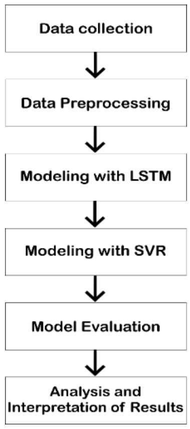

Figure 1. Research Stages

Based on Figure 1, the researcher provides an explanation to help readers understand the research stages clearly and systematically.

a. Data Collection, This stage involves the process of collecting historical data on gold prices against the United States dollar (XAU/USD), obtained from the Kaggle platform under the title XAU/USD Gold Price Historical Data (2004–2025). The dataset includes attributes such as date, opening price (open), highest price (high), lowest price (low), closing price (close), and daily trading volume.
b. Data Preprocessing At this stage, data cleaning and preparation are carried out to ensure the dataset is ready for modeling. The steps include handling missing or invalid data, normalizing the data to ensure uniform value ranges, and dividing the dataset into training data and testing data.
c. Modeling with LSTM, This stage employs the Long Short-Term Memory (LSTM) model for time series forecasting. LSTM is chosen for its ability to learn long-term patterns and dependencies from historical data, thereby enabling more accurate gold price predictions.
d. Modeling with SVR, In addition to LSTM, modeling is also conducted using the Support Vector Regression (SVR) method for comparison. SVR works by finding an optimal regression function that minimizes prediction errors and is effective in handling non-linear data.
e. Model Evaluation, After both models have been trained, performance evaluation is conducted using several metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score. This evaluation aims to assess the accuracy and performance level of each model in predicting gold prices.
f. Analysis and Interpretation of Results, This final stage involves analyzing the model evaluation results to assess the effectiveness of each method and interpreting the predicted trends in gold prices.

2.2 Data Collection

Data collection is a systematic process undertaken to obtain primary and secondary information relevant to the research objectives in order to address the research questions. This activity includes determining data sources, selecting appropriate methods, and conducting data collection ethically to ensure its validity and reliability [15][16]. In the context of machine learning, data collection encompasses the processes of data acquisition through data discovery, augmentation, and the generation of synthetic data using models such as Generative Adversarial Networks (GANs) [17].

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

This process also involves data labeling through crowdsourcing and weak supervision. Approaches such as active learning are employed to select the most informative samples, thereby minimizing the need for manual labeling, while data programming utilizes heuristic-based labeling functions to manage large-scale datasets [18]. The use of crowdsourcing through platforms such as Amazon Mechanical Turk helps enhance efficiency in managing large-scale datasets [19].

2.3 Prediction

Prediction is a process of estimating the likelihood of future events by utilizing data and information from the past and present, with the aim of minimizing the error rate in the resulting forecasts [14]. Prediction is similar to classification; however, its primary focus is on estimating events that have not yet occurred, often referred to as early prediction, which aims to prevent the occurrence of undesirable outcomes through preliminary evaluation or assessment [15].

2.4 Data Preprocessing

The data preprocessing stage is a crucial step in machine learning–based research, particularly for gold price prediction using time series data. The primary objective of this stage is to enhance data quality, eliminate noise, and adjust feature scaling to enable the model to learn optimally [20].

a. Data Cleaning
The first step in preprocessing is cleaning the data from missing values and outliers. To handle missing values, the linear interpolation method is applied, which estimates the values between two data points based on a connecting straight line. The linear interpolation formula can be expressed as follows:

$$Y_t = Y_{t-1} + \frac{(Y_{t+1}-Y_{t-1})}{(t+1-(t-1))} \times (t-(t-1)) \quad (1)$$

where Y_t is the interpolated value at time t, and $Y_{t-1}$and Y_{t+1} represent the preceding and succeeding values, respectively.

b. Gold price data are highly susceptible to sharp fluctuations caused by global economic factors such as monetary policy, geopolitics, and inflation. Extreme fluctuations that do not represent normal market conditions are referred to as outliers.
To detect outliers, a statistical approach known as the Interquartile Range (IQR) method is used, with the following formula:

$$IQR = Q3 - Q1 \quad (2)$$

Data are considered outliers if:

$$x < Q1 - 1.5 \times IQRataux > Q3 + 1.5 \times IQR \quad (3)$$

Values identified as outliers are replaced using the median or linear interpolation results to ensure a more stable data distribution.

c. Data Normalization
The next step is to normalize the data scale so that each feature has a uniform value range. This is important because differing feature scales can introduce bias during the model training process.
The technique used in this study is Min-Max normalization, which transforms the original value range into a scale between 0 and 1 using the following formula:

$$X' = \frac{X-X_{min}}{X_{max}-X_{min}} \quad (4)$$

where X'represents the normalized value, $X$is the original value, and $X_{\min}$and $X_{\max}$denote the minimum and maximum values, respectively.

