Vol. 12 No.1 Tahun 2026, pp 1-9
Jurnal Teknologi dan Manajemen Informatika
http:// http://jurnal.unmer.ac.id/index.php/jtmi
P-ISSN: 1693-6604 E-ISSN: 2580-8044

Comparative Analysis of LSTM-Based Models for Daily Gold Price Forecasting Using Time Series and Sentiment Features

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Article Info

Article History
Received : 15-10-2025
Revised : 24-11-2025
Accepted : 05-01-2026

Keywords
Gold price forecasting;
LSTM;
Prophet;
Sentiment analysis;
Time Series Prediction

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ABSTRACT

This study examines the performance of three forecasting approaches for predicting daily gold prices: a Pure Long Short-Term Memory (LSTM) model, a Hybrid LSTM + Prophet model, and an LSTM model enhanced with sentiment features. Daily price data from 2013 to 2023 were used, and all evaluation metrics were computed on inverse-transformed values to ensure accurate interpretation. The Pure LSTM model shows strong predictive capability, achieving a testing RMSE of 17.4500, MAE of 12.9924, R^2 of 0.9431, and a MAPE of 0.72%. The Hybrid LSTM + Prophet model performs considerably worse on unseen data, with a testing RMSE of 71.6272 and an R^2 close to zero, indicating that Prophet's decomposition is unsuitable for highly volatile price movements. The LSTM + Sentiment model provides the best overall performance, with a testing RMSE of 17.2769, MAE of 12.5515, R^2 of 0.9442, and a MAPE of 0.70%, showing modest but consistent improvement over the baseline LSTM. These findings highlight the suitability of LSTM-based models for non-seasonal financial time series and demonstrate that sentiment can contribute additional predictive value.

INTRODUCTION

Gold is widely recognized as a strategic investment asset due to its role as a store of value and safe haven during periods of macroeconomic uncertainty, financial crises, and geopolitical tensions. The price of gold is influenced by multiple variables—including global demand, exchange rates, inflation, and interest rate movements—making the forecasting process highly challenging [1], [2]. Understanding gold price dynamics is therefore crucial for investors and policymakers.

Numerous forecasting techniques have been proposed in prior studies, ranging from traditional econometric models such as ARIMA and GARCH [1], [3], to machine learning approaches including Support Vector Machines (SVM), linear regression, and Random Forests [4][5]. However, because gold exhibits non-linear and highly volatile behavior, deep learning models—particularly Long Short-Term Memory (LSTM) —have become increasingly popular for financial time series prediction due to their ability to capture long-term dependencies and non-linear temporal patterns [6], [7], [8]. Recent work published in JTMI also demonstrates that LSTM performs effectively for macroeconomic time-series forecasting in Indonesia, further reinforcing its suitability for volatile financial data [9]. Several works demonstrate that LSTM provides improved forecasting accuracy compared to conventional methods when

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DOI: https://doi.org/10.26905/jtmi.v12i1.16309

applied to commodity prices, cryptocurrencies, and other financial assets [10], [11], [12], [13].

Prophet, a decomposable time series model introduced by Taylor and Letham [14], has also attracted attention due to its interpretability, automatic seasonality detection, and robustness to missing values. Some studies have attempted to integrate Prophet with LSTM under the assumption that Prophet captures trend and seasonality, while LSTM captures non-linear residual components [15], [16], [17]. Although these hybrid models have shown promising results in certain domains, most existing Prophet-LSTM combinations rely on relatively smooth dataset (e.g., agricultural production, tourism demand, monthly patterns), which differ substantially from the high-volatility characteristics of daily gold prices.

Another active research direction involves augmenting forecasting models with sentiment derived from news or social media. Sentiment is known to influence short-term price fluctuations and investor behavior, especially during periods of heightened uncertainty [18], [19], [20]. Several studies have incorporated sentiment into LSTM models for predicting cryptocurrency and stock prices, showing that sentiment can improve the model's responsiveness to sudden market movements [11], [13]. However, there is limited empirical analysis on whether sentiment can meaningfully enhance daily gold price prediction, particularly when combined with deep learning architectures.