2.5 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an extension of the Recurrent Neural Network (RNN) architecture, equipped with memory cells that enable the retention of information over long periods. This mechanism allows LSTM to overcome the vanishing gradient problem that often occurs in RNNs when processing long sequential data [21]. In the LSTM architecture, there are four types of gate units: the forget gate, input gate, cell gate, and output gate. Each gate has its respective function and mathematical equation, as follows [22]:
Forgate Gate (f_t) :

$$ft = \sigma(Wf \times Xt + Uf \times ht - 1 + bf) \quad (5)$$

This gate functions to determine how much information from the previous cell state (c_{t-1}) should be retained or forgotten. The value of f_t ranges between 0 and 1, where a value of 1 indicates that the information is fully retained, while a value of 0 indicates that the information is completely discarded. This function is crucial for maintaining the relevance of memory, ensuring that the network does not retain information that is no longer needed.
Input Gate (i_t) :

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

$$it = \sigma(Wi \times Xt + Ui \times ht - 1 + bi) \quad (6)$$

This gate functions to determine how much new information from the current input (X_t) will be stored in the cell state. The value U_i represents the weight connecting the input to the previous hidden state, b_i denotes the bias term, while $\sigma$is the sigmoid activation function that produces values between 0 and 1, acting as a gate controller. When the output value approaches 1, a large amount of new information is stored; conversely, when it approaches 0, little to no information is retained.
Cell Gate (Candidate Cell State) (c_t)

$$ct' = tanh(Wc \times Xt + Uc \times ht - 1 + bc) \quad (7)$$

This component functions to generate candidate new values (candidate cell state) that can be added to the cell state based on the current input (X_t) and the previous hidden state (h_{t-1}). The tanh activation function maintains stability by constraining the values between -1 and 1. The result of the cell gate is then multiplied by the input gate (i_t) to ensure that only important information is retained, thereby determining which new information will be stored in long-term memory.
Output Gate (o_t)

$$ot = \sigma(Wo \times Xt + Uo \times ht - 1 + bo) \quad (8)$$

The output gate functions to regulate how much information from the cell state (c_t) is passed on as the hidden state (h_t). The sigmoid activation function (σ) produces values between 0 and 1, serving as a control mechanism, which are then multiplied by the result of tanh (c_t)to ensure that only relevant information is transmitted. Thus, the output gate determines which portion of information is released from memory to influence the outcome in the subsequent step.

2.6 Support Vector Regression (SVR)

Support Vector Regression (SVR) is an extension of the Support Vector Machine (SVM) method that is used for regression problems or the prediction of continuous values. SVR operates by finding the optimal function that can predict the output based on the input, utilizing the concept of an optimal hyperplane that minimizes prediction errors while maintaining the maximum margin between training data points [23]. The main objective of Support Vector Regression (SVR) is to find a regression function $f(x)$in the form of a hyperplane that can represent all input data with the smallest possible error level (ε). In other words, SVR aims to construct a model that minimizes the deviation between the predicted results and the actual data[24]. SVR operates by finding a function that has the smallest possible deviation from the actual data within a specified tolerance margin ε [25].
The main equation of SVR:

$$f(x) = \langle w, x \rangle + b \quad (9)$$

with the optimization function:

$$\min \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} (\xi i + \xi i *) \quad (10)$$

subject to the following conditions:

$$yi - \langle w, xi \rangle - b \leq \varepsilon + \xi i \quad (11)$$

$$\langle \mathrm{w}, \mathrm{xi} \rangle + \mathrm{b} - \mathrm{yi} \leq \varepsilon + \xi \mathrm{i} * \quad (12)$$

The parameter C controls the trade-off between model complexity and error tolerance, while the kernel function (commonly the RBF kernel) is used to capture non-linear relationships.

3. RESULTS AND DISCUSSION

3.1 Data Collection

This study utilizes historical data of global gold prices paired with the XAU/USD (Gold vs US Dollar) currency pair, obtained from a public dataset available on Kaggle. The dataset contains records of gold prices against the United States Dollar from 2004 to 2025, with a daily time interval. The following is an example of the dataset table used in this study:

Table 1. Gold Price Data

Date	Open	High	Low	Close	Volume
2004-06-11	384	384.8	382.8	384.1	272
2004-06-14	384.3	385.8	381.8	382.8	1902
2004-06-15	382.8	388.8	381.1	388.6	1951
2004-06-16	387.1	389.8	382.6	383.8	2014
2004-06-17	383.6	389.3	383	387.6	1568

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

Date	Open	High	Low	Close	Volume
...	...	...	...	...	...
2015-01-02	1186.94	1195.03	1167.33	1188.82	97717
2015.01.05	1187.73	1207.28	1178	1204.32	122116
...	...	...	...	...	...
2025-09.29	3759.47	3834.05	3756.58	3833.28	494753
2025-09-30	3832.81	3871.61	3792.98	3858.15	522111
2025-10-01	3859.31	3875.57	3854.53	3865.88	47836

Table 1 presents a snapshot of the historical global gold price data against the United States Dollar (XAU/USD) used in this study. The data covers the period from June 11, 2004, to October 1, 2025, with a daily recording frequency. Each row in the table represents gold trading activity on a specific day in the global market. The columns in the table consist of several key variables, namely Date, Open, High, Low, Close, and Volume. The Date column indicates the date of the transaction or gold price recording, while Open represents the opening price of gold at the beginning of the trading session. The High column provides information about the highest price reached during the trading session, and Low indicates the lowest price on the same day. The Close column represents the closing price of gold at the end of the trading session, which serves as the main variable in this study because it reflects the final value of daily transactions and is considered the most stable indicator for trend analysis. Meanwhile, the Volume column shows the amount of gold trading volume that occurred on that particular day. The data presented in this table serves as the foundation for the analysis and the development of the gold price prediction models using the Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) algorithms. Through this historical data, both algorithms are trained to identify patterns, trends, and the dynamics of gold price movements over time, thereby enabling more accurate forecasting of future gold prices.

3.2 Data Preprocessing

The data preprocessing stage was carried out to prepare the historical gold price data (XAU/USD) for modeling using LSTM and SVR. This process included data cleaning, converting date formats into datetime, and sorting the data chronologically. Missing values were handled using linear interpolation to maintain data continuity. Next, feature selection was performed, where the LSTM model utilized the Close attribute as the primary focus due to its time series nature, while the SVR model used Open, High, Low, and Volume as input variables with Close as the target variable. All data were then normalized using the Min-Max Scaler within the range [0,1] to ensure that each feature had a uniform scale and to improve model performance. Finally, the data were divided into training (80%) and testing (20%) sets sequentially to preserve the temporal order. As a result, the preprocessing stage produced a clean, standardized dataset that was ready for training and evaluating both prediction models.

The following figure presents a graph illustrating the movement of gold prices (XAU/USD) over the observation period. This data is used to examine the long-term patterns of gold price fluctuations and to understand the trends that have occurred over the years. The visualization also serves as a foundation for analyzing changes in value and the stability of gold prices in relation to global economic conditions.

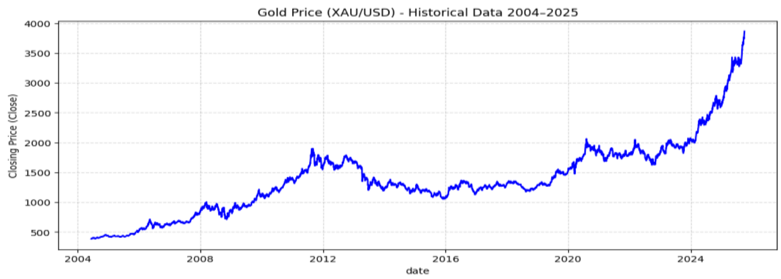

Figure 2. Gold Price Chart Before Normalization

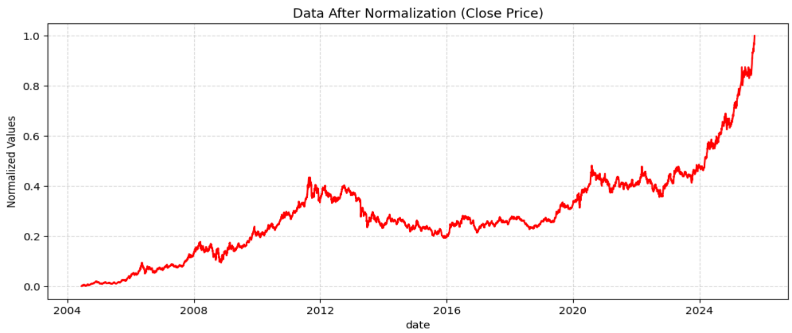

Figure 3. Gold Price Chart After Normalization

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

Based on the two figures (2 and 3), it can be observed that the gold price (XAU/USD) experienced a significant upward trend during the period from 2004 to 2025. In Figure 2, it is evident that the gold price gradually increased from a relatively low range at the beginning of the period to much higher values in the later years. This pattern indicates that gold prices tend to rise in the long term, although accompanied by several sharp fluctuations caused by global economic conditions such as financial crises, pandemics, and changes in global monetary policies.