Despite these advancement, important gaps remain in the literature. First, prior hybrid LSTM-Prophet studies seldom evaluate their performance on highly volatile daily gold price datasets, which may challenge Prophet's assumptions about smooth trends. Second, only a few studies have provided a systematic comparison among pure LSTM, Prophet-LSTM hybrid models, and LSTM enhanced with sentiment features under consistent experimental settings. Third, previous research often does not compute evaluation metrics using inverse-transformed values, potentially leading to inaccurate conclusions—an issue highlighted by the reviewer. Finally, the degree to which sentiment contributes to gold price forecasting remains unclear, especially when economic shocks may outweigh sentiment-driven fluctuations.

To address these gaps, this study compares three forecasting models on daily global gold price data from 2013-2023: (1) Pure LSTM, (2) Hybrid LSTM + Prophet, and (3) LSTM augmented with sentiment features extracted from financial news [21], [22]. All models are trained under consistent hyperparameters, and evaluation metrics are calculated after inverse transformation to ensure mathematical validity. This design allows us to evaluate the suitability of Prophet for volatile daily gold prices and assess whether sentiment contributes measurable predictive value.

Accordingly, the research is guided by the following questions:

RQ1: How effective is the hybrid LSTM + Prophet model compared to pure LSTM in forecasting daily gold prices?

RQ2: Does integrating sentiment analysis into the LSTM architecture significantly improve forecasting accuracy?

Overall, this study contributes to the literature by comparing three forecasting approaches, empirically demonstrating the limitations of Prophet in modelling volatile daily gold price data, and showing that sentiment analysis delivers a marginal but consistent improvement in accuracy. These findings offer practical insights for researchers and practitioners seeking reliable forecasting strategies in dynamic financial markets.

METHODS

Research Process

This study follows a structured research workflow consisting of several sequential stages, beginning from data acquisition and ending in model evaluation. The overall research framework is illustrated in Figure 1, which summarizes the steps performed to develop and compare the three forecasting models proposed in this study: Pure LSTM, Hybrid LSTM + Prophet, and LSTM enhanced with News Sentiment.

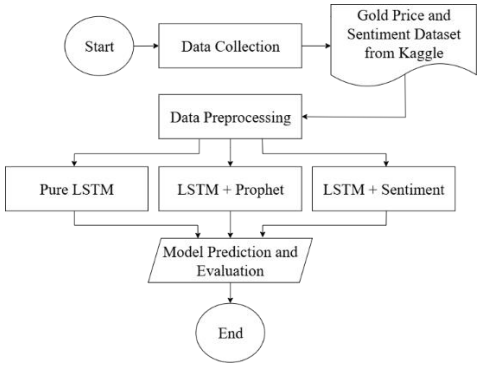


Figure 1. Research Process

The process begins with data collection Kaggle, followed by data preprocessing, model development, and prediction and evaluation. Three forecasting models are developed under identical settings and evaluated using training and testing data. Figure 1 illustrates this workflow and the development of the three model variants from the same preprocessing pipeline.

Data Collection

Two datasets were used in this study, both retrieved from the Kaggle repository.

1. Gold Price Dataset

   Daily gold price data for the period 2013-2023 is obtained from Kaggle [21]. A sample of the raw gold price used in this study is shown in Table 1 to illustrate the actual structure of the dataset. This table demonstrates the daily time-series nature of the dataset, where each row represents one trading day and all price values are expressed in USD per ounce. Only the closing price is used for prediction since it is the most stable and commonly referenced indicator in gold forecasting literature.

Table 1. Sample of Raw Gold Price Data

Date	Price	Open	High	Low	Vol.	Change %
01/02/2013	1,689.90	1,675.80	1,695.00	1,672.10	0.06K	0,78
01/03/2013	1,675.60	1,688.00	1,689.30	1,664.30	0.19K	-0,85
01/04/2013	1,649.90	1,664.40	1,664.40	1,630.00	0.31K	-1,53

2. News Sentiment Dataset

   A sentiment dataset containing labeled news headlines related to gold commodities is obtained from Kaggle [22]. Each record includes the publication date, the news headline, and a sentiment label. Table 2 provides a sample of raw news headlines used in this study to illustrate the structure of the sentiment dataset.

Table 2. Sample of News Sentiment Dataset

Date	News	Sentiment
04-01-2013	Gold futures down at Rs 30,800 on global cues	negative
05-01-2013	Gold, silver rebound on aggressive buying	positive
06-01-2013	Turning off the gold import tap	none

   In the original dataset, neutral sentiment may appear as none, which is treated equivalently to neutral sentiment and mapped to a numerical value of 0 during preprocessing. Since the dataset contains daily news headlines, multiple entries may occur on the same date, while certain dates have no associated news. This condition requires alignment during the preprocessing stage.

Data Preprocessing

The preprocessing stage ensures that both datasets—the gold price series and the news sentiment data—are properly cleaned, standardized, aligned, and transformed into supervised learning format before model training. The following procedures were applied:

1. Data Cleaning and Validation

   Both datasets were inspected for missing or duplicated records. Duplicate rows were removed, and missing numerical values in the gold price dataset were forward-filled to

preserve the continuity of the time series. Non-numeric characters (e.g., commas) in the price column were converted to numerical format.

2. Date Formatting and Chronological Ordering
   The *Date* column in both datasets was converted into a standard datetime format. All records were sorted chronologically to maintain temporal consistency, which is essential for time-series modeling.
3. Sentiment Transformation and Aggregation
   The sentiment dataset provides multiple news headlines per day, each labeled as positive = 1, neutral = 0, and negative = -1. Since several headlines may occur on the same day (typically between 1-5 articles), the daily sentiment score was calculated using the mean of all sentiment values for that date:

$$S_{daily} = \frac{1}{n}\sum_{i=1}^{n} s_i \quad (1)$$

   If no news appeared on a given day, the sentiment value was set to 0, representing a neutral market stance—an approach commonly used in financial sentiment modeling.
4. Dataset Integration
   The aggregated sentiment series was merged with the gold price dataset using a left join on the *Date* column. This ensured that each gold price entry contained a corresponding sentiment value. Missing sentiment values (occurring on days without news) were set to 0. For the Pure LSTM and LSTM + Prophet models, only the price feature was used. For the LSTM + Sentiment model, the merged dataset containing the sentiment feature was used.
5. Feature Scaling
   To improve model convergence and maintain numerical stability, Min-Max normalization was applied to transform all numerical features to the range [0,1]:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

   Scaling was applied separately to price values and sentiment scores.
6. Time-Series Structuring (Sliding Window Method)
   To convert the time series into a supervised learning format, a sliding window of 90 days was used. Each input sample contains prices from the previous 90 days, predicting the price on day 91:

$$X_t = [p_{t-90}, \ldots, p_{t-1}], \quad y_t = p_t \quad (3)$$

   For the LSTM + Sentiment model, the sentiment value for day *t* was appended to the input vector.
7. Train-Test Split and Reshaping
   The transformed dataset was split into 80% training and 20% testing, following common practice in deep learning forecasting studies. Finally, the input arrays were reshaped into 3D format required for LSTM layers in Keras:

$$(n_samples, time_steps, features) \quad (4)$$

Model Development

This study develops three forecasting models to compare the performance of pure deep learning, trend-based hybrid modeling, and sentiment-augmented prediction. All models are trained using the same dataset partition, window size, and hyperparameters to ensure fair comparison across experimental settings.

1. Pure LSTM Model
   The baseline forecasting model uses a Long Short-Term Memory (LSTM) neural network to capture nonlinear dependencies in the gold price series. LSTM is selected due to its proven ability to model long-term temporal patterns in financial time-series data [6], [7], [10]. The Pure LSTM architecture consists of (a) 1 LSTM layer with 50 units. Justification: Prior studies in financial forecasting commonly use 50-64 units, which provide a balance between model complexity and stability for volatile data such as daily gold or cryptocurrency prices.