Meanwhile, Figure 3 presents the gold price data after the normalization process. With the values scaled to the range of 0–1, this graph displays the same pattern of price changes as the original data but in a form that is easier to compare and analyze. This normalization helps highlight the overall trends without being affected by the magnitude of the nominal gold price values.

3.3 Gold Price Prediction Using LSTM

At this stage, the gold price (XAU/USD) prediction modeling process was carried out using the Long Short-Term Memory (LSTM) method, which is one of the artificial neural network (Recurrent Neural Network) architectures effective for handling time series data. The model was trained using historical gold price data from the 2004–2025 period, which had previously undergone preprocessing and normalization within the range [0,1]. The following figure presents a comparison between the actual gold prices (Actual Price) and the LSTM model predictions (Predicted Price) in the form of a time series graph. The purpose of this visualization is to demonstrate the extent to which the LSTM model can learn the patterns of gold price movements and generate predictions that closely approximate the actual data.

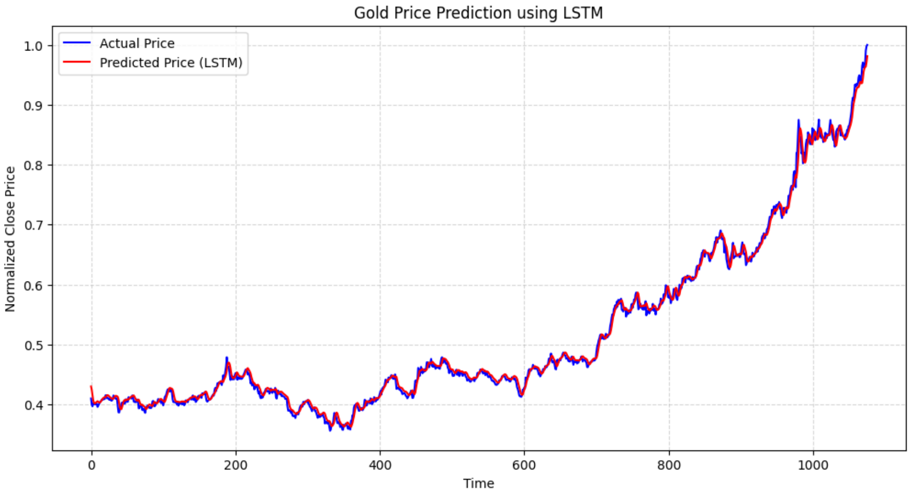

Figure 4. Gold Price Prediction Graph Using the LSTM Method

Figure 4 presents the results of gold price (XAU/USD) prediction using the Long Short-Term Memory (LSTM) model based on historical data from the 2004–2025 period. Visually, the red line representing the model's predicted values appears almost entirely overlapping with the blue line representing the actual prices. This indicates that the LSTM model is capable of effectively learning and representing the patterns of gold price movements. The model successfully captures long-term trend directions, including periods of price increases and decreases, and can follow short-term fluctuations without significant deviations. Based on the model evaluation results, the Root Mean Square Error (RMSE) value was 0.0082, the Mean Absolute Error (MAE) value was 0.0060, and the coefficient of determination (R^2) was 0.9969. The very small prediction error values indicate that the differences between the actual and predicted prices are minimal. Meanwhile, the R^2 value, which is close to 1, indicates that approximately 99.69% of the variation in gold prices can be explained by the model. Thus, the LSTM model demonstrates a high level of generalization capability on the test data. Furthermore, since the data were normalized within the range [0,1], the upward movement of the graph approaching a value of 1 toward the end indicates a tendency for gold prices to increase as 2025 approaches. The LSTM model successfully replicates this upward trend with high accuracy, demonstrating that the model is effective in capturing gold market trends and price dynamics.

3.4 SVR Gold Price Prediction Using SVR

After the modeling process using the LSTM method, this study also applied the Support Vector Regression (SVR) approach to compare the performance of both methods in predicting gold prices (XAU/USD). The SVR model was employed due to its ability to handle non-linear relationships between the input variables (Open, High, Low, Volume) and the closing price (Close). The training process was conducted using the same dataset, namely the historical gold price data for the 2004–2025 period, which had been normalized to the range [0,1] to ensure consistency with the previous model. The following figure presents a comparison between the actual gold prices (Actual Price) and the SVR model predictions (Predicted Price). This visualization aims to demonstrate the SVR model's capability to follow the pattern of gold price movements over time and to evaluate the level of prediction accuracy achieved in comparison with the actual values.

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

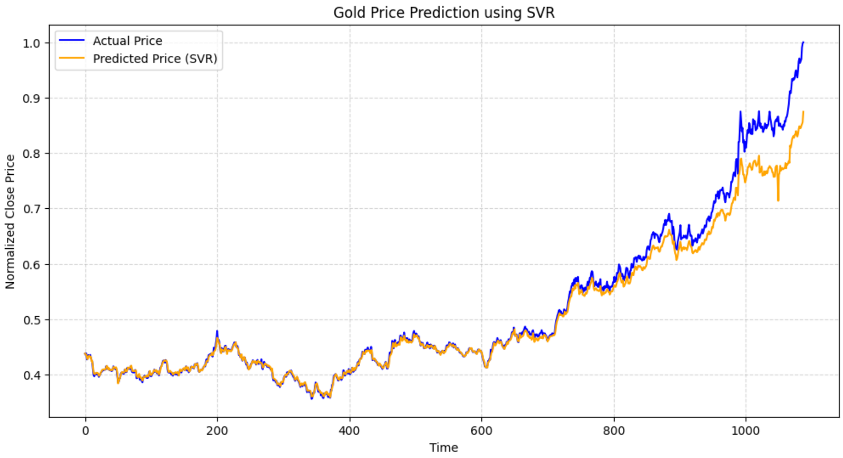

Figure 5. Gold Price Prediction Graph Using the SVR Method

Figure 5 presents the results of gold price (XAU/USD) prediction using the Support Vector Regression (SVR) method based on historical data from the 2004–2025 period. The graph shows that the orange line, representing the SVR model's predicted values, generally follows the overall direction of the blue line, which represents the actual prices. This indicates that the SVR model is capable of recognizing the general pattern of gold price movements, particularly in stable long-term trends. However, in several parts of the graph especially during sharp price increases toward the end of the period the prediction line begins to deviate from the actual values. This deviation suggests that the SVR model has limitations in capturing highly volatile market dynamics. The model evaluation results show an RMSE of 0.0289, an MAE of 0.0143, and an R^2 of 0.9611. These values still indicate reasonably good performance, with an accuracy level of approximately 96.11%. Nevertheless, the prediction errors of the SVR model (RMSE and MAE) are relatively higher compared to those of the LSTM model, meaning that the SVR predictions are slightly less precise when compared to the actual data. This difference may be attributed to the nature of the SVR model, which is less optimal in handling temporal dependencies and complex non-linear patterns commonly found in time series data such as gold prices.

3.5 Comparison of LSTM and SVR Model Performance

After conducting the modeling and evaluation processes for the two prediction methods Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) the next step is to compare their performance based on several key evaluation metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The following figure presents a comparison of the performance results of both models in the form of a bar chart. The purpose of this visualization is to clearly illustrate the differences in accuracy levels and prediction errors between the two approaches. Through this comparison, it can be determined which model produces predictions that are closest to the actual values and demonstrates the best capability in capturing the patterns and trends of gold price (XAU/USD) movements.