(b) Dropout layer (rate = 0.2) helps reduce overfitting. And (c) Dense layer with 1 neuron for scalar output prediction.

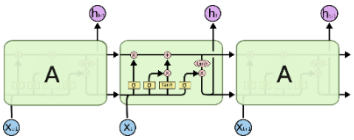


Figure 2. LSTM Model Architecture for Gold Price Prediction

All LSTM-based models in this study were trained using a consistent configuration to ensure a fair comparison. Each model was trained for 100 epochs with a batch size of 32, using Mean Squared Error (MSE) as the loss function and the Adam optimizer with its default learning rate (0.001). A batch size of 32 is widely adopted in deep learning-based time series forecasting because it provides a good balance between gradient stability and computational efficiency, especially for datasets of moderate size such as daily gold price with a 90-day input window. Training for 100 epochs allows the models to adequately learn temporal dependencies without excessively increasing training time.

These hyperparameters were chosen based on both empirical testing and prior studies that applied LSTM to financial time-series forecasting, which commonly employ similar settings for units, epochs, and batch sizes [6], [7], [10].

2. Hybrid LSTM + Prophet Model

The hybrid approach combines Prophet—a decomposable time-series model—with an LSTM network. Prophet models the trend and seasonality components, while LSTM captures nonlinear residuals. Prophet is first trained on the training portion of the gold price series. The following parameters were used yearly_seasonality=True, daily_seasonality=True, changepoint_prior_scale = 0.05, seasonality_mode = "additive", and interval_width = 0.80. These parameters follow the standard Prophet configuration for time-series forecasting, where additive seasonality and a moderate changepoint prior scale are recommended for non-seasonal financial data [14]. Prophet is designed to model trend components effectively under default or near-default settings, particularly when strong periodic seasonality is not present. Then, residual series is computed as:

$$r_t = y_t - \hat{y}_t^{Prophet} \tag{5}$$

An LSTM model with the same architecture as the pure model is trained to learn this nonlinear residual sequence. The final hybrid prediction is obtained by combining Prophet's trend forecast with the LSTM residual prediction. This design allows Prophet to capture smoother structures while LSTM addresses irregular fluctuations.

$$\hat{y}_t = \hat{y}_t^{Prophet} + \hat{r}_t^{LSTM} \tag{6}$$

3. LSTM + Sentiment Model

This model incorporates daily news sentiment as an additional feature to evaluate whether sentiment improves predictive accuracy. Daily sentiment values—computed as the mean of all headlines for each date—are merged with the gold price dataset. The sentiment value range is positive = 1, neutral = 0, and negative = -1. If no news is available on a given day, the sentiment is assigned 0, consistent with financial sentiment modeling practices. For each prediction target y_t, the input consists of the previous 90 days of prices and the daily sentiment score on day t. Thus:

$$X_t = [p_{t-90}, \ldots, p_{t-1}, S_{daily}] \tag{7}$$

This creates a multivariate input vector of shape:

$$(90\ time\ steps, 2\ features) \tag{8}$$

The Long Short-Term Memory (LSTM) network used in this study follows a standard architecture commonly applied in time-series forecasting. The model consists of a single LSTM layer with 50 hidden units, followed by a Dropout layer with a rate of 0.2 to reduce overfitting, and a Dense output layer with one neuron to produce the predicted gold price.

This architecture is widely adopted in financial time-series prediction due to its ability to capture long-term dependencies while maintaining model simplicity and stability [6][7][15].

Evaluation Metrics

To assess the predictive accuracy of each model, five statistical indicators were used. All evaluation metrics were computed using the inverse-transformed predictions and actual values, ensuring that the errors are measured in the original price scale.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

Mean Squared Error (MSE) calculates the average squared difference between predicted and observed values. Smaller values indicate higher accuracy.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (10)$$

Root Mean Squared Error (RMSE) expresses the prediction error in the same unit as the target data, where lower values mean better precision.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (11)$$

Mean Absolute Error (MAE) represents the average absolute deviation between the predicted and actual values.

$$\text{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (12)$$

Coefficient of Determination (R2) indicates how much of the variance in the data is explained by the model. A value closer to one reflects stronger performance.