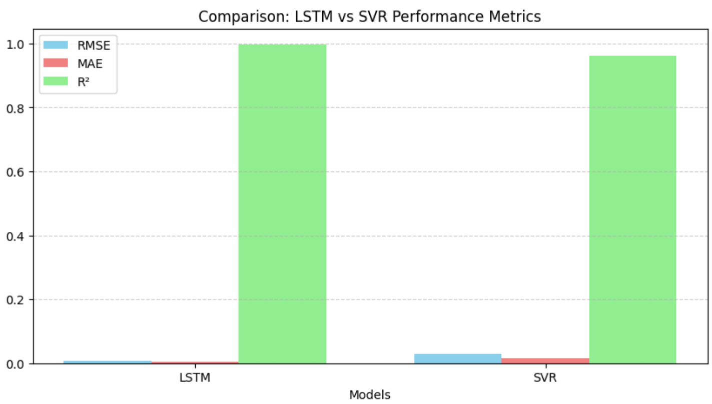

Figure 6. Performance Comparison Visualization Between the LSTM and SVR Models

Figure 6 illustrates the performance comparison between the Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) models based on three key evaluation metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The visualization shows that the LSTM model consistently produces lower RMSE and MAE values compared to the SVR model, indicating that the prediction error in LSTM is significantly smaller. Conversely, the R^2 value for the LSTM model is nearly 1.0, demonstrating that it can explain almost all variations in gold price data with high accuracy. Meanwhile, the R^2 value for the SVR model is

ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

slightly lower, suggesting that although SVR maintains a fairly good level of accuracy, its ability to capture complex patterns in time series data is inferior to that of LSTM. This difference indicates that LSTM delivers superior predictive performance compared to SVR, primarily due to its capability to recognize temporal relationships and long-term patterns in historical gold price data. The SVR model tends to perform well with simpler non-linear patterns but struggles with highly fluctuating price dynamics. Overall, the graph reinforces that the LSTM model is more suitable for long-term gold price prediction based on time series data, while the SVR model serves better as a comparative or baseline model with moderate accuracy.

3.6 Discussion

The results of this study demonstrate clear performance differences between the Long Short-Term Memory (LSTM) and Support Vector Regression (SVR) models in predicting gold prices (XAU/USD). Based on the evaluation metrics RMSE, MAE, and R^2, the LSTM model consistently outperforms the SVR model, indicating its superior capability in modeling complex financial time series data.

The strong performance of the LSTM model can be attributed to its architectural design, which is specifically developed to handle sequential data and long-term temporal dependencies. Gold price movements are influenced not only by immediate market conditions but also by historical trends, delayed economic effects, and cumulative investor sentiment. The memory cells and gating mechanisms in LSTM enable the model to retain relevant historical information while filtering out noise, allowing it to accurately capture both long-term trends and short-term fluctuations. This characteristic is reflected in the very low RMSE and MAE values, as well as an R^2 value close to 1, indicating that most of the variance in gold price data is successfully explained by the model.

In contrast, the SVR model shows reasonably good performance but exhibits limitations when applied to highly volatile and temporally dependent data. Although SVR is effective in modeling non-linear relationships through kernel functions, it does not inherently account for sequential dependencies in time series data. As observed in the prediction results, SVR is able to follow the general direction of gold price trends but struggles to adapt to sudden price spikes and sharp fluctuations, particularly during periods of increased market uncertainty. This limitation results in higher prediction errors compared to the LSTM model.

The findings of this study are consistent with previous research that highlights the advantages of deep learning approaches over traditional machine learning models for financial forecasting. Earlier studies have reported that LSTM-based models outperform statistical and kernel-based methods in capturing the dynamic behavior of commodity prices. Similarly, SVR has been shown to provide competitive results under relatively stable market conditions but tends to underperform when dealing with complex temporal patterns.

Overall, this comparative analysis confirms that LSTM is more suitable for long-term gold price prediction using historical time series data. The SVR model, while still useful as a benchmark or complementary method, is less effective in capturing the intricate temporal structures inherent in gold price movements. These results emphasize the importance of selecting models that align with the underlying characteristics of financial data to achieve accurate and reliable forecasting outcomes.

4. CONCLUSION

Based on the results of the study on gold price (XAU/USD) prediction using two methods, namely Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), it can be concluded that the LSTM model provides better predictive performance compared to the SVR model. This is evident from the model evaluation results, where LSTM achieved an RMSE value of 0.0082, an MAE value of 0.0060, and an R^2 value of 0.9969, while SVR obtained an RMSE value of 0.0289, an MAE value of 0.0143, and an R^2 value of 0.9611. The smaller prediction errors and the coefficient of determination value approaching 1 indicate that LSTM has a superior ability to recognize historical data patterns and predict gold price movements with a high level of accuracy. The LSTM model outperforms SVR due to its capability to handle time series data and capture long-term temporal dependencies between periods, whereas SVR is more limited in identifying complex non-linear patterns present in gold price fluctuations. Nevertheless, the SVR model still produces reasonably good prediction results and can serve as a comparative or baseline model in gold price prediction analysis.

REFERENCES

[1] A. Ainur, "Pengaruh Ketidakpastian Ekonomi Global Terhadap Inflasi, Kurs, Foreign Direct Investment(Fdi), Harga Emas, Dan Pertumbuhan Ekonomi Di Indonesia," *J. Ekon. Perjuangan*, vol. 6, no. 1, pp. 43–54, 2024, doi: https://doi.org/10.36423/jumper.v6i1.1649.

[2] A. E. Wicaksono and I. D. Rahmawati, "The Effect of Inflation and Interest Rates on Investment Decision Making Through Gold Prices of Indonesian Sharia Bank Customers," *Amkop Manag. Account. Rev.*, vol. 5, no. 2, pp. 605–634, 2025, doi: https://doi.org/10.37531/amar.v5i2.2992.

[3] S. Singh, M. Singh, and S. Attri, "Dynamic volatility linkages among crude oil, exchange rate, interest rate, gold and equity markets: an empirical Asian perspective," *Manag. Financ.*, vol. 52, no. 1, pp. 160–182, 2025, doi: https://doi.org/10.1108/MF-01-2025-0016.

[4] A. M. Potcovaru, E. Nica, and E. Labudova, "Price Development Of Gold And S & P 500 Index As A Determinant of

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 2078−2086
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8605

Investment Behavior : A Comparative Analysis," *Ekon. spektrum*, vol. 19, no. 1, pp. 39–54, 2025, doi: dx.doi.org/10.26552/ems.2025.1.39-54.

[5] M. Mohtasham, K. Sahand, and V. Alireza, "A Deep Learning - Based Method for Forecasting Gold Price with Respect to Pandemics," *SN Comput. Sci.*, vol. 2, no. 4, pp. 1–12, 2021, doi: https://doi.org/10.1007/s42979-021-00724-3.

[6] N. Patria, "Optimasi Prediksi Saham dengan Neural Network pada PT Xyz," *Decod. J. Pendidik. Teknol. Inf.*, vol. 4, no. 3, pp. 928–936, 2024, doi: https://doi.org/10.51454/decode.v4i3.782.

[7] V. Afnita, H. P. Dolonseda, Y. Otoluwa, and M. Dwi, "Model Struktural Sem-Pls : Intelligent Tutoring Systems Dan Adaptive Learning Systems Dalam Kaitannya Dengan Kreativitas Belajar," *J. Adm. Manaj. Sumber Daya Mns. Dan Ilmu Sos.*, vol. 4, no. 1, pp. 1–14, 2025, doi: https://doi.org/10.37606/jaeis.v4i1.298.

[8] D. A. Adha, A. Ramadhan, H. Maulana, P. P. H. Harahap, and E. Ismanto, "Gold Price Forecasting Based on Time Series Using the LSTM Deep Learning Architecture," *J. Comput. Sci. Inf. Technol.*, vol. 6, no. 2, pp. 329–336, 2025, doi: https://doi.org/10.37859/coscitech.v6i2.9980.

[9] A. Rahman, V. Paramarta, A. N. Ida, and M. H. Akbar, "Perbandingan Kinerja SVR dan XGBoost untuk Peramalan Emisi CO_2 Global berbasis Machine Learning," *J. Komtika (Komputasi dan Inform.*, vol. 9, no. 1, pp. 37–44, 2025, doi: https://doi.org/10.31603/komtika.v9i1.13449.

[10] I. F. Riziq and A. R. Dzikrillah, "Impelementasi Algoritma LSTM Dan SVR Untuk Prediksi Harga Bitcoin Menggunakan Data Yahoo Finance," *METIK J.*, vol. 9, no. 2, pp. 284–291, 2025, doi: https://doi.org/10.47002/90ypad22.

[11] A. B. Nagata, M. S. Hidajat, and D. A. Wibowo, "Predicting Gold Price Movement Using Long Short-Term Memory Model," *J. Appl. Intell. Syst.*, vol. 9, no. 1, pp. 19–28, 2024, doi: https://doi.org/10.62411/jais.v9i1.10305.

[12] F. Nathaniel, S. Putra, M. Pradana, and F. S. Papilaya, "Analisa Prediksi Harga Emas Dengan Kemungkinan Terjadinya Resesi Menggunakan Metode SVR," *SINTECH (Science Inf. Technol. J.*, vol. 6, no. 1, pp. 37–46, 2023, doi: https://doi.org/10.31598/sintechjournal.v6i1.1329.

[13] Y. R. Madhika, Kusrini, and T. Hidayat, "Gold Price Prediction Using the ARIMA and LSTM Models," *Sink. J. Dan Penelit. Tek. Inform.*, vol. 7, no. 3, pp. 1255–1264, 2023, doi: https://doi.org/10.33395/sinkron.v8i3.12461.