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (13)$$

Mean Absolute Percentage Error (MAPE) expresses prediction errors as percentages, with smaller values showing higher forecasting accuracy.

RESULTS AND DISCUSSION

Results

Table 3 presents the complete evaluation results for the three forecasting models developed in this study. The table reports five performance metrics, namely MSE, RMSE, MAE, R2, and MAPE, which are calculated using inverse-transformed predictions so that all error values reflect the true scale of daily gold prices.

Table 3. Model Performance Evaluation Results

Model	Dataset	MSE	RMSE	MAE	R^2	MAPE (%)
Pure LSTM	Train	188.6738	13.7359	9.3842	0.9952	0.69%
Pure LSTM	Test	304.5022	17.4500	12.9924	0.9431	0.72%
LSTM + Prophet	Train	182.2231	13.4990	9.4387	0.9954	0.69%
LSTM + Prophet	Test	5130.4538	71.6272	63.4906	0.0412	3.56%
LSTM + Sentiment	Train	189.0679	13.7502	9.5148	0.9952	0.70%
LSTM + Sentiment	Test	298.4896	17.2769	12.5515	0.9442	0.70%

Following the results summarized in Table 3, the Pure LSTM model demonstrates stable and accurate performance across both the training and testing datasets. Training results achieve an R^2 of 0.9952 and MAPE of 0.69%, while testing results achieve an R^2 of 0.9431 and MAPE of 0.72%. These results indicate strong generalization and effective capture of nonlinear short-term patterns in daily gold prices. In contrast, the Hybrid LSTM + Prophet performs well in training but poorly on testing, with MSE = 5130.4538, RMSE = 71.6272, and MAE = 63.4906. The low R^2 (0.0412) and higher MAPE (3.56%) indicate poor generalization and lower accuracy for volatile gold prices.

The LSTM + Sentiment model shows a modest but consistent improvement over the baseline model, with an MSE of 298.4896, and RMSE of 17.2769, and an MAE of 12.5515. The R2 increases to 0.9442 and the MAPE decreases to 0.70%. These results suggest that sentiment contributes additional market information that helps the model better capture subtle

variations in price movements, improving its predictive stability. Overall, the comparative results show that the Pure LSTM provides a strong baseline for forecasting daily gold prices, the LSTM + Prophet hybrid performs poorly due to structural incompatibility with the dataset, and the LSTM + Sentiment model offers the best generalization performance, albeit with moderate improvement.

Visualization of Prediction Results

To complement the numerical results presented in Table 3, Figures 3 – 5 illustrate the prediction patterns generated by each model on the testing dataset. These visualizations help verify whether the predictions follow the actual price movements of daily gold prices and provide additional evidence supporting the interpretation of the evaluation metrics.

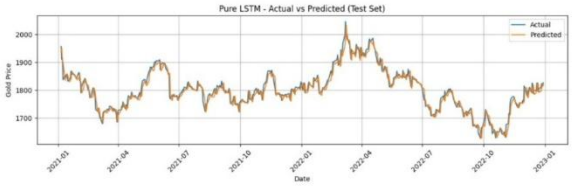


Figure 3. Actual vs Predicted Gold Prices Using Pure LSTM (Testing Dataset)

The prediction plot in Figure 3 shows that the Pure LSTM model is able to closely track the actual gold price trajectory during the testing period. This visual alignment is consistent with the low testing errors reported in Table 3, especially the RMSE of 17.4500 and MAPE of 0.72%. The figure confirms that the model effectively captures nonlinear temporal dependencies and produces stable short-term forecasts.