[14] A. B. Sena, "Pemodelan Data Harga Emas Dengan Support Vector Regression," Universitas Sebelas Maret, 2025. doi: https://doi.org/10.37010/nuc.v5i02.1767.

[15] N. Hafizah, T. C. P. P, M. Sari, R. Winanda, R. Hidayatullah, and H. Harmonedi, "Identifikasi Variabel Penelitian , Jenis Sumber Data Dalam Penelitian Pendidikan," *QOSIM J. Pendidik. Sos. Hum.*, vol. 3, no. 2, pp. 586–596, 2025, doi: https://doi.org/10.61104/jq.v3i2.1025.

[16] R. Hidayat, R. A. Fitri, and D. Hermina, "Langkah Penelitian Manajemen Pendidikan: Penemuan Masalah, Telaah Pustaka, Persiapan Penelitian, Pengumpulan Data, Analisis Data Dan Penyimpulan/Pemaknaan, Dan Pelaporan & Evaluasi Penelitian," *J. Ris. Multidisiplin Edukasi*, vol. 2, no. 6, pp. 509–523, 2025, doi: https://doi.org/10.71282/jurmie.v2i6.509.

[17] D. Leni, A. U. Berli, D. S. Kesuma, H. Haris, and R. Sumiati, "Evaluasi Pemodelan Augmentasi Data Sifat Mekanik Aluminium Menggunakan Generative Adversarial Networks," *J. Engine Energi, Manufaktur, Dan Mater.*, vol. 8, no. 1, pp. 9–21, 2024, doi: https://doi.org/10.30588/jeemm.v8i1.1645.

[18] H. Utama, E. Daniati, and A. Masruro, "Weak Supervision Dengan Pendekatan Labeling Function Untuk Analisis Sentimen Pada Twitter," *Indones. J. Comput. Sci. Res.*, vol. 3, no. 1, pp. 49–57, 2024, doi: https://doi.org/10.59095/ijcsr.v3i1.93.

[19] L. Judijanto, "Tinjauan Bibliometrik Komprehensif tentang Crowdsourcing dalam Penelitian Ilmiah dan Dunia Akademik," *Sanskara Manaj. Dan Bisnis*, vol. 3, no. 02, pp. 89–99, 2025, doi: https://doi.org/10.58812/smb.v3i02.538.

[20] M. S. A. Habibi, A. H. Abdillah, M. Idhom, and T. Trimono, "Perbandingan Kinerja Gru dan SVR untuk Prediksi Emas di Indonesia," *Inform. J. Tek. Inform. dan Multimed.*, vol. 5, no. 1, pp. 141–150, 2025, doi: https://doi.org/10.51903/informatika.v5i1.1105.

[21] A. Hanafiah, Y. Arta, H. O. Nasution, and Y. D. Lestari, "Penerapan Metode Recurrent Neural Network dengan Pendekatan Long Short-Term Memory (LSTM) Untuk Prediksi Harga Saham," *Bull. Comput. Sci. Res.*, vol. 4, no. 1, pp. 27–33, 2023, doi: https://doi.org/10.47065/bulletincsr.v4i1.321.

[22] T. B. Sianturi, I. Cholissodin, and N. Yudistira, "Penerapan Algoritma Long Short-Term Memory (LSTM) berbasis Multi Fungsi Aktivasi Terbobot dalam Prediksi Harga Ethereum," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 7, no. 3, pp. 1101–1107, 2023, [Online]. Available: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/12384

[23] R. F. Almahdy and W. M. P. D, "Prediksi Harga Rumah Di Kabupaten Bantul Menggunakan Algoritma Support Vector Regression," *J. Tek. Inform. dan Sist. Inf.*, vol. 11, no. 2, pp. 152–165, 2024, doi: https://doi.org/10.35957/jatisi.v11i2.6001.

[24] N. K. Tran, L. C. Kühle, and G. W. Klau, "A critical review of multi-output support vector regression," *Pattern Recognit. Lett.*, vol. 178, pp. 69–75, 2024, doi: https://doi.org/10.1016/j.patrec.2023.12.007.

[25] S. A. Rohma, "Prediksi Urban Heat Island (UHI) berdasarkan penginderaan jauh satelit menggunakan Support Vector Regresion," UIN Malang, 2024. [Online]. Available: http://etheses.uin-malang.ac.id/id/eprint/65942