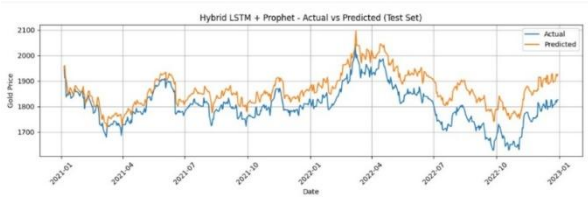


Figure 4. Actual vs Predicted Gold Prices Using Hybrid LSTM + Prophet (Testing Dataset)

Figure 4 shows that the predicted curve frequently diverges from the actual price movements, especially in periods of rapid fluctuation. These discrepancies visually reflect the high error metrics obtained during testing, such as an RMSE of 71.6272 and an MAE exceeding 63.4906. The figure also illustrates the structural limitation of Prophet in modeling non-seasonal, high-volatility financial data.

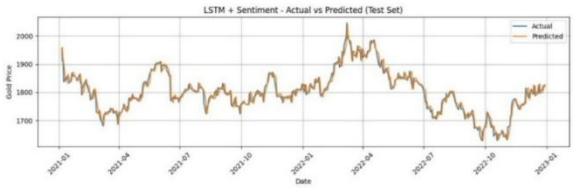


Figure 5. Actual vs Predicted Gold Prices Using LSTM with Sentiment Features (Testing Dataset)

Figure 5 shows that incorporating sentiment information improves the alignment between predicted and actual price. The model reduces the small lag observed in the Pure LSTM predictions. These visual improvements correspond with the lower RMSE of 17.2769 and MAE 12.5515, as well as the higher R^2 value of 0.9442 reported in Table 3. Although the enhancement is moderate, the figure confirms that sentiment adds useful contextual information that enhances short-term predictive stability.

Discussion

The results show that the Pure LSTM model provides strong and stable forecasting performance, as reflected by its low error values and high R^2 in both training and testing. This indicates that LSTM is capable of capturing nonlinear temporal dependencies present in daily gold price fluctuations, consistent with previous studies that reported strong performance of LSTM for financial time-series forecasting, particularly in volatile markets where linear models

tend to underperform [6][7][8]. The close visual alignment between actual and predicted values further confirms the model's ability to generalize effectively beyond the training data.

In contrast, the Hybrid LSTM + Prophet model exhibits substantially weaker generalization performance, as indicated by a sharp increase in testing errors and significant divergence in the prediction plot. Prophet's trend-based decomposition assumes smoother seasonal and trend structures, which are not dominant characteristics of highly volatile daily gold price series. Similar limitations have also been reported in prior comparative studies, where Prophet was found to perform less effectively than LSTM in datasets lacking clear seasonal components [15][16]. These results provide a clear empirical answer to RQ1, demonstrating that the hybrid approach does not improve forecasting accuracy compared to the Pure LSTM.

The LSTM + Sentiment model achieves the best overall performance, showing modest but consistent improvements across all evaluation metrics on the testing set. The improved alignment observed in its prediction plot suggests that sentiment information contributes additional contextual signals that reflect short-term market reactions to news events. This finding is in line with earlier studies that demonstrated the positive impact of sentiment analysis when combined with deep learning models for financial prediction tasks [11]. Although the improvement is not large, it is stable and measurable, providing a clear answer to RQ2 that sentiment-based features can enhance predictive accuracy when integrated with LSTM. Overall, the comparative results reinforce that LSTM-based architectures are well-suited for volatile financial time series, while Prophet-based hybrid models may be less appropriate when seasonal patterns are weak or inconsistent.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that LSTM-based models are effective for forecasting daily gold prices characterized by high volatility and limited seasonality. The empirical results show that the Pure LSTM model provides a strong baseline, while the integration of sentiment features yields a modest but consistent improvement in predictive performance. In contrast, the Hybrid LSTM + Prophet approach performs poorly due to structural incompatibility with the dataset. Based on these findings, future research may explore the integration of richer sentiment sources, alternative deep learning architectures, or multivariate inputs to further enhance forecasting accuracy. Additionally, future studies may investigate adaptive hybrid frameworks that dynamically select modelling components based on market conditions, ensuring better robustness across different financial time-series characteristics.

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